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A COMPREHENSIVE REVIEW OF MEDICAL IMAGING DATA USING DEEP LEARNING TECHNIQUES FOR CANCER DETECTION

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Abstract

Cancer remains a significant public health issue due to the uncontrolled growth of abnormal cells that can harm normal tissues. Early detection is vital for improving treatment outcomes and survival rates, yet over the past decade, more than 0.4 million new cancer cases were diagnosed, with over 0.17 million fatalities. Current diagnostic methods, such as CT, MRI, PET, ultrasound, and biopsies, often struggle to identify subtle signs of early-stage cancer and do not fully leverage the available data from medical imaging and histopathology. This research aims to summarize studies that use deep learning algorithms on medical imaging data for early-stage cancer diagnosis. By integrating diverse data types, including imaging and histopathology, we seek to empower clinicians with enhanced diagnostic tools that reduce false positives and negatives. Ultimately, the goal is to improve patient treatment options and survival rates. Addressing the challenges of early cancer detection and treatment remains crucial in modern medicine. The development of innovative diagnostic technologies has the potential to improve the effectiveness of cancer treatments, thereby reducing mortality rates associated with the disease. Traditional clinical diagnostic methods have had limited success in detecting early-stage cancers because of the early subtle nature of their manifestations. Using Deep Learning to analyze large volumes of medical images that are taken from patients diagnosed with many different forms of cancer to develop a system that will allow clinicians to take advantage of medical images to make an early diagnosis of cancer, thereby enhancing the quality of care for patients. This is a literature review of medical imaging modalities commonly used in clinics, including X-ray, CT, PET, and MRI, which are commonly insufficient to detect early-stage cancer using Machine Learning, and there has been limited research on analyzing Optical Coherence Tomography medical images in conjunction with a Hybrid Convolutional-Recurrent Neural Network.

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1.0 INTRODUCTION

Cancer in India is largely a result of genetic, environmental, dietary, and lifestyle factors. The way that people live their lives and what they eat may raise their chances of getting cancer. Programs for screening, vaccination, promoting healthy lifestyles, and increasing awareness about cancer, as well as improving access to health care, will all help lower rates of cancer diagnosis and death. Oral cancer has been ranked 18th among primary cancers worldwide, and there were 377,731 new cases and 177,757 oral cancer deaths in 2020 [1]. Skin, breast, leukemia, prostate, brain, lung, and esophageal cancers occur at high rates. It is predicted that there will be approximately 13.1 billion cancer-related deaths by 2030, making it the second-highest cause of death worldwide and affecting one out of ten people. The significant number of cancer deaths are the direct result of late-stage diagnosis, as such it is essential that patients are diagnosed early so they have good treatment options [2]. For these reasons, the use of medical imaging is critical for early detection, monitoring and assessing how effective treatments are. There are still many problems associated with medical imaging, as symptoms of the onset of cancer are often difficult to diagnose using non-invasive methods; as well as the large amount of complex medical data that is not being used to its full potential by traditional diagnostic tools [3].

In addition to exploring the deep-learning (DL) based detection method proposed by the authors, the purpose of this literature review is to provide an efficient, reliable, and scalable clinical tool to support clinicians in accurately identifying early-stage cancer, while reducing both false positive and false negative results, and subsequently improving the quality of life for cancer patients. Several studies have demonstrated that, through the application of DL [4] in conjunction with Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) and Transformers [5-6] as well as other architectures, it is possible to identify complex, nonlinear relationships between a large dataset of features and early-stage cancer signs or symptoms that are difficult to find using conventional techniques.

2.0 TYPES OF CANCER

Cancer is a group of many related diseases. It is characterized by abnormal cell growth. There are five basic types of cancer: carcinoma, sarcoma, leukemia, lymphoma, and myeloma. All cancers originate from different tissues and have similar traits. Understanding each type is necessary for an accurate diagnosis and successful treatment because of differences in behavior and responses to treatments.

i. Carcinoma: Carcinomas are the most common form of cancer and occur from epithelial tissues of the skin or lining of other organs. Examples of carcinomas include breast cancer, lung cancer, colon cancer, and prostate cancer [7-8]. These cancers are commonly associated with environmental factors (e.g., smoking, exposure to carcinogens) [8-11]

ii. Sarcoma: Sarcomas arise from the connective tissue, including bone, cartilage and muscle. They are less common than carcinomas [12]; however, they are aggressive and are typically treated with surgery [13- 16], radiation therapy [17-19], or chemotherapy [20-23].

iii. Leukemia and Lymphoma: Leukemias affect the blood cells causing excessive white blood cells [24]and lymphomas begin in the lymphatic system [25]. Both diseases can seriously compromise the immune system and overall health of an individual [26].

iv. Myeloma: Cancer can occur when uncontrolled cell division occurs; this can result from genetics, the environment, or an individual's lifestyle [26]. Cancer is not one disease; it is a group of diseases caused by a combination of genetics, the environment, and lifestyle [26]; therefore, there will continue to be a need for ongoing research and the creation of treatments that are specific to everyone who is diagnosed with cancer [26]. Because myeloma damages plasma cells in the bone marrow, it can lead to a variety of issues related to the production of normal blood cells [25-26].

3.0 DEEP LEARNING FOR MEDICAL IMAGE MODALITIES

Deep learning has transformed many of the most widely used imaging technologies in medicine: Magnetic Resonance Imaging (MRI), Computed Tomography (CT), Optical Coherence Tomography (OCT), and Positron Emission Tomography (PET), by significantly increasing both the quality of images and their ability to accurately diagnose a wide range of diseases [27, 28]. For example, it is now possible to use deep learning to improve segmentation, classification, and anomaly detection in MRI scans, and to improve reconstructed CT scans by removing noise and artifacts. In addition, deep learning can be applied to PET imaging to provide precise measurements of metabolic activity, which can be

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critical for diagnosing cancer and guiding its treatment [29-32]. Furthermore, there have been significant advances in the application of deep learning to analyze X-rays and diagnosed problems such as pneumonia and fractures [33-38], and deep learning has improved OCT's role in non-invasive imaging across multiple areas of medicine, including ophthalmology, cardiology, oncology, and dermatology [39-43]. Finally, deep learning has improved the segmentation of ultrasound images, enabling rapid tumor detection [44-47]. All of these examples illustrate the profound impact that deep learning has had across imaging modalities [48-52].

3.1 Magnetic Resonance Imaging (MRI)

Deep Learning Technology has dramatically improved the analysis of MRI images using techniques such as advanced image segmentation, automated diagnostic approaches, and predictive modeling [53-56]. Convolutional neural networks (CNNs) can identify patterns in MRI images by segmenting the images into meaningful portions [57-61]. Also, transfer learning allows fine-tuning pre-trained models for specific MRI tasks when labeled data is limited [62-65]. Moreover, radiomics uses deep learning to extract quantitative features from MRI images, which enhance diagnostic capabilities [66-69]. All these improvements are aimed at automating the diagnostic process so that radiologists' time will be dedicated more to patient care [70-72], as shown in Figure 1.

