

From Pixels to Diagnoses: Deep Learning's Impact on Medical Image Processing-A Survey

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ABSTRACT: In healthcare, medical image processing is considered one of the most significant procedures used in diagnosing pathological conditions. Magnetic resonance imaging (MRI), computed tomography (CT), ultrasound, and X-ray visualization have been used. Health institutions are seeking to use artificial intelligence techniques to develop medical image processing and reduce the burden on physicians and healthcare workers. Deep learning has occupied an important place in the healthcare field, supporting specialists in analysing and processing medical images. This article will present a comprehensive survey on the significance of deep learning in the areas of segmentation, classification, disease diagnosis, image generation, image transformation, and image enhancement. This survey seeks to provide an overview of the significance of deep learning in the early detection of diseases, studying tumor localization behaviors, predicting malignant diseases, and determining the suitable treatment for a patient. This article concluded that deep learning is of great significance in improving healthcare, enabling healthcare workers to make diagnoses quickly and more accurately, and improving patient outcomes by providing them with appropriate treatment strategies.

Keywords: Deep Learning, Medical Images, Artificial Intelligence, Predication, X-rays



1. INTRODUCTION

Today, deep learning contributes to revolutionizing the growth of healthcare institutions through the application of artificial neural networks in the analysis of medical data [1] [2]. Medical imaging techniques such as X-ray, magnetic resonance imaging (MRI), and computed tomography (CT) that are used in the magnifying detection, diagnosis, and treatment of diseases. These images are interpreted by radiology specialists in this field in clinics or hospital laboratories. Therefore, with the great diversity of these images, the development of diseases, and the significant tiredness of specialists, human errors may occur, and a wrong interpretation of the disease may be given. Healthcare institutions seek to integrate computers into the healthcare field and support healthcare workers and physicians in interpreting images efficiently and without errors [3–5]. In addition, interpreting images takes a long time to provide results and monitor the progress of

the disease, which may affect the patient's life. Here, artificial intelligence has emerged through deep learning, which mimics the neural networks of the human brain, in solving all the issues facing physicians and radiology specialists in interpreting medical images [6–9]. Through deep learning, it has become possible to support radiology specialists in diagnosing, treating and preventing diseases using medical images with high accuracy and efficiency, using customized models to make diagnoses and predictions and provide satisfactory accuracy that contributes to improving the patient's condition. Thanks to these advanced models, machines can recognize, distinguish, and clearly interpret patterns without complexity. Deep learning is one of the artificial intelligence techniques that allows devices to solve complex situations such as decision-making, prediction, and diagnosis through a mechanism similar to the work of the human brain [10–12]. This technique relies on a series of algorithms inspired by the structure and operation of the brain, and it has become one of the most popular tools in data science. Deep learning technique is used in many domains, including medicine, space, image recognition, and natural language processing. Figure 1 illustrates the application of machine learning to extract information from medical images.

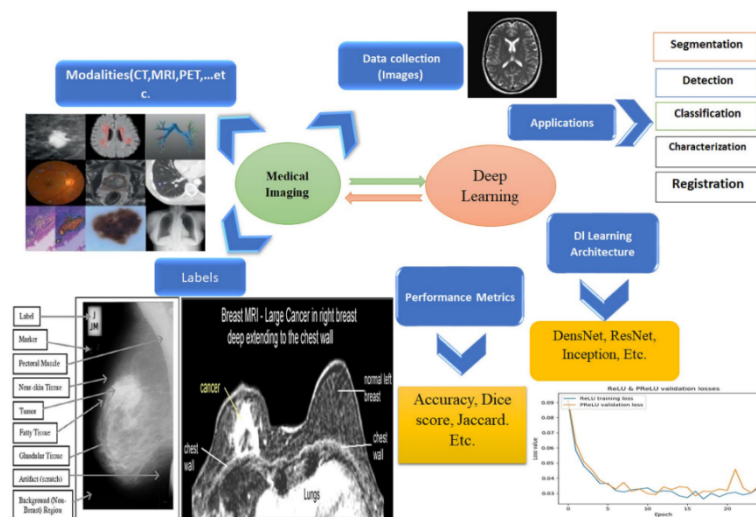


FIGURE 1. Leveraging deep learning in medical image analysis [13].

