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A Study of Using Deep Learning with Medical Images: Starting from Fundamental Artificial Neural Networks to Generative Models

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Abstract

Recently, deep learning has shown significant progress and is advancing quickly in various automated applications with minimal errors. One such application is in medical image analysis for disease detection, where deep learning has demonstrated high accuracy and precision due to its automatic feature representations. This article presents an overview of essential deep learning concepts related to the generation of medical images. It offers brief summaries of research utilizing some of the most advanced models from recent years applied to medical images of various injured body areas or organs affected by diseases (e.g., brain tumors and COVID-19 lung pneumonia). The objective of this study is to provide a comprehensive summary of artificial neural networks (NNs) and deep generative models in medical imaging to encourage more groups and authors unfamiliar with deep learning to consider its use in medical research. Furthermore, it presents a compilation of commonly used public medical datasets containing magnetic resonance (MR) images, computed tomography (CT) scans, and standard images.

Keywords: Deep Learning; Classification; Computed Tomography Images; Magnetic Resonance Images; Medical Images.

1 | Introduction

Medical imaging involves using techniques and processes to capture images of the internal structures of the human body for diagnostic and treatment purposes. It also includes a database of normal human images to aid in the identification of abnormalities. The use of medical imaging in healthcare enables doctors to obtain more precise results and make informed decisions [1].

Medical image analysis involves image classification, object detection, and segmentation[2]. Image classification [3] aims to identify the class of an image from many possible options. Object detection involves locating or identifying objects within an image using a bounding box to locate the object [4]. Segmenting medical images is essential as it provides non-invasive insights into human body structures [5].This analysis can help in detecting various diseases and evaluating a patient's condition using different medical image generation methods [6]. Medical image analysis has a wide range of applications. It can assist doctors in identifying the nature of pulmonary nodules using chest X-rays or CT scans [7], detecting Alzheimer's disease [8] and Parkinson's disease, identifying brain tumors [9], and even detecting COVID-19 [10, 11].By analyzing

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medical images, doctors can detect diseases, pinpoint issues, and assess tumor growth rates. These examples underscore the significance of image analysis across all medical disciplines.

When diagnosing patients, most physicians rely on medical imaging as their main source of data. However, analyzing medical imaging data can be time-consuming and error-prone due to its complexity and uncertainty [12]. Applying deep learning models to medical image processing improves accuracy, saves time, and automates results that were previously done manually by physicians and doctors [13].

Deep learning models have achieved remarkable achievements in the field of medical image analysis [14]. Convolutional neural networks (CNNs) are used to distinguish between healthy tissue and tumors [15]. By learning from raw data, CNNs allow doctors to obtain significant insights without manual intervention [16]. Several studies show the growing interest of using CNNs in improving the accuracy and efficiency of tumor detection [17].

The primary objective of this paper is to conduct a comprehensive investigation of various models and techniques for medical imaging. While many researchers have explored medical imaging and image processing methods using deep learning, this study stands out due to its thorough exploration of almost every category of disease in medical diagnosis, with a recent focus on COVID-19 and brain tumors. Our main objective is to highlight recent advancements in medical imaging and image processing.

This is the outline of the survey paper. Section 2 covers the applications of medical image analysis. Section 3 outlines the survey's search criteria. Deep learning models for medical image processing are detailed in Section 4. Section 5 discusses various datasets for classifying medical images. The metrics for evaluating performance are explored in Section 6. Finally, Section 7 covers the conclusions and future trends.

2 | Practical Uses of Medical Image Analysis

When it comes to diagnosing patients, various types of medical images are commonly used. These include MRI (Magnetic Resonance Imaging), X-ray, and Computer Tomography (CT)[18].

