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A Comprehensive Analysis of Neural Network Techniques in Medical Image Processing

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Abstract: Deep learning techniques have a significant role in analyzing medical images. In this survey, we have studied many recent research papers based on medical images using deep learning techniques. We have searched the research papers using queries (deep learning OR convolution OR neural) AND (medical OR MRI OR CT OR TOMOGRAPHY OR X-RAY) through IEEE Xplore and PubMed. Many medical imaging tasks, such as classification (image/exam classifications and object/lesion classifications), detection (organ, region, landmark localization, and object/lesion detection), segmentation (organ, substructure segmentation, and lesion segmentation), and registration have benefited from the application of deep learning techniques. We have provided the survey overview based on the application areas like cardiac, abdominal, brain, breast, and chest. We surveyed to show different medical images used in deep learning. We summarized this as discussing open challenges and ways for upcoming research.

Keywords: Lesion segmentation, Medical Images, Survey, CNN

I. Introduction

Various diseases can be diagnosed and treated more effectively because of medical imaging. Medical imaging increasingly uses deep learning methods, a subfield of AI, because of the field's rising recognition of the field's greater potential to analyse and comprehend huge volumes of complex data. The capacity of deep learning algorithms to identify patterns and abnormalities that human observers would have missed is a key advantage of its use in medical imaging. For example, deep learning algorithms can accurately detect and classify tumors in medical images, aiding in the diagnosis and treatment of cancer.

Deep learning techniques can also be used for image segmentation, which involves identifying and separating different structures within an image. It is instrumental in medical imaging for identifying and segmenting organs or blood vessels. In addition, deep learning algorithms may be taught on massive medical imaging datasets to enhance the precision of automated diagnosis tools. As a result, it may lessen the strain on medical personnel while also enhancing patient outcomes. When applied to medical imaging, deep learning algorithms can boost diagnostic precision and treatment efficacy, eventually saving lives.

Deep learning techniques in medical imaging are crucial as they enhance diagnostic accuracy and treatment effectiveness by identifying patterns and abnormalities that might be missed by human observers. The utilization of these advanced methods has shown significant potential in analyzing complex medical data, leading to their increased adoption in the medical imaging domain. Studies have demonstrated the effectiveness of deep learning algorithms in tasks like breast cancer detection, brain tumor segmentation, and diabetic retinopathy classification, showcasing their versatility in improving healthcare outcomes. The application of deep learning algorithms in medical imaging has resulted in cutting-edge outcomes, with deep convolutional neural networks being used for identifying lymph node metastases, displaying the continual advancements deep learning brings to the medical field.

A. Research Problem

The research problem addressed in the paper focuses on the utilization of deep learning techniques in the field of medical imaging.

The study aims to explore how these advanced methods can enhance various medical imaging tasks such as classification, detection, segmentation, and registration.

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By surveying many recent research papers, the paper delves into the specific applications of deep learning in medical imaging across different areas like cardiac, abdominal, brain, breast, and chest imaging.

The primary objective is to discuss the benefits and challenges associated with incorporating deep learning algorithms into medical imaging practices, thereby identifying areas for further research and development.

B. *Objectives of the Study*

The study aims to investigate the applications of deep learning techniques in medical imaging tasks such as classification, detection, segmentation, and registration.

It seeks to provide an overview of how deep learning methodologies can benefit various medical imaging areas like cardiac, abdominal, brain, breast, and chest imaging.

The study also aims to summarize the different types of medical images utilized in deep learning, emphasizing the diverse range of applications within the medical imaging domain, such as organ localization, lesion segmentation, and region detection.

Additionally, the research focuses on identifying the current challenges and opportunities for future research in the integration of deep learning techniques into medical imaging practices, highlighting areas where further advancements and improvements are needed for optimal utilization of these technologies.

II. Use of Deep Learning Applications in Medical Imaging

Breast cancer detection and classification, brain tumor segmentation, airway segmentation with leak detection, diabetic retinopathy classification, prostate segmentation, and nodule identification are just some of the medical imaging tasks that have been studied using deep learning algorithms. We looked at previous research in the field of medical imaging and found that deep learning has produced state-of-the-art outcomes on multiple occasions.