In medical imaging, deep learning algorithms have proven effective in detecting and diagnosing various conditions as they can analyse X-rays, MRIs, and CT scans while giving complete and timely details about diseases and injuries [14] [15]. These algorithms support radiologists in identifying tumors, fractures, and other complex conditions that are difficult to explain through traditional methods, identifying areas where the disease is present, and determining the most appropriate treatment for each disease a person may suffer from. Deep learning learns from the features found in the deep neural network architecture, where features are automatically extracted from the data without the necessity for human ability because it programs itself automatically [16–18]. Moreover, deep learning is characterized by working on a large number of data with better experience and high performance, as the network is assigned to classify the data and then automatically learns from the data practices. Thus, deep learning is considered one of the techniques that have succeeded in explaining diseases from skin diseases to heart diseases, as it can conduct an accurate examination to search for malignant tumors within the body or use electrocardiograms (ECGs) to detect irregular heartbeats and identify the possibility of cardiac arrest. Among the most famous machine learning methods frequently used in interpreting medical images are convolutional neural networks (CNNs) [19] and recurrent neural networks (RNNs) [20], through which significant details can be extracted from medical images, analysed, and provided accurate and accurate results about the disease. Deep learning contributes to drug discovery by generating appropriate procedures to accelerate drug searches and developing basics for designing drugs that keep pace with developments in diseases, for example, coronavirus diseases. Another crucial aspect of deep learning is natural language processing (NLP), through which valuable information can be extracted from clinical textual data, contributing to making clinical decisions based on the patient's condition. Deep learning works to enhance diagnosis and develop treatments, as it has the ability to interpret models, focus on the course of the disease within the body, and set the patient's condition. It works to improve healthcare and enable the most effective treatments while providing a complete survey of the patient's condition based on clinical data. Likewise, data can be collected from wearable devices that monitor patients' health on a daily and continuous basis and provide care workers with complete details about the patient. The main contribution of this article is to provide a comprehensive survey of the importance of

deep learning in processing and analysing medical images and the services it provides to healthcare workers. And doctors who contribute to developing the environment of health institutions.

2. DEEP LEARNING ALGORITHMS AND APPLICATIONS

Deep learning algorithms are practices within machine learning that work like the human brain to analyse and solve the situations it faces. These algorithms have gained great fame in the field of scientific research and have been applied in many domains, especially the medical field. These algorithms solve all the issues encountered through speech or image recognition, natural language processing, and computer vision. The emergence of deep learning technology has contributed significantly to the analysis of images and sound, the development of robots and self-driving vehicles, the diseases diagnosis, and the development of virtual reality in the education process. The noteworthy reason for its use in many domains is the high accuracy in the performance of deep learning models in solving problems without human intervention. In other words, the human mind has been surpassed in some issues, such as voice recognition, image recognition, pattern analysis in medical images, and prediction of disease growth. Also, deep learning models are applied to colorize images and videos, transforming artworks from black and white into works with colors closer to reality. Contributing to analysing people's speech through their lip movements in a silent video clip utilizing these advanced models. While the success rate of people making predictions by reading lip movements is 52%, the success rate in these models is more than 90%. This demonstrates the ability of deep learning to compete with and outperform the human mind. Moreover, deep learning draws maps and people quickly and efficiently. The emergence of the GPT technique has changed many ideas about the use of artificial intelligence in many fields. Artificial intelligence now communicates to humans through conversations and answers all their inquiries more efficiently and with a high ability to program. Companies such as Facebook, Google, and Netflix utilize deep learning to study the requirements of their users, follow their paths, and assist them in suggesting products that meet their needs. Deep learning can predict many diseases, including diabetes, heart disease, pneumonia, etc. In addition, deep learning models have been employed in voice recognition, natural language processing, robotics, and medical fields. The most famous of these algorithms are:

2.1 CONVOLUTIONAL NEURAL NETWORKS

It is considered one of the most widely employed types of models for image analysis, through which images are displayed and analysed. This algorithm contains several layers that transform the input into small regions using convolution filters (see Figure 1). CNN requires more than one layer to find all the features in images, as it consists of the input layer, convolution layer, activation layer, pooling layer, fully connected layer, and output. During work, the input data is submitted to a network, and the size and accuracy of the input must be determined, as the larger the input size, the longer the training time, and thus the success of the algorithm increases. The most critical layer in this algorithm is the convolutional layer, where a new matrix is extracted by passing a filter over the input image. Filters play a major role, through which the convolution process is applied to the previous image, and a set of output data is created according to the image entered into the network. All its layers are important in medical image processing, where the use of different architectures designed for concerns such as segmentation, classification, diagnosis, and transformation are used.

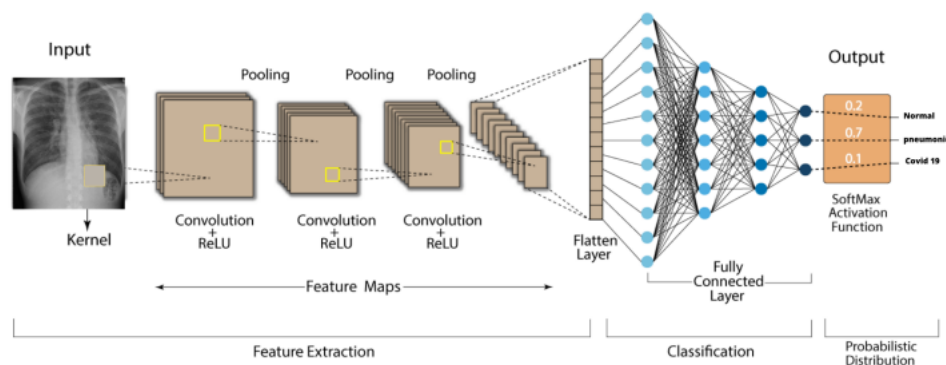


FIGURE 2. Convolutional neural networks architectures [21].

2.2 GENERATIVE ADVERSARIAL NETWORKS

It is a network that aims to expand the image data set, obtain a high-resolution image, and transfer the pattern from one image to another image. This algorithm was created in 2014 and is designed for the task of creating new data samples that resemble a specific data set and is also subject to supervision. The tasks in which this algorithm is used are generating sound, creating and composing video, and converting text into images through complicated mathematical equations. This network consists of a generator and a discriminator (see Figure 3). In the generator, the network samples random noise and attempts to create samples that resemble the real data as well as create fake data that is indistinguishable from the real data. In the discriminator, a distinction is made between real data from the training set and samples of fake data generated by the generator, where the data is differentiated, and the samples are classified into two categories, real and unreal, with high accuracy. Figure 3 illustrates the architecture of generative adversarial networks. Through this form, the generator yields random samples and is trained on the basis of these samples. The most useful way to separate fake data from real data is generated in the discriminator. The generator improves as it generates more convincing data for the discriminator by generating fake data that is closer to reality so that the discriminator is unable to distinguish between the real and fake dataset.