Magnetic resonance imaging (MRI) is an advanced and non-invasive medical imaging method that is extensively employed to gather detailed information about the internal structure and function of different organs in the body, whether they are in a healthy or diseased state. It relies on non-ionizing electromagnetic fields of three distinct frequency bands: a Static Magnetic Field (SMF), time-varying Gradient Magnetic Fields (GMF) in the kHz range, and pulsed Radiofrequency Fields (RF) in the MHz range [19].The MRI scanner's primary element is the static magnetic field, which is always operational [20]. MRI uses magnetic fields to align atoms in the body, and then a computer processes this information to produce a detailed image of the body [21]. Tesla (T) is the measurement unit for the strength of a magnetic field, and the magnets used for imaging purposes are notably robust [21].MRI generates a magnetic field with a strength between 1 and 3 T, which is up to 60,000 times more powerful than the Earth's magnetic field [22]. MRI scans are commonly used to diagnose brain tumors because they provide detailed images of the brain and can detect even small tumors [23], [24]. MRI scans also help in monitoring changes in the tumor over time, which allows doctors make better decisions about treatment options [25].

X-rays consist of electromagnetic waves with a short wavelength, meaning they have high energy. Soft X-rays, which have a wavelength of around 0.1–10 nm (corresponding to X-ray energies of 0.124–12.4 keV), are not able to penetrate dense substances. Therefore, they are utilized for imaging organisms or polymers composed of light elements like silicon, carbon, oxygen, hydrogen, and nitrogen[26] . Chest X-ray images can be used to detect various diseases such as pneumonia[27], lung cancer[28], and COVID-19 [29]. They are also helpful in identifying fractures in different parts of the body. Pneumonia is characterized by the filling of air sacs with fluid or air, resulting in breathing difficulties and the presence of white patches in the chest X-ray. Pulmonary nodules, which can be cancerous or non-cancerous, appear as white spots in the lungs on X-ray images and can also be identified through low dose computed tomography. Additionally, COVID-19 can be detected using X-ray images, and there are numerous deep learning models available for achieving higher accuracies in COVID-19 detection.

Computed tomography, commonly referred to as CT, is also known as computed axial tomography or CAT scanning. It was introduced to the clinical field in the 1970s and was considered the most advanced machine since the development of the X-ray machine [30]. The CT scanner starts by capturing one image at a time, with the x-ray tube and detector rotating 360 degrees or less, while the patient and table remain stationary [31]. This imaging technique offers diagnostic radiology improved insight into the body's pathogenesis, revealing subtle contrast discrepancies and enhancing the chances of recovery. CT scans are utilized for identifying hemorrhage (blood vessel bleeding) and patterns related to COVID-19[32].

In this survey will concentrate on three types of tumors: brain tumor, pneumonia, and COVID-19.

3 | Survey Search Criteria

In order to conduct this survey, we have utilized the following databases: Google Scholar, IEEE Xplore Digital Library, Science Direct, Wiley Online Library, and MDPI.

We utilized search criteria such as "Medical Imaging," "Medical imaging using deep learning," "Medical Imaging and Classification," and "Deep learning," "convolutional neural network," "CNN," or "neural network" for Medical Image, as well as "Transfer Learning" to select papers. Our review encompassed over 100 recent research papers, from which we shortlisted 50 focusing on Medical Image classification using Deep Learning techniques. Our exploration and study included research papers published from 2019 to 2024. The distribution of articles on Deep Learning in Medical Imaging is outlined in Table 1, and Figure 1 displays the paper distribution over the years.

Table 1. Number of reviewed articles according to each source.

S. No.	Articles in journals/book chapters	Count
1	Computational and Structural Biotechnology Journal	1
2	Medical Hypotheses	1
3	International conference on computer and knowledge engineering	1
4	IEEE Access	2
5	Computerized Medical Imaging and Graphics	1
6	Biomedical Signal Processing and Control	2
7	Healthcare	1
8	Journal of Ambient Intelligence and Humanized Computing	1
9	IEEE Journal of Biomedical and Health Informatics	1
10	Measurement: Sensors	1
11	Neural Computing and Applications	2
12	Brain Research	1
13	Neurocomputing	1
14	Biocybernetics and Biomedical Engineering	1
15	Computers in Biology and Medicine	3
16	Information Processing & Management	1
17	Chaos, Solitons & Fractals	1
18	Computers, Materials & Continua	1
19	Applied Sciences	1
20	Soft Computing	1
21	Informatics in Medicine Unlocked	2
22	Multimedia Tools and Applications	4
23	SN Computer Science	1
24	Applied Intelligence	3
25	Journal of Imaging	2
26	Procedia Computer Science	1