A. *Classification*

Classification tasks in medical images involve categorizing images into specific classes or categories. These tasks are essential in medical diagnosis and treatment planning as they help doctors accurately identify the presence and severity of medical conditions. Some important considerations for applying deep learning techniques for medical image categorizations are as follows: Categorization issues have been vastly enhanced by deep learning strategies based on convolutional neural networks (CNN).

- CNN has been used to classify lung nodules on CT images with great effectiveness.
- Training deep neural networks to do specific deep-learning tasks in the medical profession requires large volumes of labeled data.
- Classification is a crucial step in the processing of medical photos.
- Other medical imaging modalities used for classification tasks using deep learning approaches include X-ray, mammography, and digital histopathology images.

Here are a few examples of research works on classification tasks in medical images. Ardila et al.'s "Deep Convolutional Neural Networks for Lung Cancer Detection in CT Screening Images" [1] study proposes using a deep convolutional neural network to detect lung cancer in CT screening images. High accuracy in identifying lung cancer is achieved by the suggested technique once it is trained on a large dataset of patient pictures.

Using deep convolutional neural networks, "Multi-Instance Learning for Breast Cancer Diagnosis with Deep Convolutional Neural Networks" by Li et al. [2] study introduces a multi-instance learning strategy for diagnosing breast cancer. The suggested technique is trained on a large dataset of patient photos and makes use of both global and local characteristics. The results show that the proposed method outperforms the state-of-the-art in classification tasks.

An article by Wang et al. titled "Multi-Task Deep Learning for Pancreatic Cancer Detection in CT Scans" proposes a multi-task deep learning strategy for identifying pancreatic cancer in CT scans [3]. The suggested technique is trained on a large dataset of patient photos and includes both image-based and patient-based features. The findings show how well the recommended method for detecting pancreatic cancer works.

B. *Detection*

The article "Automatic Detection of COVID-19 Using Chest X-ray Images with Deep Learning" by Hemdan et al. [4] is one of the most current instances of work in medical image detection. This research provides support for the use of deep learning to automate the detection of COVID-19 in chest X-rays. The proposed approach makes use of the

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capabilities of a convolutional neural network that has been trained to detect anomalies in a large database of patient pictures.

In the "Deep Learning-Based Automated Detection of Diabetic Retinopathy Using Fundus Images" by Fu et al. [5] study, we describe an automated technique for detecting diabetic retinopathy in fundus pictures that are based on deep learning.

The article "Lymph Node Metastasis Detection in Breast Cancer Patients Using Deep Convolutional Neural Networks" by Roy et al. [6] suggests using deep convolutional neural networks to identify lymph node metastases in individuals with breast cancer.

High accuracy in identifying lymph node metastases is achieved by training the suggested approach on a large dataset of patient photos. The convergence of these works demonstrates the promise of deep learning methods for use in medical image recognition.

C. Segmentation

The "Deep Learning-Based Segmentation of Organs at Risk in Head and Neck CT Images" by Guo et al. demonstrates the potential of this strategy. In this paper, we detail a deep learning-based method for segmenting potentially dangerous structures in CT scans of the head and neck. The method relies on a massive collection of patient photos to train a 3D U-Net model with residual connections.

A study by Xue et al., titled "Deep Learning-Based Segmentation of Cerebral Vasculature from CT Angiography" [8] suggests a technique for extracting the brain's blood vessels from CT angiography scans. The findings demonstrate that the suggested approach successfully segments the cerebral vasculature.

"Automated Segmentation of Prostate Gland in MRI using Convolutional Neural Networks" by Liu et al. presents a fully automated approach to segmenting the prostate gland from MRI images by utilizing convolutional neural networks. According to the findings, the proposed method is a significant improvement over the current segmentation scenery.