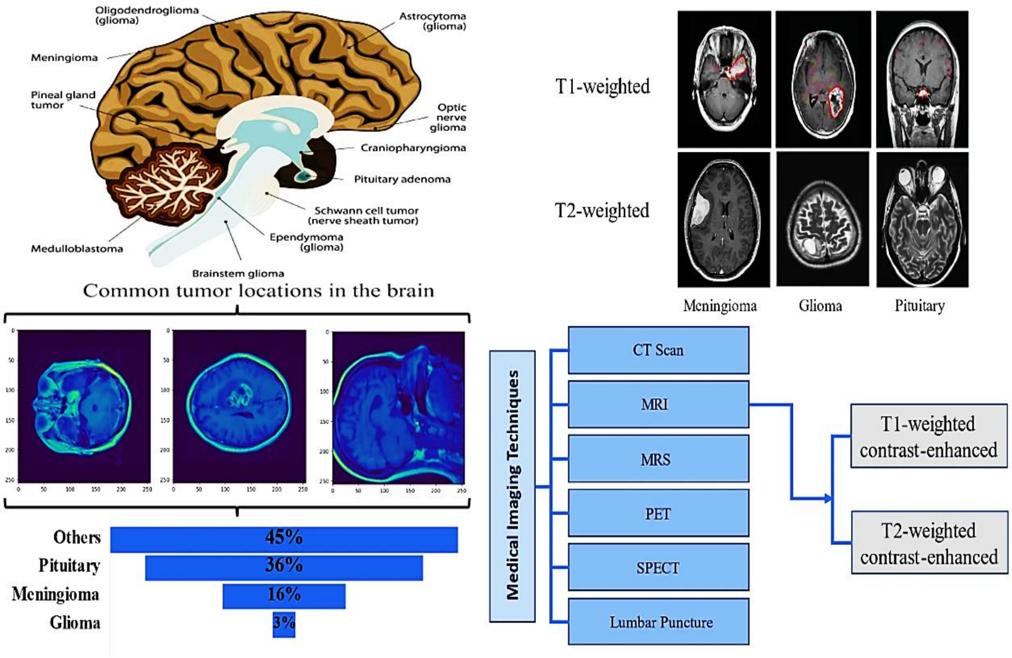

Figure 1: T1 weighted MRI based tumor classification using deep learning [72].

3.2 Computed Tomography (CT)

CT scans are an important tool for medical imaging, and they can be significantly improved by incorporating AI or deep learning (DL). Improved diagnostic speed and accuracy can be achieved through the application of DL to medical imaging, particularly CT scans [53-56]. However, there are significant barriers to using DL for image classification, segmentation, and disease detection, such as COVID-19 and cardiovascular disease [61-65]. Thus, the use of DL to analyze CT scans has the potential to transform how clinicians view and use CT scans; produce higher-quality images from CT scanners; enhance clinical workflow efficiency; and reduce patient exposure to ionizing radiation from CT scans.

3.2.1 Cardiovascular disease diagnoses

The predictive analysis capabilities of DL algorithms applied to CT scans will also provide increased accuracy of cardiovascular disease diagnosis [62]; and Customized Convolutional Neural Network (CNN) models have provided high levels of accuracy (up to 93%) in detecting COVID-19 from CT scans [37].

3.2.2 Low dose CT image restoration

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Deep learning (DL) algorithms are increasingly being used to enhance image quality of low-dose CT scans while minimizing patient radiation exposure [63] as DL technology evolves the need for large datasets highlighting the importance of standardized data preparation practices [66] in addition, overfitting and memory requirements complicate the use of deep neural networks (DNN's) [67-69] as AI technologies in medical imaging continue to develop ethical and regulatory concerns regarding patient data and high performance computing equipment will be a barrier to adoption [64, 65]; furthermore, poor data preparation can lead to unreliable results,

confidentiality must also be addressed future research could focus on developing efficient algorithms for image processing; promoting data sharing between institutions; establishing formal regulatory frameworks to ensure safe and responsible use of ai in healthcare [70-73].

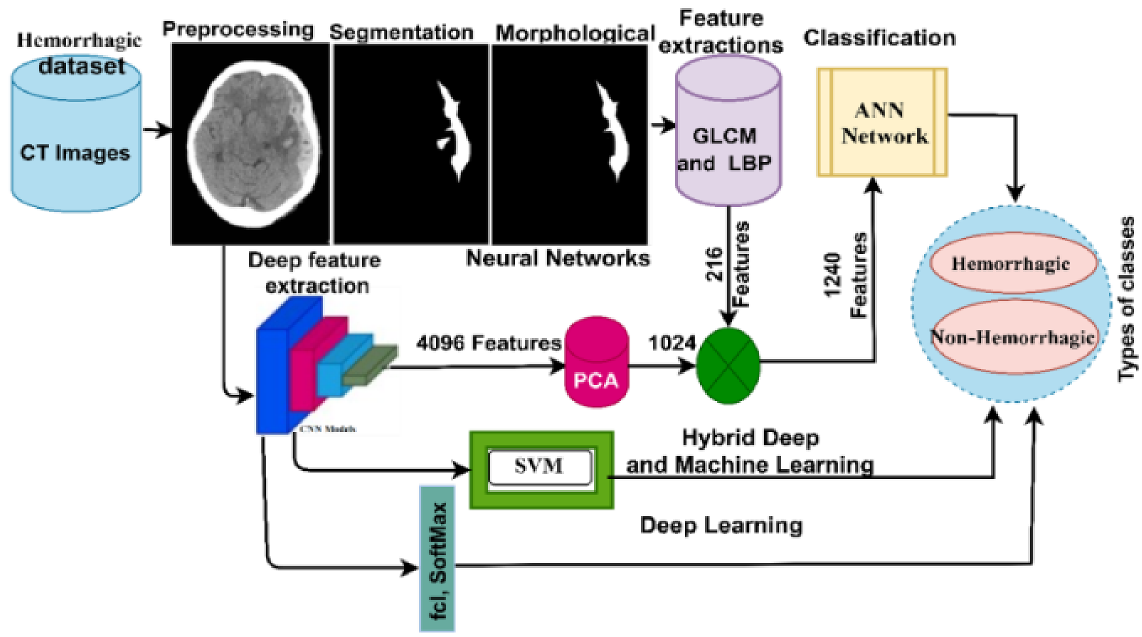

Figure 2: Example of CT image classification using DL technique [74].

3.3 Positron Emission Tomography (PET)

Through this synthesis of research, the authors have found that deep learning techniques are rapidly improving PET imaging diagnostics in oncology and neurology through improved image quality and automated processing, allowing for faster and more accurate diagnosis., as shown in Figure 3.