27	Algorithms	**1**
28	Neural Processing Letters	**1**
29	Electronics	**1**
30	Expert Systems with Applications	**1**
31	Advances in Engineering Software	**1**
32	Journal of Ambient Intelligence and Humanized Computing	**1**
33	International Journal of Environmental Research and Public Health	**1**
34	International journal of medical informatics	**1**
35	Multimedia Systems	**1**
36	European Journal of Radiology	**1**
37	Cognitive computation	**2**
	Total	**50**

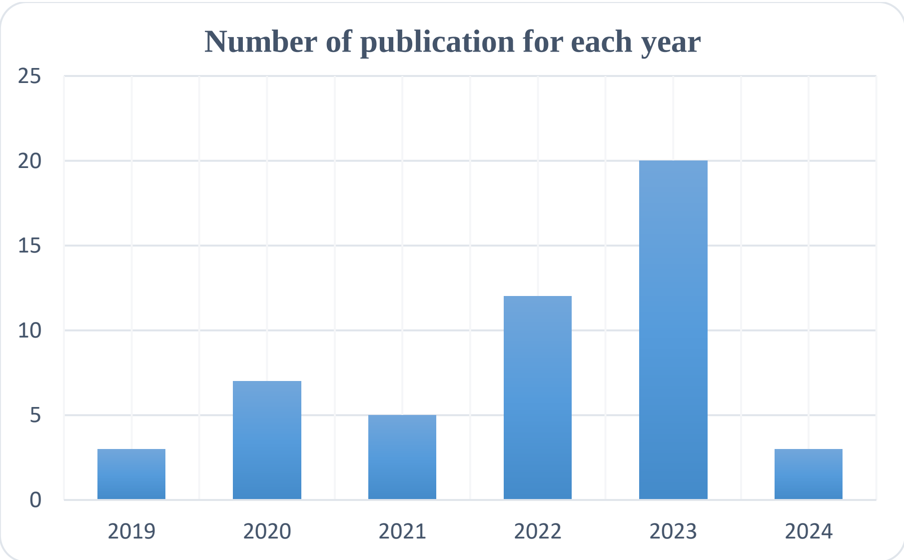

Figure 1. Temporal distribution of the selected research paper from 2019 to 2024.

4 | Deep Learning

Medical image classification is the process of identifying the category or class of an image, and it is an important application in digital image analysis that utilizes deep neural networks[33]. The image's class is determined by a neural network that extracts features from the image. Convolutional neural networks are commonly used as a foundation for image classification, and there are also transfer learning models based on CNN[34]that have been created for classification purposes. Unsupervised deep learning can be utilized for feature extraction, enabling the network to autonomously derive features from data to generate efficient representations for classification purposes. Autoencoders and generative adversarial networks (GAN) exemplify unsupervised deep learning techniques[35]. GANs are also used for classification and data generation [36].

4.1 | Convolutional Neural Network

In the field of DL, convolutional neural networks (CNNs) are the most recognized and widely utilized algorithms[37].The primary advantage of CNNs is their ability to automatically detect significant features without human intervention[38]. CNNs have achieved remarkable results in various computer vision tasks, such as image classification, object detection in images and videos, semantic segmentation, video restoration, and even medical diagnosis [39].

The structure of CNNs was inspired by neurons in human They are made up of neurons, where each neuron has a learnable weight and bias[40]. It contains an input layer, an output layer and multiple hidden layers, where hidden layer consists of a convolutional layer, pooling layer, fully connected layer (FC) and various regularization layers.

- Convolutional Layer

  In CNN architecture, the most significant component is the convolutional layer. It consists of a collection of convolutional filters (so-called kernels). The input image, expressed as N-dimensional metrics, is convolved with these filters to generate the output feature map.

- Pooling Layer

  The pooling layer also has a user-defined filter size. It performs dimensionality reduction of the input data. There are two types of pooling operations Max pooling and Average pooling.