"Multi-Organ Segmentation using Spatially Aware Deep Networks" by Taha et al. [10] research suggests using a deep network that is aware of its geographical context. The suggested technique is trained on a large dataset of patient photos using a mix of 2D and 3D convolutional neural networks. The results verify the efficacy of the suggested approach in properly segmenting many body systems.

Overall, these studies demonstrate the potential usefulness of applying deep learning methods to the segmentation of medical images. In addition, they highlight the importance of using large datasets for training deep learning models and the need for continuous development and improvement of automated segmentation methods to aid in diagnosing and treating various medical conditions.

D. Registration

Image registration is a fundamental technique in computer vision that involves aligning two or more images of the same scene taken at different times, from different viewpoints, or by different sensors. The article "Atlas-Based Automatic Segmentation of Pelvic Lymph Nodes in CT Images for Prostate Cancer Radiotherapy" [11] written by Zhang et al. presents an atlas-based method for automatically segmenting pelvic lymph nodes in CT images for prostate cancer radiotherapy. The suggested approach is trained on a large dataset of patient photos using a mix of registration methods and machine-learning algorithms.

According to Wang et al.'s "Deep Learning-Based Non-rigid Medical Image Registration using Structural Similarity" [12], this technique may be used to register medical images that lack structural rigidity. In this paper, we present a deep learning-based approach to the problem of registering medical images that lack perfect linear correspondences but exhibit identifiable structural correlations. The proposed method makes use of a convolutional neural network that was taught to recognize medical anomalies in a large collection of patient images. The results demonstrate that the suggested technique is effective in non-rigid image registration and may boost the standard of medical image analysis.

The paper "Deep Learning-Based Image Registration for Adaptive Radiotherapy" [13] by Li et al. suggests this is feasible. In this paper, we suggest a deep learning-based image registration technique for use in individualized radiotherapy. The proposed method makes use of a convolutional neural network that was taught to recognize medical anomalies in a large collection of patient images.

These findings show the significant potential for medical picture registration offered by deep learning and other machine-learning approaches. In addition, they highlight the importance of using large datasets for training and the need for continuous development and improvement of automated registration methods to aid in diagnosing and treating various medical conditions.

III. Use of Medical Images in Deep Learning

Analyzing medical pictures such as X-rays, MRIs, CT scans, mammograms, and digital histopathology images is discussed in this study from a deep learning perspective. Medical pictures from these many modalities have been classified, detected, and segmented using deep learning techniques. Here we reflect on the use of various medical images in deep learning.

A. X-RAY Image

A variety of medical conditions, such as tuberculosis, atelectasis, consolidation, pleural effusion, pneumothorax, and periventricular inflation, can be diagnosed with the help of X-ray imaging [4]. The medical community routinely employs X-ray imaging for tracking, treating, and diagnosing a wide range of illnesses. In addition, x-ray imaging is accessible, affordable, and has a low radiation dose, making it a practical and effective tool in medical imaging.

B. Magnetic Resonance Imaging

Magnetic resonance imaging (MRI) [8] is an invaluable diagnostic tool because it provides clear pictures of the body's interior organs and tissues. Some of the common uses of MRI in medical images include:

- Diagnosing brain and spinal cord conditions: Brain and spinal cord tumors, MS, and stroke are just a few of the diseases that can be detected and diagnosed with MRI. It can produce high-resolution images of the brain and spinal cord, allowing for more precise diagnosis and treatment.
- Examining the musculoskeletal system: MRI can also be used to examine the bones, joints, and soft tissues of the musculoskeletal system, providing detailed images that can help diagnose conditions such as osteoarthritis, ligament tears, and herniated discs.
- Detecting breast cancer: An additional imaging technique utilized in the evaluation of breast cancer staging and diagnosis is MRI. It can produce high-resolution images of breast tissue, which aids in the diagnosis of cancer and in determining its extent.
- Identifying cardiovascular diseases: MRI can be used to examine the heart and blood vessels, providing detailed images of the heart's structure and function and blood flow through the vessels. It can help diagnose conditions such as heart disease and aneurysms.
- Planning and monitoring cancer treatment: MRI is used to monitor the effectiveness of cancer treatment and help plan and guide radiation therapy or surgery.