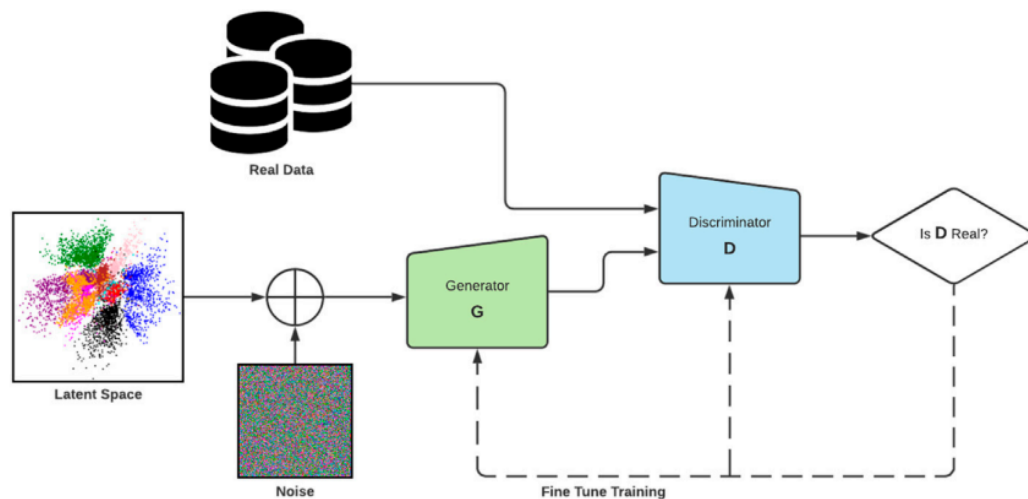


FIGURE 3. Generative adversarial networks architecture [22].

2.3 RECURRENT NEURAL NETWORKS

It is considered an artificial neural network designed to process data sequences according to a specific structure that makes it suitable for natural language processing tasks. This algorithm has a feedback mechanism that allows it to keep all inputs in a hidden memory where it can capture the temporal dependencies of its input data. Also, sequences of different lengths can be processed, as texts can be created, speech can be overlaid on video, and subtitles can be created for any content. This algorithm is used for the tasks of language modeling, text classification, and machine translation of any content, regardless of its size. This algorithm has significant improvements in the field of voice recognition and converting spoken language into editable text. In addition, this algorithm is practical in prediction as it can predict future values based on inputs, which makes it appropriate for analysing medical data and predicting disease outcomes. This algorithm suffers from being computationally expensive to train and being slow in long sequences. It consists of a repetitive layer containing neurons or repeating units. Many variants of this network were developed, such as Long Short-Term Memory (LSTM) networks and Recurrent Unit (GRU) networks, to solve all the problems they faced. Therefore, this algorithm is considered a basic building block in developing deep learning in the medical field.

The second part of this section will address applications of deep learning in medical image segmentation, classification, disease diagnosis, and image creation and improvement. Segmentation, also known as partitioning, is the process of dividing an image into meaningful regions where different features are preserved. That is, labels are extracted for each pixel, and some inferences are made by creating predictions about these labels. It is the first and crucial component of diagnosis and treatment in medical images and is widely used to separate homogeneous regions in CT or MRI images. Medical image segmentation, which determines the pixels of organs or lesions, is critical in providing important information about the shapes and sizes of these organs and lesions. While these tasks were previously performed by applying different