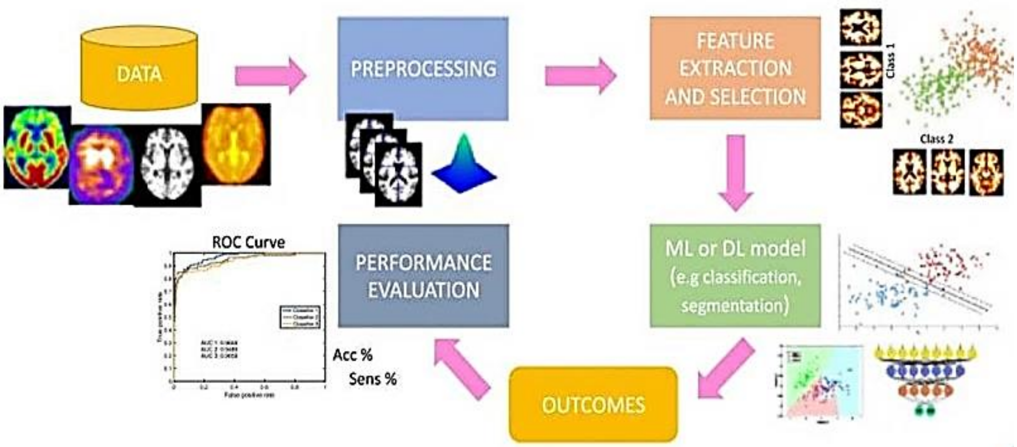

Figure 3. Application of deep learning in PET imaging [77].

The application of DL algorithms enhances the quality of PET scan images by filtering noise, increasing transparency, and improving clinicians' ability to interpret images [68, 70, 71]. The techniques can identify and segment tumors with to develop more transparent and interpretable DL algorithms [69]. Thus, future research should be directed toward developing DL algorithms that demonstrate greater accuracy in analyzing PET scans; exploring novel applications of multimodal imaging; and addressing the potential loss of human judgment associated with the use of DL algorithms in diagnostic settings.

3.4 Ultrasound Imaging

The use of ultrasound imaging is becoming greater accuracy than current methods. While there is substantial interest in utilizing DL algorithms to improve PET scanning, several issues remain as barriers to implementation, including limited availability of high-quality training data and the need increasingly prevalent for medical diagnostics, and it is utilizing a wide array of technologies, including but not limited to DL (deep learning) and PET. All these technologies can be utilized to create a high degree of synergy among themselves, which can further increase their diagnostic capabilities, while also improving the efficiency of workflow when they are used collectively; therefore, the development of these technologies represents significant advancements in the field of healthcare technology.

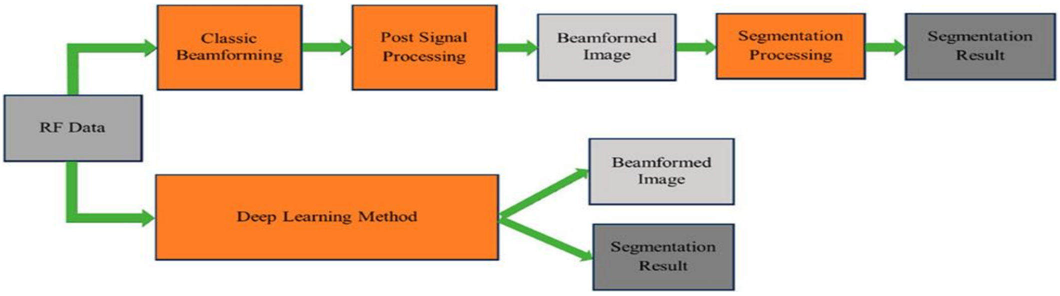

Figure 4. Deep learning in medical ultrasound.

It is a highly prevalent modality that is being utilized within several medical specialties (such as Obstetrics, Cardiology, and Emergency Medicine) for imaging organs in real-time. It assists in both the diagnosis and treatment of patients [76,77]. In addition to diagnostic capabilities, there are therapeutic uses of ultrasound, such as breaking up kidney stones. By incorporating AI into ultrasound systems, it is anticipated that image quality will be enhanced, diagnostic support will be increased, and efficiency of the workflow process will be increased. Operator variability will decrease [78]. Furthermore, by integrating ultrasound with PET, additional diagnostic information will be obtained which can be especially beneficial for diagnosing cancer [79]. Enhanced image classification and segmentation using DL on ultrasound images will provide more accurate diagnoses [80]. Challenges still exist regarding how to validate DL algorithms in multiple clinical environments, as shown in Figure 4.

3.5 Optical Coherence Tomography (OCT)

OCT is an imaging modality which is becoming increasingly important for the diagnosis and treatment of retinal conditions. The combination of OCT and DL enhance the ability to interpret images of OCT scans through improved diagnostic accuracy and improved workflow efficiency. In this article we reviewed how OCT can be utilized, as well as the advantages of utilizing OCT in combination with DL. OCT may also serve as a tool to identify esophageal cancer at an early stage and is typically most useful when combined with other imaging modalities. As OCT provides a high-resolution 3-Dimensional representation of tissue structure and morphology, it can detect pre-cancerous states, such as Barrett's esophagus and early-stage cancers. The use of NIRF in conjunction with OCT improves the sensitivity of OCT in detecting dysplastic lesions and tumor margins [38-40]. The applications of Optical Coherence Tomography include oncology and otolaryngology, as they illustrate the medical imaging applications of OCT [37] and allow for accurate assessment of disease [38].

Advancements in OCT using deep learning techniques

a) DL has made major advances in OCT Image Classification for the diagnosis of AMD, especially when there is no prior knowledge of the disease [39, 41].

b) For segmentation and prognosis, DL can segment the retina and predict the development of the disease, which will allow clinicians to make better decisions [39].
c) Clear Resolution Imaging, OCT allows for sub-cellular imaging; therefore, it provides a very clear picture of the tissue structures of the eye and is crucial for the detection of early malignancies [38].

d) Improvement in Molecular Imaging, OCT combined with NIRF imaging provides a means to visualize biological processes at a cellular level and improves the precision of diagnoses [42].
e) Evaluation of Tumor Margins, Polarization-Sensitive OCT has shown promise in evaluating tumor margins, which will help in determining the best course of treatment and surgical planning [40].

f) Future Direction and Challenges: While the use of DL in OCT shows much promise, there are still many challenges to be addressed before these technologies can be used in real-time in clinical settings, such as developing more robust models and increasing the size of the training dataset [41].

Despite the potential advantages of combining DL and OCT in medical imaging, some challenges could limit the widespread adoption of OCT in clinical settings, including the requirement of molecular contrast agents to improve specificity, as well as the need for trained personnel to interpret OCT images, and the potential for variability in image interpretation to impact diagnostic outcomes [42].

3.5.1 CNN-DL technologies in medical imaging

Convolutional Neural Networks (CNNs) are specifically designed deep learning models intended for processing information with a topological structure (grid-like); they have become primary tool in many fields, particularly in the domain of medical imaging.

A). Architecture and applications

A typical CNN architecture consists of several fundamental layers, as shown in Figure 5:

i. Input Layer: Accepts the raw pixel data from an image, which is generally represented as a multi-dimensional array.

ii. Convolutional Layers: Apply a group of trainable filters (kernels) to identify local characteristics, such as edges, texture, and patterns. Each filter convolves throughout the input volume to produce a feature map representing certain characteristics at specific spatial positions [4].