C. Mammography Images

In medical imaging, deep learning methods have been employed in many studies for mammography imaging processing [2]. Some of the key findings from the literature survey are:

- Deep learning approaches showed promising results in detecting and classifying breast cancer using mammography images.
- High accuracy in identifying breast cancer in mammography images has led to the widespread use of convolutional neural networks (CNNs).
- Transfer learning, which involves using pre-trained CNN models, has improved the performance of deep learning models for mammography image analysis.
- The accuracy of breast cancer detection using mammography images has also been shown to be improved by the use of ensemble methods, which combine multiple deep-learning models.
- Some studies have also investigated deep learning approaches for breast density estimation, a significant risk factor for breast cancer.

The use of deep learning algorithms for mammography image analysis has shown encouraging results, but these methods are not without their limitations. These include the need for vast volumes of annotated data and the risk of model overfitting.

D. CT Imaging

In this study, we specifically examine how CT scans can benefit from the adoption of deep learning methods for image processing. CT imaging is used in various applications, including:

- Detection and classification of lung nodules, liver lesions, and brain tumors
- Image segmentation and registration in CT imaging
- Estimation of bone mineral density
- Assessing the efficacy of potential treatments for a wide range of medical issues

The paper provides a literature survey of studies that have used deep-learning approaches for CT image analysis in medicine.

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E. Histopathology

Histopathology is the study of illness and disorder diagnosis via the examination of tissue samples [5]. Some studies have used deep learning approaches to analyse digital histopathology images". Using digital histopathology pictures, these studies have demonstrated encouraging results in identifying and diagnosing several forms of cancer, including breast and lung cancer. However, the paper mainly focuses on using deep learning approaches for medical image analysis, including computerized tomography (CT) imaging. [7] discussed that Biomedical and anatomical data are made simple to acquire because of progress accomplished in computerizing picture division. More research and work on it has improved more viability to the extent the subject is concerned. A few tech- niques are utilized for therapeutic picture division, for example, Clustering strategies, Thresholding technique, Classifier, Region Growing, Deformable Model, Markov Random Model and so forth.

IV. Use of various techniques in Deep Learning

Biological neural networks have inspired the development of neural networks. The simplest artificial neural network model is the perceptron, and back propagation is a learning technique that modifies the weights of neural networks to reduce the error between expected and actual output. In a new invention called deep learning, complicated data representations are learned using deep neural networks with multiple layers. Several deep learning techniques have proven useful in medical imaging, including convolutional neural networks (CNNs), deep belief networks (DBNs), and recurrent neural networks (RNNs). Problems including data augmentation, object identification, segmentation, and picture classification have all been addressed using these techniques. These techniques have been effectively used in medical imaging, as proved by several studies, to identify lung nodules in CT scans, breast cancer in mammography images, and brain tumors in MRI scans, to name just a few instances.

A. Autoencoder

Autoencoder is an unsupervised deep learning technique for feature extraction and dimensionality reduction. It consists of a pair of networks, an encoder network, and a decoder network, with the former used to map data onto a representation in a lower-dimensional latent space and the latter used to map the latent space representation back onto the input space [1][2]. Autoencoders can be used for various tasks such as image denoising, image compression, and anomaly detection. The Stacked Autoencoder (SAE) is mentioned as an unsupervised algorithm representation that is briefly discussed in the paper. Each layer of the SAE is built from automated encoders, and their outputs are fed into the inputs of the next layer.

The use of the reconstruction error cost function results in error minimization in the autoencoder. The cost function is defined as the square of the difference between the original data and the reconstructed data. The reconstruction error can be minimized by optimizing this cost function during training by adjusting the weights and biases of the neural network. [9] discussed about the combination of Graph cut liver segmentation and Fuzzy with MPSO tumor segmentation algorithms. The system determines the elapsed time for the segmentation process. The accuracy of the proposed system is higher than the existing system. The algorithm has been successfully tested in multiple images where it has performed very well, resulting in good segmentation. It has taken high computation time for the graph cut processing algorithm. In future work, we can reduce the computation time and improves segmentation accuracy.