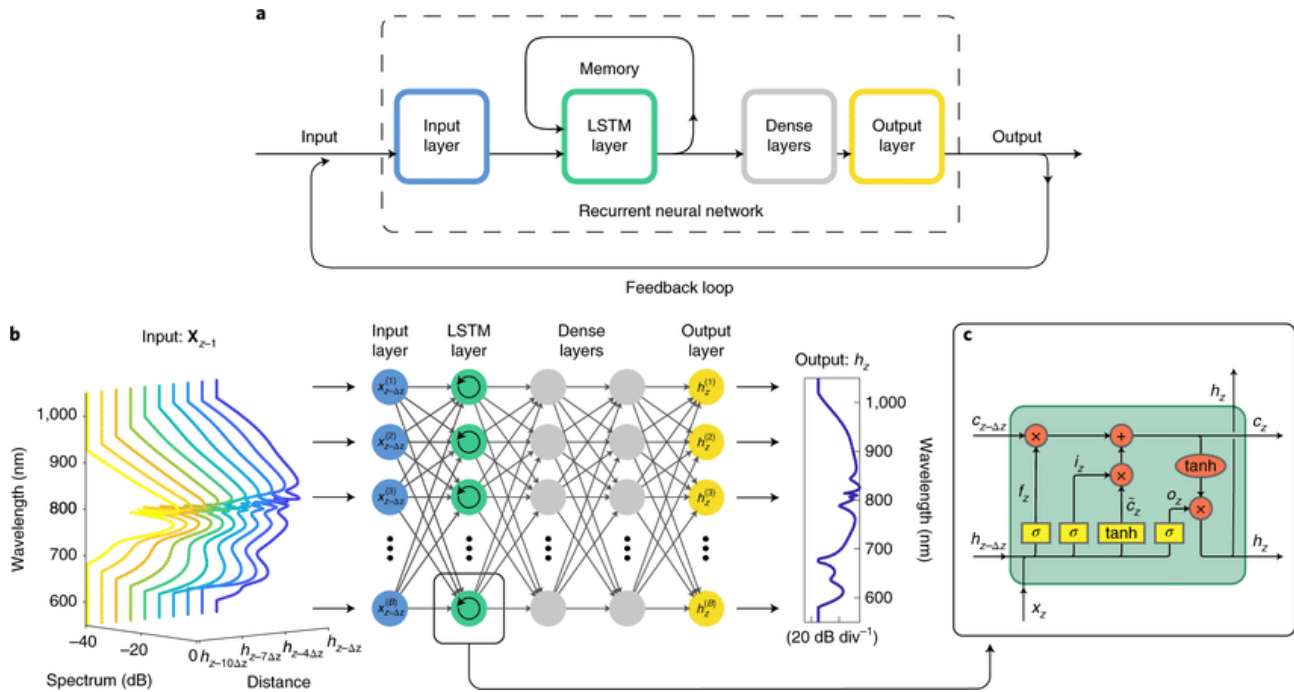


FIGURE 4. Recurrent neural networks architecture [23].

filters and mathematical formulas, in recent years, deep learning-based techniques have attracted significant attention and started to be used more frequently in this field. Healthcare institutions seek to benefit from it by segmenting images and extracting essential features to assist physicians in accurately determining the extent of the disease. Applying segmentation to medical images for analysis in computer-aided diagnostic systems is of significant value to healthcare specialists. In addition, some classification studies also rely on segmentation. First, segmentation is performed to detect the tumor or lesion, and then its type is classified. To diagnose medical images, the deep learning technique organizes a wide range of diverse data that includes medical conditions, demographics, and patients' medical history. Medical images are usually images that differ in resolution and orientation, so it is preferable to use pre-processing techniques to reduce noise within the images and standardize the data in order to be suitable for considering the implementation of deep learning models. The medical image diagnosis process requires deep learning architectures in order to automatically extract relevant features from the images, as this step is vital for analysing the most significant number of images. Deep learning models are trained on a dataset and recognize patterns and features in medical images. This process is accomplished by adjusting the models' weights through a process called backpropagation. To evaluate the performance of these models by training them and measuring their performance by using metrics to measure implementation to determine diagnostic accuracy, sensitivity, and specificity. Diagnosing medical images is significant to gaining healthcare professionals' confidence and clinical acceptance, as it can interpret the areas of the images that most affect the patient's health. Figure 5 illustrates how deep learning can determine areas of disease.