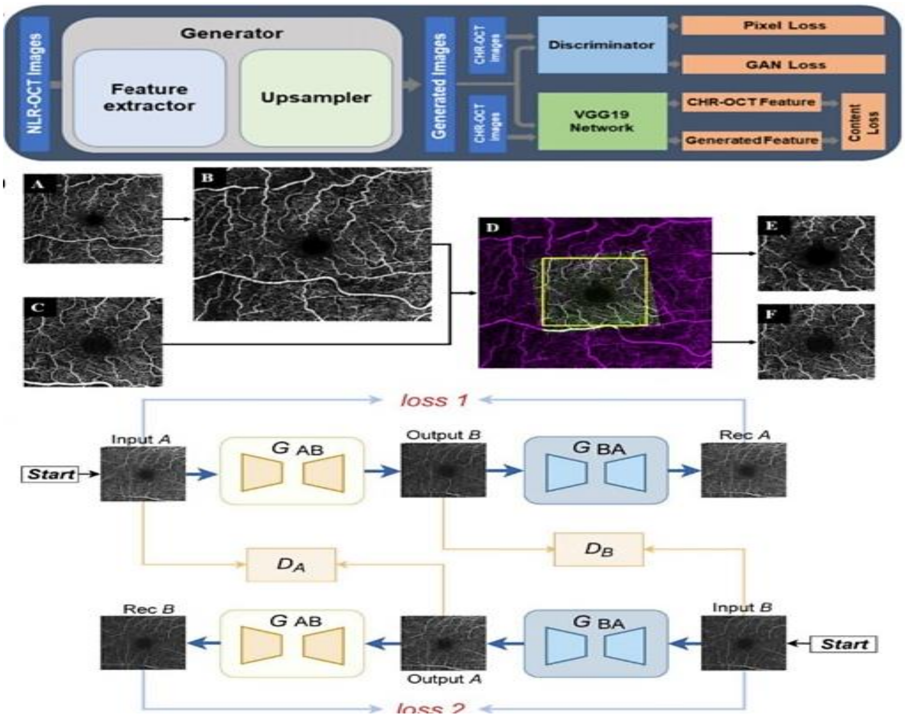

Figure 5. Example of OCT image using DL based approach [78].

iii. Activation Functions: Introduce non-linearity into the model, which permits it to identify complex relationships. ReLU (Rectified Linear Unit) is frequently utilized [4]; it is defined as:

$$f(x) = Max.\ f_0\ (0,x);\ f(x) = \max.\ (0,x);\ f(x) = \max.\ (0,x) \quad (1)$$

iv. Pooling Layers: Down sample the spatial dimensions (width and height) of feature maps by applying down sampling operations and reduce the dimensionality of feature maps and prevent overfitting. Max-pooling, which identifies the maximum value in each pooling window, is a common method.

v. Fully Connected Layers: High-level reasoning within a neural network occurs through fully connected layers, after multiple convolutional and pooling layers. These layers accept the flat output from the preceding layers and provide a vector of class probabilities or, in the case of segmentation tasks, a reshaped output that matches the original input dimensions [4, 8].

vi. Output Layer: Produces the ultimate prediction. In classification tasks, this is typically a SoftMax layer that produces probabilities for each class. For segmentation tasks, it produces a pixel-wise classification map [7].

B). Transfer learning:

Transfer learning in deep learning, as described above, represents the practice of utilizing a pre-trained neural network (usually trained on a large dataset/task) and applying it to another, similar but differing, task. The use of pre-trained networks can greatly improve your performance by leveraging learned weights, feature representations, and architectures, allowing you to quickly train deep models using much less data/computation than would be needed otherwise [4, 5]. A pre-trained network, usually trained on a large dataset (i.e., ImageNet), can be utilized for tasks such as disease classification, segmentation, and anomaly detection in medical images (e.g., X-rays, CT scans, MRIs) [9]. (Transfer learning has been extensively applied in the medical image analysis area to resolve issues such as limited labelled medical data; the cost of annotating data by medical professionals; and the necessity of developing high-performance models for many critical applications (e.g. cancer detection) [8]. Additionally, combining Transfer Learning and CNNs has increased diagnostic accuracy. An example of this is demonstrated in the article referenced above where the authors were able to achieve an accurate rate of 95.2% in the diagnosis of medical images using pre-trained models (VGG16 and ResNet) versus 85.3% using traditional methods [9]. Furthermore, in the classification of pneumonia X-ray images, researchers were able to demonstrate that real-world feature transfer learning was superior to traditional training methods; thus, further validating the effectiveness and robustness of using general purpose pre-trained models [79].

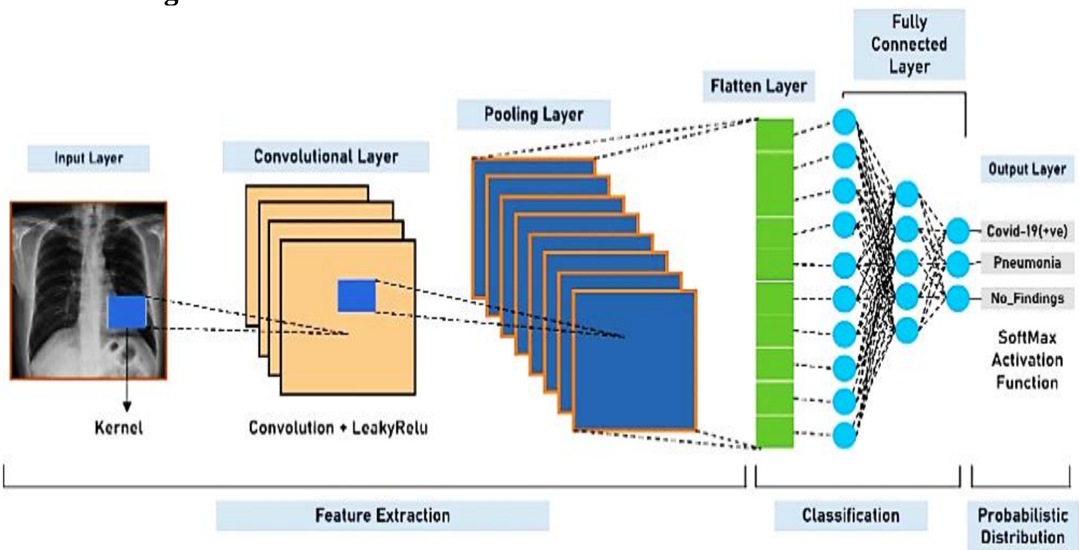

Figure 6. A standard architecture of convolutional neural network [79].