- Fully Connected Layer

  The fully connected layer, also known as a dense layer, links every neuron from one layer to all neurons in the subsequent layer using an activation function. This layer is densely interconnected, meaning that each neuron in the dense layer receives input from all neurons in the preceding layer. It also plays a role in altering the vector's dimensionality. In the context of image classification, a suitable activation function is applied to the dense layer to generate the output, indicating the categorized image.

- Regularization Layer

  In CNN models, overfitting poses a significant challenge to achieving effective generalization. A model is deemed overfitted when it shows outstanding performance on training data but struggles to replicate those results on unseen test data. This concept will be explored further in subsequent sections. On the other hand, an underfitted model fails to extract meaningful patterns from the training data. Conversely, a model that is "just-fitted" demonstrates strong performance on both training and testing datasets. To combat overfitting, several intuitive strategies are implemented for regularization such as. drop out layer, Data Augmentation, Batch Normalization.

4.2 | Transfer Learning

A variety of transfer learning models have been developed for image classification using convolutional neural networks. Transfer learning involves taking a model that has been trained on one specific task and applying it to a related task. This approach allows for the use of pre-trained models for feature extraction, fine-tuning, and integration into new models. One well-known challenge in computer vision is ImageNet, which prompts researchers to create models that can accurately classify images across a dataset containing 1,000 different categories. As a result, numerous image classification models have been created [41].

Transfer learning methods can be categorized into three main types based on the information transferred from the source data to the target data: feature-based transfer learning, instance-based transfer learning, and model-based transfer learning [42].

- Feature-based transfer learning

  Feature-based transfer learning method tackles the challenge of inductive transfer learning by highlighting the need for effective feature representations that reduce domain divergence and classification errors. The techniques used to discover these efficient feature representations vary based on the type of data available in the source domain. When there is a substantial amount of labeled data in the source domain, supervised learning techniques can be utilized to create a valuable feature representation [42].

- Instance-based transfer learning

Instance-based Transfer Learning is a commonly used model in machine learning [43]. In this approach, data that is related to a new task is directly utilized as training examples [44]. For instance, if we want to train a model to differentiate between webpages about food and those about trains, we can use webpages about restaurants as training examples for the food category, while webpages about motorcycles can be used for the trains category. In this context, we refer to the actual training examples for the new task as target data (e.g., the webpages about food and trains) and the related data as source data (e.g., the webpages about restaurants and motorcycles).

- Model-based transfer learning

  The concept involves transferring knowledge obtained from a model—such as its structure, parameters, or learned representations—from one domain (the source domain) to another (the target domain). The main idea is to utilize or adapt components of a pre-trained model that has been optimized for a similar task or domain, instead of starting the training process with an entirely new model [45].

4.3 | DNN and Auto Encoders

Autoencoders are a type of neural network that belongs to the realm of unsupervised learning, specifically for the purpose of representation learning [46]. These networks serve the purpose of data compression. An autoencoder consists of two main components: the encoder and the decoder. The encoder compresses the data, while the decoder reconstructs the original data from this compressed encoded information. It employs backpropagation to produce an output value that closely resembles the input value. Consequently, the encoder effectively identifies essential features needed for reconstructing the input at the decoder. After training, the encoder model is saved because it performs both feature extraction and data compression. The various kinds of autoencoders include concrete autoencoders, denoising autoencoders, contractive autoencoders, sparse autoencoders, and variational autoencoders [47].

Autoencoders can be trained to recreate the original input, after which the decoder component can be removed, allowing the encoder's output to serve as a feature vector in supervised learning models[48]. To encode an image, the autoencoder utilizes a sequence of convolutions, resulting in the input image being transformed into a compressed vector.

A similar application of autoencoders, combined with wavelet transforms, has been used for brain MRI image classification aimed at cancer detection [49].This method uses a deep neural network based on a deep wavelet autoencoder for detection. The autoencoder is trained to produce output images that mirror the input images by using the Discrete Wavelet Transform (DWT) to create high-level feature vectors. To achieve this, input images are encoded and processed through low-pass and high-pass filters during the DWT operation. The images are then reconstructed through an inverse wavelet transform. The autoencoder generates these feature vectors, which serve as input for the deep neural network that uses a sigmoid activation function to classify images for cancer detection. This method is suitable for brain MRI images. The CNN and autoencoder model is complex and requires extended training time. A substantial input image dataset is necessary for this approach.