Physicians and healthcare workers can integrate validated deep learning results with clinical practices to facilitate the process of monitoring patients and analysing images of disease progression. Deep learning models are not static and can be enhanced through new data and ongoing analysis into applying these models to other diseases. These models must be revised regularly to obtain high diagnostic accuracy. Integrating deep learning models with clinical data has facilitated a lot of work between radiologists and data providers in healthcare institutions. Medical image classification is one of the most vital tasks carried out by deep learning models to identify healthy images from unhealthy images. CNN is the most suitable and typical architecture for image classification and automatic feature recognition (see Figure 6). The data is pre-processed, scaled to a standard resolution, and pixel values are normalized to make it easier for models to classify images. Specialists and physicians collect images based on a specific medical condition or category.

Deep learning models are trained on a dataset of medical images, and these models adjust their weights to recognize new patterns in each class. The performance of the trained models is verified to ensure their ability to classify image categories through measures of classification accuracy, sensitivity, specificity, and F1 score. Deep learning models have been utilized to analyse chest X-rays and CT scans to detect COVID-19 and diagnose the disease by identifying pneumonia-associated patterns. In addition, these models were utilized to predict the spread of the disease, the daily infection rate,

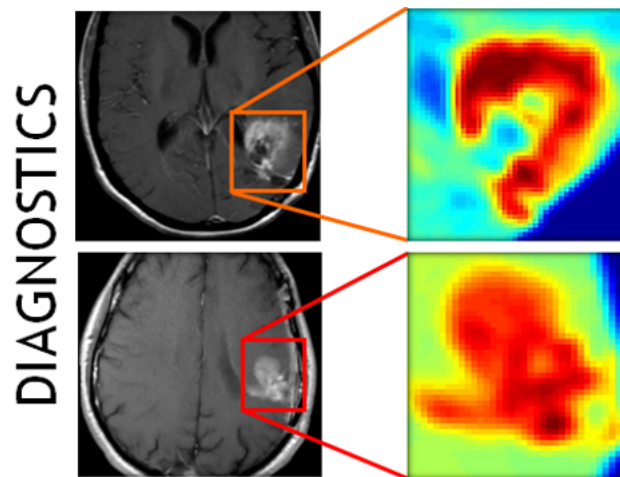


FIGURE 5. The potential of deep learning in determining tumor locations [24].

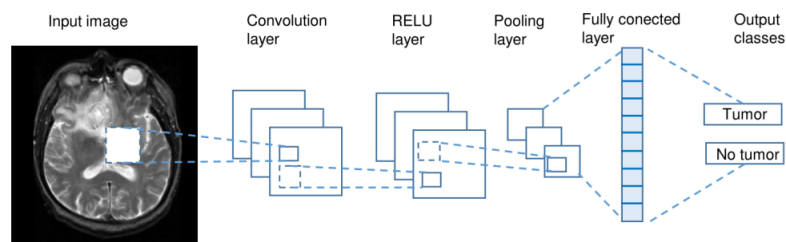


FIGURE 6. Image classification using deep learning [25].

and the number of deaths. Deep learning techniques have been combined with computer vision to track people and monitor social distancing compliance within cities. Furthermore, deep learning models have been integrated with mobile applications to track and detect COVID-19 symptoms, and these applications can provide residents with all the required data and monitor their condition. When we look at the areas where deep learning models are involved, it can be seen that success has been accomplished in many aspects. In addition, another primary reason behind its widespread use can be explained by the creation of open-source software libraries and the abundance of datasets. The most significant drawback of deep learning is the limitations imposed by hardware resources in models' training and testing phase. Two different keys can be offered to eliminate this problem. The first is that deep networks are designed with memory usage and test times in mind when running in real-time. The second is to conduct hardware and software studies on operating deep networks with lower computational costs. Ultimately, deep learning has proven to have a significant role in enhancing the environment of health institutions through its application in diagnosing and predicting diseases. Deep learning contributes to enhancing the accuracy of image diagnosis to assist specialists and doctors in organizing sound healthcare for their patients and providing them with appropriate treatment.