B. Deep Belief Networks

Unsupervised deep learning uses Deep Belief Networks (DBNs), which are constructed from multiple layers of Restricted Boltzmann Machines (RBMs). The RBMs are trained in an unsupervised way, layer by layer, with the learned weights being used to initialize the weights of the next layer. Once the DBN's layers have been trained, they may be fine-tuned for classification tasks using supervised learning.

C. Convolution Neural Networks

In the realm of image processing, convolutional neural networks (CNNs) have emerged as a leading deep learning technique [2]. The use of CNNs for medical image processing has been widely documented in the literature, with particular success in the detection of lung nodules in CT scans, breast cancer in mammograms, and brain tumors in MRI scans. In addition, they go over the fundamentals of CNN design, including the convolutional, pooling, and fully connected layers.

D. Recurrent Neural Networks

In artificial intelligence, recurrent neural networks (RNNs) are a type of neural network that can be used to analyse both time series and text. RNNs use recurrent connections

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between their hidden nodes in contrast to FFNNs. RNNs can be used for medical image analysis, specifically for analyzing electroencephalogram (EEG) signals to detect epileptic seizures.

E. Generative Adversarial Networks

Deep generative models like Generative Adversarial Networks (GANs) may produce synthetic data that accurately mimics the real data. A generator neural network and discriminator neural networks are combined and trained concurrently to create a GAN. While the discriminator is occupied attempting to identify the difference, the generator tries to fool the discriminator by providing samples of data that seem to be the real thing. Data augmentation and image synthesis are two applications of GANs in medical image analysis.

REFERENCE	TYPE OF MEDICAL IMAGE/DATASET	METHOD	APPLICATION
[14] Li et al. 2020	4356 Chest CT images	• COVNet	COVNet detects COVID-19 in chest CAT images at various magnifications.
[15] Zhao and Zeng 2019	KiTS19 challenge	• 3D-UNet	CT kidney and tumor segmentation utilizing supervised multi-scale 3D U-Net.
[16] Pang et al. 2020	Shandong Provincial Hospital	• CNN (DenseNet)	Lung cancer classification using CT scans and DenseNet.
[17] Fan et al. 2020	COVID-19 infection dataset	• Inf-Net	Lung CT infection segmentation network for COVID-19.
[18] Rajaraman and Antani 2020	RSNA, Paediatric pneumonia, and Indiana	• CNN	Identification of tuberculosis (TB) with a variety of deep learning models adapted to various modalities
[19] Abbas et al. 2020	196 X-ray images	• CNN	Composition, Decomposition, and Transfer (DeTraC) for Classifying COVID-19 CXR Images.
[20] Wang & Wong 2020	13,975 X-ray images	• CNN	In particular, a deep convolutional neural network-based one To find the COVID-19 virus, the COVID-Net was developed.
[21] Loey et al. 2020	306 X-ray images	• AlexNet GoogleNet Resnet18	Introduced a GAN trained with deep transfer learning for COVID-19 detection in CXR images.

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[22] Murphy et al. 2019	5565 CXR images	• CAD4TB	Deep learning evaluation of the CAD4TB program
[23] Xu et al. 2019	chest X-ray14	• CNN, CXNet-m1	Used a hierarchical convolutional neural network to build a new network for Chest X-ray anomaly detection using CXNet-m1

Table 1. Literature survey of studies

V. Use of Various Techniques in Deep Learning

A. *Strengths of Existing Methods*

- Existing methods in medical imaging using deep learning exhibit high accuracy in tasks such as image classification, detection, segmentation, and registration.
- Deep learning techniques have shown strength in providing precise results in challenging medical imaging tasks, contributing to improved diagnostic capabilities.
- The application of deep learning algorithms in various medical imaging areas like cardiac, abdominal, brain, breast, and chest imaging highlights the versatility and effectiveness of these methods.
- Researchers have identified the potential for deep learning to enhance healthcare outcomes by effectively analyzing medical images to aid in diagnosis and treatment planning.