4.4 | Deep Convolutional Generative Adversarial Networks

Deep convolutional generative adversarial Networks, or DCGAN, are deep learning architecture for generating images.A GAN, or Generative Adversarial Network, is utilized for generative modeling through deep neural networks like convolutional neural networks. These models generate new data instances that mimic the training data. Consequently, GANs can produce images that resemble the training images[50]. A GAN's architecture consists of a generator and a discriminator. The discriminator differentiates between real samples and counterfeit ones, whereas the generator seeks to mislead the discriminator and learns from its feedback. Because the gradients of the generator depend on both generated sequences and the discriminator, sequence GANs do not suffer from exposure bias [51].

The primary limitation of the original GAN is its inability to produce images belonging to a specific class, as the discriminator in the GAN framework converts images from a random latent space without any control. To address this issue, the conditional generative adversarial network (cGAN) was developed. This model extends the basic GAN by enabling conditional image generation through a generator model. The image generation can be based on specific conditions, allowing the cGAN to incorporate particular patterns during training, enabling the discriminator network to create output images that meet desired criteria [52]. The cGAN architecture has been decisively applied to medical imaging tasks, demonstrating its effectiveness and reliability in this critical field [53, 54].

5 | Medical Images Classifications Dataset

New research has revealed that medical imaging can diagnose a range of conditions including COVID-19, Breast Cancer, TB, Brain Tumor, and Blood cell classification. Some studies suggest that radiological imaging may be a superior method for identifying medical diseases. Convolutional Neural Networks are used to automatically classify computer tomography images of medical disease cases. When employing deep learning methods, a significant amount of data is required to train and test the model. A dataset is a collection of instances, with each row of data referred to as an instance. In the field of medical imaging, specific types of datasets are needed for various methods. This section will outline publicly available datasets from various data providers such as Kaggle. Medical Imaging Datasets can be in the form of images for multiple classes or in a compiled dataset in CSV format. The dataset consists of different labeled classes, and for each class, there are multiple images available for training the model. While some datasets were discovered in studies in journals, others were found in the dataset repository.

5.1 | Brain Tumors Datasets

i). Figshare Dataset

Figshare Dataset [55] comprises 3064 MRI images obtained from 233 patients at the General Hospital, Tianjin Medical University, and Nanfang Hospital in China. The dataset includes three types of tumor classes in MRI images: meningioma, glioma, and pituitary, with 708, 1426, and 930 images, respectively.

ii). Harvard Medical Dataset

Harvard Medical Dataset [55] includes 152 MRI images, comprising of 71 MRI images without tumors and 81 MRI images depicting tumors that may include Glioma, Metastatic adenocarcinoma, Metastatic bronchogenic carcinoma, Meningioma, and Sarcoma.

iii). Brain MRI Images for Brain Tumor Detection dataset

The Brain MRI Images for Brain Tumor Detection dataset can be found on the Kaggle website [56] will be (referred to as Brain tumor dataset in this paper). The dataset comprises a total of 253 MRI images, with 98 images representing the normal class and 155 MRI images representing the abnormal class.

5.2 | Chest Tumors Datasets

i). Chest X-ray (Covid-19 & Pneumonia) Dataset

The dataset containing chest X-ray images for COVID-19 and pneumonia [57] consists of posterior-anterior (PA) view images falling into three categories: COVID-19, pneumonia, and normal. In total, there are 6432 chest X-ray images, with 576 from COVID-19 patients, 4273 from pneumonia patients, and 1583 from normal patients.

ii). COVID-19 dataset

The Covid19-dataset [58] comprises chest X-ray images for COVID-19 detection. It includes approximately 137 curated images of COVID-19 and a total of 317 images, including those of Viral Pneumonia and Normal Chest X-Rays.

iii). SARS-COV-2 Ct-Scan Dataset

SARS-COV-2 Ct-Scan Dataset [59] comprises 2482 CT scans obtained from hospitals in Sao Paulo. This includes 1252 scans from patients who tested positive for COVID-19 and 1230 scans from patients who tested negative for COVID-19.

iv). Tuberculosis (TB) Chest X-ray Dataset

A team of researchers from Qatar University in Doha, Qatar, and the University of Dhaka in Bangladesh, in collaboration with medical professionals from Pakistan and Malaysia, has compiled a dataset of Chest X-ray images. This dataset [60] contains COVID-19 positive cases and consists of four classes: COVID-19, Normal, Viral Pneumonia, and Lung Opacity images. It includes 3616 CXR images of COVID-19 cases, 10,192 Normal images, 6012 Lung Opacity (Non-COVID lung infection) images, and 1345 Viral Pneumonia images.