3.5.2 `Recurrent neural network (RNNs):

Recurrent Neural Networks (RNNs) are a specific type of artificial neural network developed specifically to work with sequential data using an internal state that enables each node to "remember" previous input values. They are successfully applied in areas such as natural language processing, speech recognition, and time-series forecasting. They have difficulty with long range dependency as well, mainly due to the vanishing gradient issue. The vanishing gradient problem has been solved with newer models to address the vanishing gradient problem, including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models that improved the memory retention of the RNN, and consequently decreased the effects of the vanishing gradient problem.

i) Architecture and applications

The areas of segmentation and classification of medical images can be evaluated with Recurrent Neural Networks (RNNs); however, RNNs have demonstrated success in medical imaging, particularly in finding temporal and hierarchical patterns within large datasets. Therefore, RNNs are an effective method to assess the complexity of medical images. Moreover, the increased accuracy of image segmentation provided by RNNs provides a greater ability to identify anatomical structures and pathologies in medical images. In addition, the following section(s) will include additional information on the architecture and applications of RNNs in medical image analysis and the applications of RNNs in medical image analysis [11].

ii) Architecture of RNNs in medical image analysis

Hierarchical representation: RNNs can identify low- and high-level representations of medical images, thereby providing a holistic representation of medical images [14]. *Multi-Scale Techniques*: Multi-Scale RNNs (MS-RNNs) utilize multiple CNN and RNN layers to analyze medical images at different resolutions, since resolution plays a significant role in achieving accurate classifications [13]. Graph-Based Input Data: Recent advancements include utilizing graph-based input data to RNN-based segmentation methods to increase the models' ability to capture the complex relationships between data points in medical datasets [10], as shown in **Figure 7** [80].

iii) Applications of RNNs in Medical Images

a) Automated Anatomical Segmentation with RNN**s:** RNNs can also perform automated anatomical segmentations (i.e. organs, tumors), which can potentially increase the reliability of diagnoses [15] and automate the anatomical segmentation process that is laborious and requires a high level of technical expertise [17].

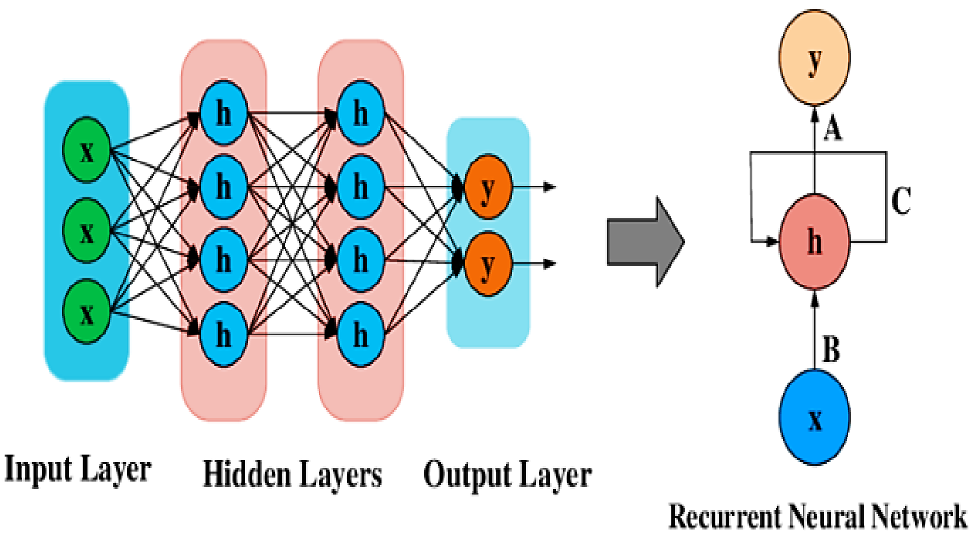

Figure 7. A simple example of a recurrent neural network [80].

b) Temporal analysis of disease progression: RNN's can temporal analysis of image sequences taken of patients over time; this will allow clinicians to better understand disease progression and ultimately provide the best possible care for their patients [15].

c) Automatic segmentation and classification: RNN's will perform many segmentation and classification tasks automatically, thereby decreasing the amount of work for healthcare professionals, enabling them to quickly make overcome before they can become useful tools in the clinic. For example, there is a significant need for large amounts of high-quality data with extensive annotations, and significant computational power is required to train these types of models. Thus, future studies could examine ways to overcome these challenges to increase the usefulness of RNNs in clinical medicine.

3.5.3 Generative adversarial network (GANs)

Generative Adversarial Networks (GANs), represent another major advancement in deep learning and have been shown to be particularly useful in medical image analysis. A GAN consists of two deep learning networks; one network called the generator, creates synthetic images while the second network called the discriminator determines whether the synthetic images created by the generator are accurate. The competition between the generator and the discriminator causes both networks to get better at creating and determining the accuracy of the images created by the generator, as depicted in **Figure 8** [81]. Therefore, GANs are beneficial for a wide range of applications in the medical field. Below are the primary characteristics of GANs in medical image analysis.

decisions [14]. Although there are some exciting opportunities for RNNs in medical imaging, there are also several challenges that need to be

4.0 MEDICAL IMAGE SEGMENTATION

i. Methods & approaches

The purpose of medical image segmentation is to provide a detailed outline of anatomic structures and pathologic areas for use in the diagnostic and treatment-planning process in medicine. The role of image segmentation in medicine has developed significantly because of advances in computer-based algorithms and deep-learning that have enhanced both accuracy and speed of segmentation with different imaging modalities, e.g., MRI and CT scans. Machine-learning based segmentation approaches have been widely adopted instead of many traditional segmentation methods including thresholding and region growing. CNNs and their variants, such as U-net and FCN, have addressed most complex segmentation problems in medical images. Some of the major characteristics of segmentation methods (see Figure 9) used in medical imaging include: a) Traditional segmentation methods use thresholding and/or region growing which are very fast and easy to compute but suffer from low accuracy due to sensitivity to image noise and variations in intensity levels. b) Conversely, Active Contour Models and Edge Detection Models are designed to find boundaries, however, both struggle with images having poorly defined boundaries [21, 22].

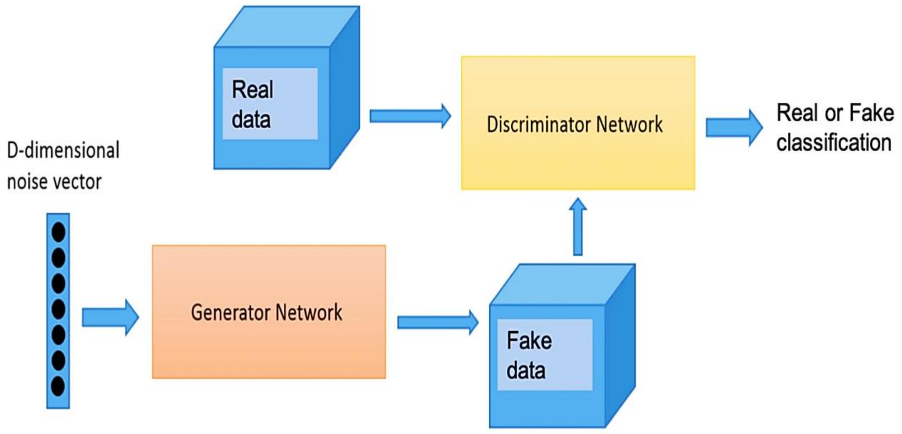

Figure 8. A sample example of GAN architecture for medical imaging. The figure shows the generator and discriminator networks' respective inputs and outputs [81].

ii. Machine learning and deep learning methods

Convolutional Neural Networks (CNNs), especially U-net and its variants, are currently considered state-of-the-art for medical image segmentation because of their ability to learn hierarchical spatial information and recognize subtle patterns [22, 23]. Transformer-based models, i.e., Trans UNet, have shown potential for using global context information, however they are computationally expensive [23]. Hybrid approaches combining machine learning and artificial intelligence with traditional methods are also being investigated to improve segmentation accuracy and reliability [22].

iii. Clinical Implications and Future Directions

a) Applications in oncology and cardiology: U-net based methods help to delineate tumor boundaries and assess coronary artery disease, thus helping to increase the accuracy of diagnosis and improve treatment planning [24].