3. CONCLUSIONS

Deep learning is one of the most famous practices utilized in medical imaging analysis. It contains algorithms with various network architectures, and is widely employed in healthcare, particularly in medical images. These practices are continually utilized in areas such as early diagnosis of diseases, reducing healthcare workers' density, reducing expert ideas, and early treatment. Although concerns such as the inability to access sufficient data and inadequate mathematical model construction still represent problems for deep learning models, the point that there are several investigations in the literature with a success rate of more than 90% demonstrates the potential of deep learning models in healthcare domain. This article reviews deep learning architectures and processes used in image description. In the future, more articles will be published on the possibility of applying deep learning in medical images, providing illustrations in image segmentation, classification, and diagnosis, highlighting the role of deep learning in detecting tumors, cancers, and coronaviruses.

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CONFLICTS OF INTEREST

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REFERENCES

- [1] J. Kumari, E. Kumar, and D. Kumar, "A Structured Analysis to study the Role of Machine Learning and Deep Learning in The Healthcare Sector with Big Data Analytics," *Archives of Computational Methods in Engineering*, vol. 30, pp. 3673–3701, 2023.
- [2] M. Yagi, K. Yamanouchi, N. Fujita, H. Funao, and S. Ebata, "Revolutionizing Spinal Care: Current Applications and Future Directions of Artificial Intelligence and Machine Learning," *Journal of Clinical Medicine*, vol. 12, no. 13, pp. 4188–4188, 2023.
- [3] S. U. D. Wani, N. A. Khan, G. Thakur, S. P. Gautam, and M. Ali, "Utilization of Artificial Intelligence in Disease Prevention: Diagnosis, Treatment, and Implications for the Healthcare Workforce," *Healthcare*, vol. 10, no. 4, pp. 608–608, 2022.
- [4] A. H. Al-Mistarehi, M. M. Mijwil, Y. Filali, M. Bounabi, G. Ali, and M. Abotaleb, "Artificial Intelligence Solutions for Health 4.0: Overcoming Challenges and Surveying Applications," *Mesopotamian Journal of Artificial Intelligence in Healthcare*, vol. 2023, pp. 15–20, 2023.
- [5] S. K. Umamaheswaran, G. L. V. Prasad, B. Omarov, D. S. Abdul-Zahra, P. Vashistha, B. Pant, and K. Kaliyaperumal, "Major Challenges and Future Approaches in the Employment of Blockchain and Machine Learning Techniques in the Health and Medicine," *Security and Communication Networks*, vol. 2022, no. 5944919, pp. 1–11, 2022.
- [6] M. Arabahmadi, R. Farahbakhsh, and J. Rezazadeh, "Deep Learning for Smart Healthcare-A Survey on Brain Tumor Detection from Medical Imaging," *Sensors*, vol. 22, no. 5, pp. 1960–1960, 2022.
- [7] Z. Gao, L. Lou, M. Wang, Z. Sun, X. Chen, and X. Zhang, "Application of Machine Learning in Intelligent Medical Image Diagnosis and Construction of Intelligent Service Process," *Computational Intelligence and Neuroscience*, vol. 2022, no. 9152605, pp. 1–14, 2022.
- [8] S. Nazir, D. M. Dickson, and M. U. Akram, "Survey of explainable artificial intelligence techniques for biomedical imaging with deep neural networks," *Computers in Biology and Medicine*, vol. 156, pp. 106668–106668, 2023.
- [9] Z. Amiri, A. Heidari, M. Darbandi, Y. Yazdani, and N. J. Navimipour, "The Personal Health Applications of Machine Learning Techniques in the Internet of Behaviors," *Sustainability*, vol. 15, no. 16, pp. 12406–12406, 2023.