6 | Performance Metrics

It's crucial to understand the performance of our model and strive to enhance it for better accuracy. Prior to delving into evaluation metrics, there are certain definitions we need to be familiar with.

- **True positive (TP):** When we correctly predict that a data point belongs to a particular class.
- **True negative (TN):** When we correctly predict that a data point does not belong to a particular class.
- **False positive (FP):** When we incorrectly predict that a data point belongs to a class, but it does not belong to that class.
- **False negative (FN):** When we incorrectly predict that a data point does not belong to a class, but it belongs to that class.

Here are some well-known performance metrics:

- **Accuracy:** is a metric used to evaluate how well a model correctly classifies or predicts labels for a given dataset. It is typically defined as the ratio of the number of correct predictions to the total number of predictions made by the model.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

- **Precision:** This metric measures the ratio of true positives to all the positives predicted by the model. High precision requires minimizing false positives, while low precision indicates that the model predicts more false positives.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

- **Recall:** This metric calculates the ratio of true positives to all the actual positives in the dataset. There is always a trade-off between precision and recall.

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

- **F1-Score:** When we need to strike a balance between precision and recall, especially with unequal class distribution, the F1 Score is a preferable evaluation technique, especially for many actual negatives.

$$\text{F1} = 2 * \frac{recall*precision}{recall+precision} \tag{4}$$

7 | Recent Models on Medical Images

In this section, we will explore recent models developed for medical image analysis, highlighting their innovative approaches and the effectiveness of their performance. These models utilize advanced techniques such as deep learning and neural networks to enhance accuracy in various medical tasks, including disease detection, segmentation, and classification. Their results are often benchmarked using standard datasets, and performance metrics like accuracy, precision, recall, and F1-score are compared. Detailed results for each model will be summarized in the following Tables 2 and 3.

7.1 | Brain Tumors Models

Table 2. Brain tumors models.

Reference	Model	Dataset	Accuracy	Precision	Recall	F1
[61]	Transfer learning of AlexNet, VGG16, VGG19	Figshare Dataset	0.9482	0.8952	0.9425	0.9469
[62]	Custom-built CNN	Figshare Dataset	0.9613	0.9606	0.9443	0.9693
[15]	Transfer learning of GoogleNet	Figshare Dataset	0.971	0.972	0.973	0.9896
[63]	Custom built CNN	Figshare Dataset	0.9549	-	-	-
[64]	GAN + ConvNet	Figshare Dataset	0.956	0.9529	0.9491	0.9769
[65]	Multi-pathway CNN	Figshare Dataset	0.973	0.967	0.94	–
[66]	CNN-SVM	Figshare Dataset	0.958	-	-	-
[55]	Custom built CNN	Figshare Dataset	0.978	0.965	0.964	0.983
[67]	Transfer learning of GoogleNet + KNN	Figshare Dataset	0.983	-	-	-
[68]	Resize + Gray scale conversion + Augmentation + PDCNN	Figshare Dataset	0.976	0.97	0.97	0.97
[69]	CNN + KNN	Figshare Dataset	0.956	-	-	-
[70]	YOLO2 pretrained network.	Figshare Dataset	0.97	0.971	0.93	0.947
[66]	CNN-SVM	Harvard Medical Dataset	0.987	-	-	-
[55]	Custom built CNN	Harvard Medical Dataset	1	1	1	1
[71]	Custom built CNN	Harvard Medical Dataset	0.9846	1	0.9762	-
[72]	Custom LSTM network	Harvard Medical Dataset	0.993	0.992	0.991	0.993
[56]	BrainMRNet	Brain tumor dataset	0.96	0.923	0.96	0.941

7.2 | Chest Tumors Models

Table 3. Chest tumors models.