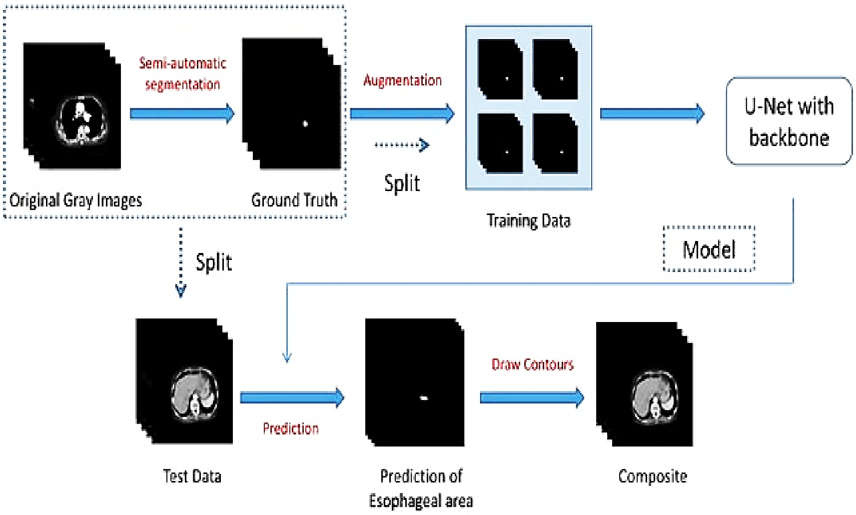

Figure 9. Schematic of segmenting the esophagus [82].

b) Challenges and innovations: Class imbalance and high computational complexity of algorithms are still major concerns. Next steps include the integration of multimodal data, and self-supervised learning techniques [22]. There are many advantages of the application of deep learning techniques in medical image segmentation. However, there are still many challenges associated with variability of medical images and noise. New approaches, including data augmentation and transfer learning, provide possible solutions to support improvement of diagnostic methods and individualized treatments of patients, and therefore lead to better patient outcomes [24].

iv. Image Classification

a) Techniques and approaches: Classification of medical images is important for medical diagnostics and treatment because it uses different methods to improve the accuracy and reliability of classifications. Research into deep learning models, data augmentation, and transfer learning has been done recently and greatly improved the results of image classifications, as depicted in Figure 10. The next few sections describe the main methods used for this.

b) Deep learning techniques*:* CNNs can identify features in images automatically, providing great improvements in diagnostic accuracy [26, 27]. Vision Transformers have emerged as an alternative to CNNs [27] and have shown them to be effective at processing complex image data.

c) Data augmentation and denoising*:* generative adversarial networks (GANs): Used for image denoising and for creating synthetic data, GANs improve the quality of the training data, and consequently improve the classification results [26].

d) Data augmentation techniques*:* Provide a method for reducing the problems created by limited data sets and allow for more reliable training of the models [26].

v. Transfer learning

Deep Transfer Learning uses pre-trained models for medical image classification [25], enhancing results despite limited datasets. Deep learning has made tremendous progress about reconstructing images of all types across many different imaging modalities which has resulted in higher diagnostic accuracy and lower costs [80, 81]. The use of autoencoders and CNNs have shown potential for both image

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denoising and super-resolution, specifically with respect to medical imaging modalities. A major advantage of deep learning is its ability to efficiently process large data sets yielding results that are both robust and highly generalized, providing a cost-effective alternative for clinical applications [82, 83], as depicted in Figure 10.
Another Medical imaging also includes a significant portion of the Three-Dimensional Reconstruction of Medical Images through 2D Scanning Signals. The various mathematical techniques utilized for reconstructing a 3D medical image from a 2D scanning signals include the Marching Cubes method and the Poisson Surface Reconstruction method [30]. In addition to providing an increase in the number of fields of research and surgical planning, these mathematical techniques have provided additional advantages with respect to reduced artifacts and increased computational efficiency. Both factors contribute to a correct diagnostic assessment [30-32].

vi. Applications and future directions of medical imaging

Image Reconstruction is an important part of many Medical Imaging Applications (including tumor detection and disease prediction) that minimize the amount of radiation patients are exposed to during imaging procedures [31]. Although advancements have been made within the area of image reconstruction, many issues continue to exist, such as optimizing the training data for Deep Learning Models to increase the quality of image reconstruction, and integrating them into standard clinical practice [29], as shown in Figure 11.

vii. Image registration

a) Approaches & techniques: Image registration in medical imaging is an important process that involves matching two or more images of the same area to show how they differ with time or location. By registering these images, it helps clinicians to understand medical data and thus improves diagnosis and treatment of patients (as shown in Figure 12). These methods can also be classified by technique as described below.

b) Approaches to image registration: Methods used in area-based Registration are: a) Intensity-based registration: The intensity-based method utilizes pixel intensity to identify corresponding areas of images based on intensity and normally employs Sum of Squared Differences (SSD), and other metrics such as Mean Square Error (MSE) as optimization metrics [33] b) Spatial domain transformation: Spatial domain transformation involves both rigid and non-rigid spatial transformations of images for registering images [34].

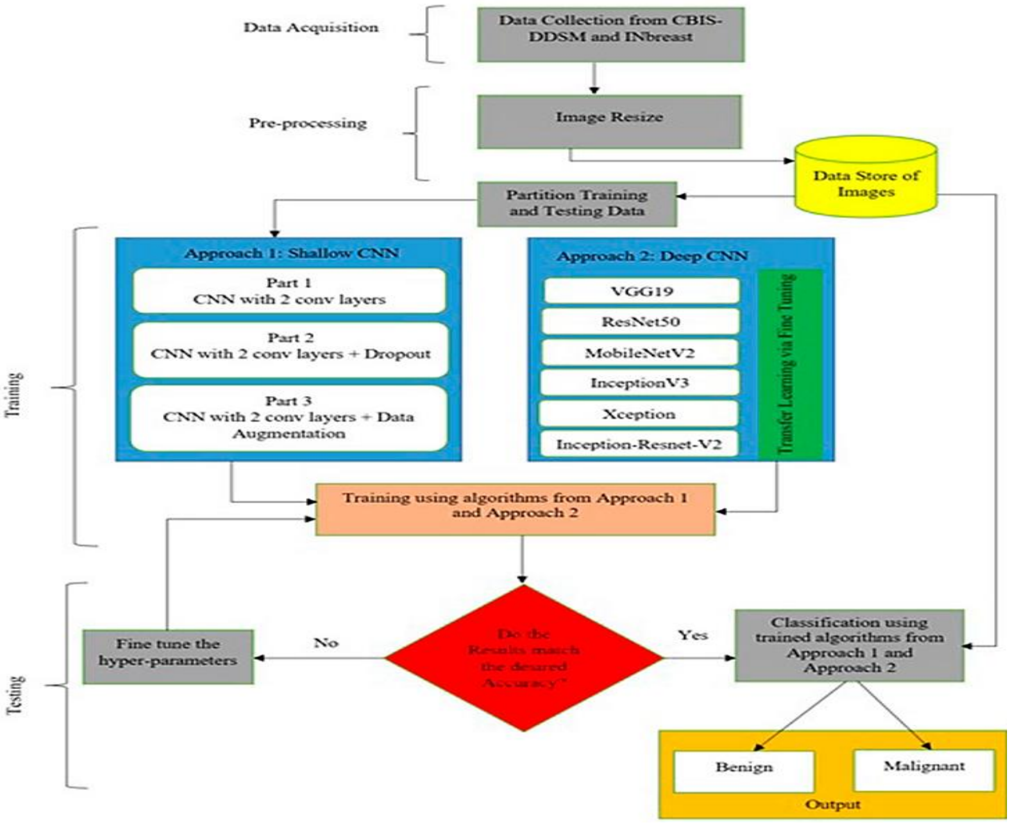

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Figure 10. Architecture of classification of breast cancer [83].