- [10] M. Shehab, L. Abualigah, Q. Shambour, M. A. Abu-Hashem, M. K. Y. Shambour, A. I. Alslibi, and A. H. Gandomi, "Machine learning in medical applications: A review of state-of-the-art methods," *Computers in Biology and Medicine*, vol. 145, pp. 105458–105458, 2022.
- [11] P. Manickam, S. A. Mariappan, S. M. Murugesan, S. Hansda, A. Kaushik, R. Shinde, and S. P. Thipperudraswamy, "Artificial Intelligence (AI) and Internet of Medical Things (IoMT) Assisted Biomedical Systems for Intelligent Healthcare," *Biosensors*, vol. 12, no. 8, pp. 562–562, 2022.
- [12] A. T. Keleko, B. Kamsu-Foguem, R. H. Ngouna, and A. Tongne, "Health condition monitoring of a complex hydraulic system using Deep Neural Network and DeepSHAP explainable XAI," *Advances in Engineering Software*, vol. 175, pp. 103339–103339, 2023.
- [13] R. Yousef, G. Gupta, N. Yousef, and M. Khari, "A holistic overview of deep learning approach in medical imaging," *Multimedia Systems*, vol. 28, pp. 881–914, 2022.
- [14] M. L. Giger, "Machine Learning in Medical Imaging," *Journal of the American College of Radiology*, vol. 15, no. 3, pp. 512–520, 2018.
- [15] M. P. Mcbee, O. A. Awan, A. T. Colucci, C. W. Ghobadi, and N. Kadom, "Deep Learning in Radiology," *Academic Radiology*, vol. 25, no. 11, pp. 1472–1480, 2018.
- [16] M. Yaqub, F. Jinchao, K. Arshid, S. Ahmed, and W. Zhang, "Deep Learning-Based Image Reconstruction for Different Medical Imaging Modalities," *Computational and Mathematical Methods in Medicine*, vol. 2022, no. 8750648, pp. 1–18, 2022.
- [17] C. A. Ronao and S. Cho, "Human activity recognition with smartphone sensors using deep learning neural networks," *Expert Systems with Applications*, vol. 59, pp. 235–244, 2016.
- [18] W. Liu, Z. Wang, X. Liu, N. Zeng, Y. Liu, and F. E. Alsaadi, "A survey of deep neural network architectures and their applications," *Neurocomputing*, vol. 234, pp. 11–26, 2017.
- [19] M. M. Mijwil, R. Doshi, K. K. Hiran, O. J. Unogwu, and I. Bala, "MobileNetV1-Based Deep Learning Model for Accurate Brain Tumor Classification," *Mesopotamian Journal of Computer Science*, vol. 2023, pp. 32–41, 2023.
- [20] I. Banerjee, Y. Ling, M. C. Chen, S. A. Hasan, and C. P. Langlotz, "Comparative effectiveness of convolutional neural network (CNN) and recurrent neural network (RNN) architectures for radiology text report classification," *Artificial Intelligence in Medicine*, vol. 97, pp. 79–88, 2019.
- [21] Z. Rguibi, A. Hajami, D. Zitouni, A. Elqaraoui, and A. Bedraoui, "CXAI: Explaining Convolutional Neural Networks for Medical Imaging Diagnostic," *Electronics*, vol. 11, no. 11, pp. 1775–1775, 2022.
- [22] R. T. Hughes, L. Zhu, and T. Bednarz, "Generative Adversarial Networks-Enabled Human-Artificial Intelligence Collaborative Applications for Creative and Design Industries: A Systematic Review of Current Approaches and Trends," *Frontiers in Artificial Intelligence*, vol. 4, pp. 1–17, 2021.
- [23] L. Salmela, N. Tspinakis, A. Foi, C. Billet, J. M. Dudley, and G. Genty, "Predicting ultrafast nonlinear dynamics in fibre optics with a recurrent neural network," *Nature Machine Intelligence*, vol. 3, pp. 344–354, 2021.
- [24] N. Ajmera, "Machine Learning in Medical," *Medium*, 2019.
- [25] J. Ker, L. Wang, J. Rao, and T. Lim, "Deep Learning Applications in Medical Image Analysis," *IEEE Access*, vol. 6, pp. 9375–9389, 2017.