B. *Weakness of Existing Methods*

- Some limitations of current methods in medical imaging using deep learning include potential challenges related to overfitting, where the model may perform well on training data but struggle with generalizing to new, unseen data.
- Another weakness is the requirement for a large amount of labeled data for training deep learning models, which can be time-consuming and expensive to acquire in the medical imaging domain.
- Current methods may also face issues with interpretability, as deep learning models are often considered black boxes, making it challenging for medical professionals to understand how and why certain decisions are made.
- Additionally, the lack of standardization in deep learning techniques for medical imaging applications can lead to variability in performance and results, hindering consistent and reliable outcomes in clinical settings.

C. *Challenges Identified in Existing Methods*

- Existing methods face challenges related to overfitting, where the models may perform well on training data but struggle with new, unseen data.
- Acquiring a large amount of labeled data for training deep learning models can be time-consuming and costly in medical imaging, posing a significant challenge for implementation.
- Interpretability issues exist as deep learning models are often considered black boxes, making it hard for medical professionals to understand the decision-making process.
- Lack of standardization in deep learning techniques for medical imaging may lead to variability in performance and results, impacting the consistency and reliability of outcomes in clinical settings.

VI. Emerging Neural Network Algorithms In Medical Image Processing

Emerging neural network algorithms are revolutionizing medical image processing by significantly enhancing diagnostic accuracy and efficiency. Convolutional neural Networks (CNNs) have emerged as a cornerstone technology, capable of automatically detecting subtle patterns in medical images such as X-rays, MRIs, and CT scans. These networks excel in tasks like tumor detection, organ segmentation, and anomaly identification by learning hierarchical representations directly from pixel data.

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Moreover, Generative Adversarial Networks (GANs) are making strides in generating synthetic medical images that closely resemble real patient data, aiding in data augmentation and training robust models under various conditions. GANs also facilitate the translation of medical images across different modalities, bridging the gap between imaging technologies and improving diagnostic capabilities.

Furthermore, attention mechanisms, inspired by Transformer models, are increasingly integrated into medical image processing pipelines to focus on relevant regions of interest within images. This approach enhances the interpretability of neural networks and enables clinicians to pinpoint critical areas for diagnosis and treatment planning. As these neural network algorithms continue to advance, their integration into medical practice holds promise for more accurate, personalized healthcare solutions, ultimately improving patient outcomes and reshaping the future of medical imaging diagnostics.

VII. Key Findings And Contribution Of Study To The Future Researchers

The study analyzed many recent research papers on deep learning techniques in medical imaging, focusing on tasks like image classification, detection, segmentation, and registration. Significant contributions of the study include identifying the application areas of deep learning in medical imaging such as cardiac, abdominal, brain, breast, and chest imaging.

Future researchers can benefit from the study by understanding the challenges faced in current methods like overfitting, data acquisition, interpretability issues, and lack of standardization in deep learning techniques for medical imaging. The study underscores the importance of addressing these challenges to improve the reliability and consistency of deep learning applications in medical imaging, ultimately aiding in better diagnosis and treatment planning.

VIII. Conclusions

The paper emphasizes the significant role of deep learning techniques in medical image processing, showcasing their effectiveness across various imaging modalities such as MRI, CT, and X-ray. A comprehensive survey of many recent research papers highlights the diverse applications of deep learning in medical imaging, including tasks like classification, detection, segmentation, and registration. The research identifies both the benefits and challenges of integrating deep learning algorithms into medical imaging practices, suggesting that while these technologies offer promising advancements, there are still hurdles to overcome for optimal utilization. The paper also points out specific areas where further research and development are needed, particularly in addressing current challenges and exploring new opportunities within the field of medical imaging. Overall, the findings indicate that deep learning has the potential to revolutionize medical image analysis, but continued efforts are necessary to refine these techniques and enhance their application in clinical settings.

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BIOGRAPHY

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