Feature-based Registration methods include: a) Key Point Detection and Matching: Matches corresponding features/points of interest in images by detecting key point detection and matching with algorithms such as Scale Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF) [33]; b) Atlas-based registration: Registers images against a pre-defined template which can be beneficial when registering images that contain anatomical correspondence [35]; c) Deep learning techniques: Utilize neural networks to improve speed and accuracy of registration; however, deep learning requires large amounts of training data and significant computational resources which can limit their application in certain clinical environments [35].

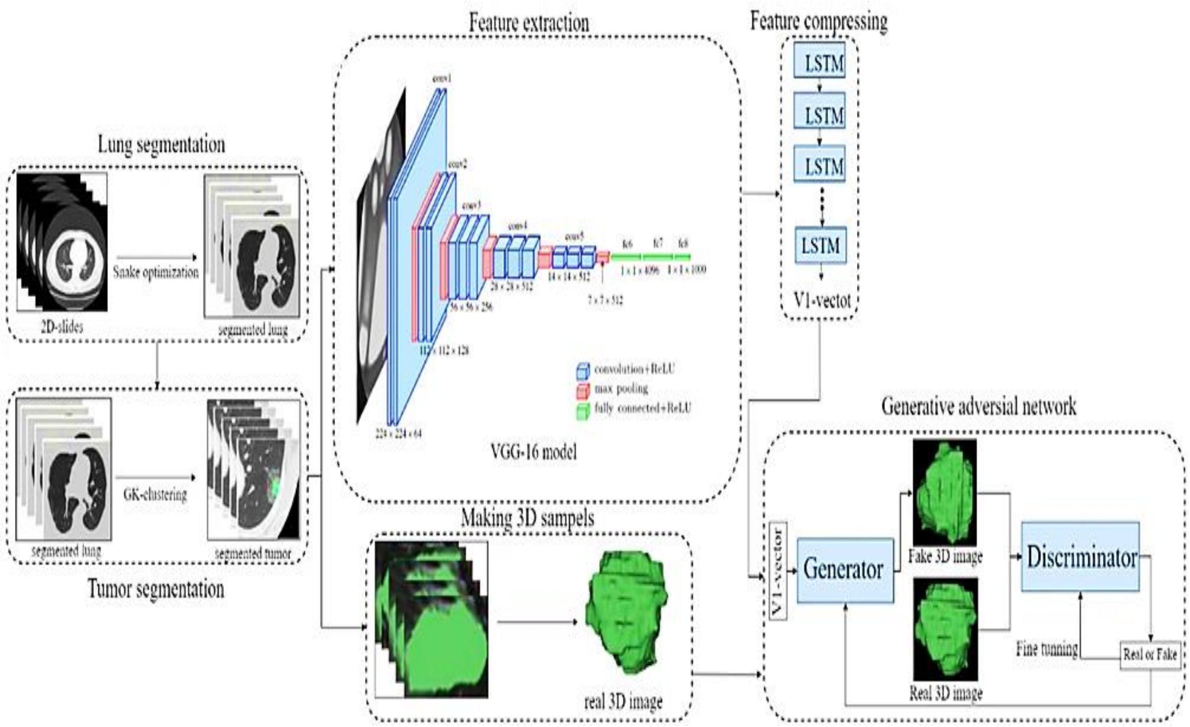

Figure 11. A GAN based method for 3D lung tumor reconstruction [84].

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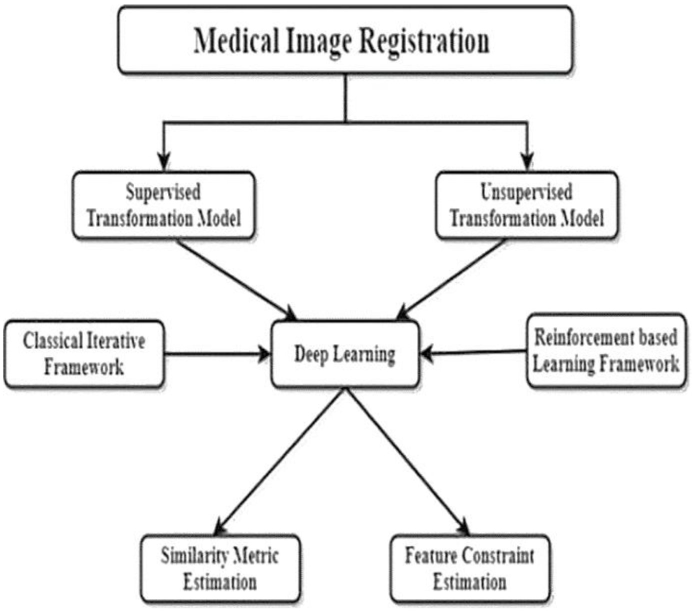

Figure 12. Diagram of medical image registration [85].

5.0 ASSESSMENT METHODS AND DATASETS AVAILABLE

The evaluation of deep learning (DL) techniques in medical imaging is essential to validate their applicability, efficacy, and reliability. In this context, numerous performance metrics have been developed to assess DL model performance and provide insights into their robustness. Therefore, these metrics enable comparison between various studies and provide the means for improvement of DL techniques.

5.1 Main Performance Evaluation Metrics

- Accuracy: The accuracy of a model represents the proportion of correct answers given by the model. Thus, it provides a general idea of how well a model performs [36-44].

- Sensitivity & Specificity: Sensitivity measures how well a model identifies cases when they exist. Specificity measures how well a model avoids false positives/False Negatives [43].

- F-score: A Harmonic Mean of Precision and Recall; therefore, it provides a measure of the Balance between True Positives and False Positives / False Negatives [44].

- Dice Similarity Coefficient and Jaccard Index: These provide methods for comparing the Overlap between Manually Annotated or Reference Segmented Areas of Interest and the Areas of Interest that have been segmented by a Deep Learning Model [43].

- Robustness and Generalizability: Measures of How Well the Model Performs Across Multiple Data Sets and Conditions. This is essential to ascertain that the model will perform reliably in all possible clinical environments [44].