Reference	Model	Dataset	Accuracy	Precision	Recall	F1
[73]	HOG + CNN	Chest X-ray (Covid-19 & Pneumonia) Dataset	0.9674	-	-	-
[74]	SEL-COVIDNET	Chest X-ray (Covid-19 & Pneumonia) Dataset	0.9852	0.987	0.985	0.987
[75]	InceptionNetV3	Chest X-ray (Covid-19 & Pneumonia) Dataset	0.9797	-	-	-
[76]	doctor consultation-inspired model	Chest X-ray (Covid-19 & Pneumonia) Dataset	0.9503	0.9503	0.9503	0.9503
[77]	TransDL	Chest X-ray (Covid-19 & Pneumonia) Dataset	0.9844	-	-	-
[78]	NN with VGG 16	Chest X-ray (Covid-19 & Pneumonia) Dataset	0.954	0.954	0.954	0.954
[79]	Custom CNN	Chest X-ray (Covid-19 & Pneumonia) Dataset	0.97	0.9866	0.9866	0.9866
[80]	Trained Output-based Transfer Learning	Chest X-ray (Covid-19 & Pneumonia) Dataset	0.9682	0.9843	0.966	0.9647
[81]	FPS Optimization	COVID-19 dataset	0.9615	-	-	-
[82]	Deep CNN (VGG-16)	COVID-19 dataset	0.957	0.889	0.888	-
[80]	Trained Output-based Transfer Learning	COVID-19 dataset	0.9647	0.9781	0.9571	0.9675
[83]	Custom CNN	SARS-COV-2 Ct-Scan Dataset	0.973	-	-	-
[84]	Custom CNN	SARS-COV-2 Ct-Scan Dataset	0.9075	0.9137	0.9	0.9068
[85]	ET-NET	SARS-COV-2 Ct-Scan Dataset	0.9781	0.9777	0.9781	0.9777
[86]	DenseNet121 with TL	SARS-COV-2 Ct-Scan Dataset	0.8505	-	-	0.8528
[87]	pre-trained model VGG16	SARS-COV-2 Ct-Scan Dataset	0.98	0.9799	0.9799	0.9799
[88]	COV-CAF	SARS-COV-2 Ct-Scan Dataset	0.9759	0.9688	0.9841	0.9763
[89]	ResNet34 pruned	SARS-COV-2 Ct-Scan Dataset	0.9547	-	0.9216	0.9567
[90]	L1-Contourlet	SARS-COV-2 Ct-Scan Dataset	0.963	0.948	0.981	0.964
[91]	CheXNet-Self-MLP	Tuberculosis (TB) Chest X-ray Dataset	93.32	93.38	93.32	94.58

8 | Conclusion

This study covers the necessity of medical imaging, its applications, and the importance of deep learning in this field. It focuses on medical image classification using deep learning and analyzes 100 research papers from various journals.

This study reviews methods such as CNN, transfer learning models, autoencoders, and GAN using CNN, along with their strengths and limitations. This study highlights that CNN models are easy to implement and can be combined with different image processing methods.

Transfer learning models require less training time but may not always yield expected results. The autoencoders, and GAN is complex and requires a longer training time and a large image dataset. The combination of image processing for texture extraction and CNN or transfer learning model is seen as a promising method for medical image classification due to its reduced training time and complexity.

This study also explores available medical imaging datasets, emphasizing the need for a sufficient amount of training data for deep learning models to perform well.

Furthermore, this study discusses different evaluation metrics for image classification and highlights the significant progress made by deep learning and artificial intelligence in the healthcare field. It emphasizes the role of deep learning in medical image analysis. The use of medical imaging data for training different deep learning models is seen as a way to reduce the burden on medical professionals and speed up their reading time. The study also emphasizes the ability of deep learning approaches to not only detect diseases but also find patterns, classify lesion areas, and provide more information about diagnosis The study concludes by highlighting the potential benefits of deep learning approaches in medical imaging for healthcare and the medical field.

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Author Contribution

All authors contributed equally to this work.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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