The statistics used to assess the performance of deep learning (DL) techniques in medical imaging may contain some degree of statistical bias; therefore, there is a requirement to standardize the evaluation metrics so that the assessment of DL techniques is based on reliable criteria [43]. Medical Imaging has been advanced by DL techniques with respect to improved performance in many tasks including registration, segmentation, and classification. However, the performance of DL techniques varies by task and are typically assessed via specific metrics and benchmark datasets. The following summary compares the results from several scientific literature sources regarding DL techniques in the medical image analysis domain.in this field.

5.2 Medical Image Registration

DL-based registration methods can be grouped into seven categories, each of them having lung and brain deformable registration benchmarks. These methods are primarily assessed based on their capacity to manage difficult deformation and their speed of computation [45].

5.3 Medical Image Segmentation

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have surpassed traditional

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methods in segmentation tasks, with U-Net demonstrating superior performance over SegNet for organ segmentation [46, 47]. Generative Adversarial Networks (GANs) enhance segmentation networks by pre-training them, especially beneficial for small datasets, as GANs produce realistic images that aid in training [47 - 49].

5.4. Image Recognition and Classification

ResNet and DenseNet architectures demonstrated greater performance than the others in tasks such as tumor detection and disease classification in image recognition. Transfer learning and ensemble techniques have successfully increased the classification accuracy; accuracy, precision and recall were the most used evaluation metrics [47].

5.5 Image Fusion and Compression

DL-based Medical Image Fusion (DLMIF) uses the features of a CNN to improve the quality of the images generated from the fusion process through metrics such as SSIM and PSNR. It is superior to classical methods when generating high-quality diagnostic images [48]. Although DL has shown significant advancements in medical imaging, it still faces many obstacles including the need for large amounts of annotated data and the need for processing power. The integration of DL with traditional methods could potentially increase performance and alleviate some of the present limitations in medical imaging.

6.0 PUBLICLY AVAILABLE DATASET AND COMPETITIONS

It has driven the advancements made in DL (deep learning), particularly in medical imaging. These sources provide the needed data to train models and create an innovative space through collective challenges.

i. Publicly Available Datasets

Varied Resources: A collection of images, MedImg contains more than 1.6 million images from 103 different datasets that include the use of multiple imaging techniques (CT, MRI etc.) and the use of multiple organs (lung, brain etc.) [49]. Comprehensive Listings: Systemic listings, such as the one created by researchers' group roughly 300 datasets into distinct medical categories, making it easier for researchers to find datasets relevant to their area of interest [50, 51].

ii. Challenges and Competitions

Evaluation Standards: Platforms such as the Learn2Reg challenge have provided a forum for the evaluation of many registration algorithms against each other for a variety of registration tasks; this will aid in the establishment of standards for the comparison of methods [52].

iii. New Innovative Methodologies:

Competition is shown to be able to result in new and better methodologies through the competitive decoupling framework for semi-supervised segmentation as demonstrated through the limitation of current methodologies [53, 81].

Although publicly available datasets and competitions provide an important resource for the progression of DL in medical imaging, there are still barriers to overcome. Barriers include the quality of annotation of datasets and the ethics involved with the utilization of datasets. However, the collaboration of individuals and organizations participating in competitions and creating publicly available datasets will continue to drive advancements in the field.

7.0 ETHICAL CONSIDERATIONS FOR USING DL METHODS

Many The ethics of using Deep Learning (DL) methods are influenced by factors such as bias, transparency, and patient autonomy. Here are the key ethical considerations

7.1 Bias in Algorithms

The learning of deep learning (DL) models will reinforce the same biases that exist in the data used for training and therefore may produce a disadvantageous outcome for certain groups of individuals when using DL-based HR platforms for hiring purposes and a hospital may provide different levels of care based on patient demographics as an example of biased treatment.

7.2 Lack of Transparency in DL Systems

Deep learning models typically act as a "black box" so the decision-making process of the model cannot be understood and the need for increased transparency to increase accountability [55, 82] and increase compliance with ethical requirements [54] must be realized.

7.3 Privacy Issues with DL Systems

Using personally identifiable information (PII) in sensitive areas of healthcare creates privacy concerns

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[55] and many DL-based tools do not comply with regulatory frameworks such as GDPR, creating a necessity for increased governance to protect against misuse [54].

7.4 Bringing DL into Clinical Workflows

Successful incorporation of DL into clinical settings will create increased diagnostic accuracy and workflow efficiencies [56, 83]. Tools such as GaNDLF aid in the incorporation of DL into clinical environments through facilitating reproducibility and multimodal functionality [57, 84].

7.5 Technical Considerations for Integrating DL

DL models can be introduced into existing clinical workflows, e.g. PACS, to support real-time testing and to improve data management in clinical trials [58, 85], providing the potential to support decision-making and reduce redundant efforts [59, 86].

8.0 FUTURE DL IN MEDICAL IMAGING

There are many advantages to deep learning (DL) when applied to medical imaging. The advantages of using DL provide both a technical and clinical advantage over other forms of image processing. There are also several disadvantages to using DL in clinical environments. Some of the disadvantages include the integration of DL into existing clinical workflow processes and training programs, and resistance from clinical personnel to utilize DL [60-65]. While there are those who believe that the advantages of DL provide greater benefit than the disadvantages [66-68], there will be no long-term benefits to the use of DL unless there is an ongoing dialogue and ethics review regarding the continued use of DL. This includes, but is not limited to, the risk of unauthorized access to patient data, as well as the requirement of adequate training data. For DL to be accepted by the clinical community, the above-mentioned issues must be addressed, stakeholders must work collaboratively, and formalized ethical guidelines must be established for the utilization of DL in a clinical environment [69, 70]. There are numerous ways that DL can be utilized to improve the quantity and quality of medical images; specifically, seven areas have been identified that can potentially have a significant impact on the quality and quantity of medical images [70-86].

- Development of more powerful and accurate DL models.
- Improved interpretation and explanation of DL models.
- Automation of medical image analysis.
- Facilitation of personalized medicine.
- Addressing ethical concerns surrounding DL.
- Collaboration between stakeholders.
- Exploration of additional DL applications in medical imaging [81-86].

9.0 CONCLUSION

Deep learning (DL) DL may represent a new and exciting approach toward early detection of cancer using multiple types of medical data (i.e., images, clinical documentation, genomic data).
The following represents some of the key points from this study:

- DL models have demonstrated a high degree of accuracy in identifying the presence of early-stage malignancies using pattern recognition, at times higher than traditional clinical diagnostic approaches.

- Bearing in mind the promising results obtained in much research-based studies, additional challenges such as model portability, model interpretability, and model incorporation into clinical workflow processes must be addressed.

- Addressing Solving the issue of data heterogeneity will improve model clarity, model portability across different population groups and imaging modalities, and will increase model applicability across multiple environments. Models such as federated learning, multimodal data fusion, and explainable AI will increase the reliability, and the clinical value of AI based systems.

- The lack of available medical imaging data in studies regarding early cancer detection was identified as an area of concern; specifically, OCT imaging data used with hybrid machine learning techniques was one type of data lacking in most of these studies to aid in the identification of potential cancer symptoms.

Overall, the ability of DL to provide clinicians with the tools necessary to identify cancers at an earlier stage, which will lead to better outcomes for patients and improved burden on the healthcare system.

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