Deep Learning Approaches for Medical Image Processing in the Big Data Era

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Received: 01 June 2024 • **Accepted:** 02 June 2024 • **Published Online:** 03 June 2024

Abstract: Diagnostics, therapy planning, and patient monitoring are areas where medical image processing has become indispensable in modern healthcare. The advent of deep learning techniques and the broad usage of big data in healthcare has brought a revolutionary shift in medical picture analysis and interpretation. An overview of deep learning techniques for medical image processing based on big data is given in this article. This article covers the pros and cons of adopting big data for medical imaging, from data storage and analysis to data capture. Beyond that, we take a look at medical image analysis using deep learning algorithms such as recurrent neural network (RNN), Convolutional Neural Network (CNN), and generative adversarial network (GAN), and we highlight its advantages and disadvantages. We also examine recent innovations such as transfer learning, multi-modal imaging fusion, and federated learning, which can improve the accuracy and efficiency of medical image processing systems. Finally, we discuss how medical image processing driven by deep learning could improve clinical decision-making, patient outcomes, and the development of personalized medicine in the era of data-driven healthcare.

Key words: Medical image processing, Deep learning, Big data, Transfer learning, Federated learning, Multi-modal imaging.

1. Introduction

The development of non-invasive techniques for examining interior structures and detecting anomalies through medical imaging has completely transformed healthcare. Medical imaging modal-

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https://doi.org/10.58599/IJSMCSE.2024.1108
Vol. 1, No. 1, June 2024, pp:24-31

ities, such as X-rays, magnetic resonance imaging (MRI), computed tomography (CT) scans, and ultrasounds, have become essential resources for detecting, evaluating, and tracking a wide range of disorders [1]. Traditional image processing methods face substantial obstacles from the enormous amount and complexity of daily medical image data. With the advent of deep learning, medical image processing has undergone a sea change, opening up new possibilities for the automated interpretation and analysis of complicated imaging data. Integrating deep learning techniques with medical image processing holds promise for enhancing diagnostic accuracy, reducing interpretation times, and unlocking insights from large-scale image datasets [2]. Convolutional neural networks (CNNs) and other deep learning techniques have been very effective in picture segmentation, object detection, and classification. Convolutional neural networks (CNNs) can create reliable predictions, regardless of the amount of noise or variability present in medical pictures, by using the hierarchical characteristics learned from data [3]. The big data characteristics is shown in Figure 1.

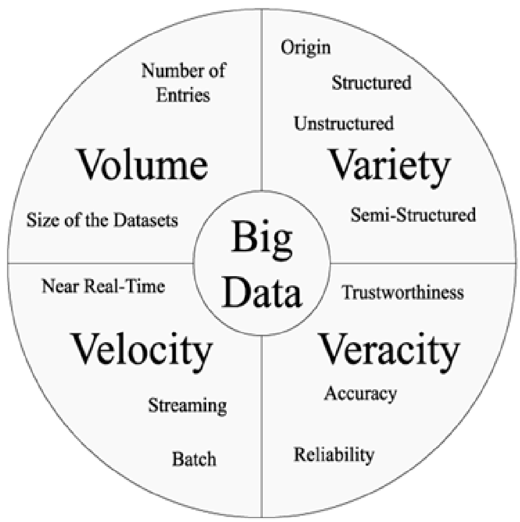

Figure 1. Big data characteristics

One critical enabler of deep learning in medical imaging is the availability of big data-vast repositories of annotated medical images that facilitate model training and validation. With the proliferation of electronic health records (EHRs), picture archiving and communication systems (PACS), and medical imaging repositories, researchers and clinicians have unprecedented access to diverse and large-scale medical image datasets [4]. This abundance of data presents unique opportunities for training robust and generalizable deep learning models capable of handling the variability inherent in medical images. However, using big data in medical imaging also poses several challenges, including data heterogeneity, privacy concerns, and the need for robust data preprocessing techniques. Medical images can vary significantly regarding resolution, modality, and anatomical structures, necessitating careful curation and standardization of datasets for practical model training [5]. Moreover, patient privacy and data security concerns mandate adherence to stringent regulations [6]. Despite these challenges, the potential impact of deep learning-based medical image processing is profound, with implications for improving clinical workflows, enhancing patient outcomes, and advancing precision medicine [7]. By automating routine tasks such as image interpretation and analysis, deep learning models can augment the capabilities of healthcare professionals, enabling faster and more accurate diagnoses [8]. Furthermore, integrating deep learning with other emerging technologies, such as telemedicine and mobile health, holds promise for extending the reach of medical imaging to underserved populations and remote regions, ultimately democratizing access to high-quality healthcare services.

2. Related Works

According to [9], CNN is a method that uses deep learning to classify images by applying networking models to medical records. These days, quick and easy diagnosis of any patient's ailment is the primary usage of health data cardinal photos. This research uses several machine learning models, including an ANN model based on neural networks. Several supervised machine learning approaches, some of which incorporate hybrid features, are compared and contrasted in this article. According to the findings, the most accurate model was the hybrid feature set that included both SVM and SoftMax features. Using the deep learning approach, there is a recommendation for image classification in [10]. Both spam detection and picture classification are accomplished with the help of deep learning algorithms. In this investigation, researchers used a convolutional neural network (CNN) method to classify images across various datasets. The methods can be applied to different datasets by utilizing visual representations. The experiments showed that convolutional neural network representations of pictures are accurate and low error using mean square error values as a criterion. From all of the datasets used to compile this essay, it is clear that CNN outperforms the alternatives.

In [11], the authors offer a method for identifying chest x-ray pictures by combining multiple CNN models. Nowadays, X-ray images are utilized extensively in numerous sectors of the healthcare industry to enhance patient care. Doctors must go through a mountain of X-rays to give patients the necessary care. For the doctor to correctly conclude each report, various technologies must be used to identify and synthesize images. The exponential increase in global population has led to a dramatic rise in the prevalence of numerous diseases and health problems, including diabetes, cardiovascular disease, and innumerable others [12]. To find abnormal chest x-rays in the dataset, this study used a CNN model with many variables. Ensuring several CNNs are working correctly is a common usage of the CNN method in DL models. An article outlining a non-medical strategy for creating deep learning algorithms to predict chest disease may be found in [13]. You'll need to draw some blood if you want to know which diseases can be shown on your chest x-ray. Based on the vast data acquired, the doctors decide on a course of action and pinpoint the source of the problem. The collection includes 433 photos, including the current chest x-rays. After applying various deep learning model algorithms to the dataset, which provides for non-medical photographs of multiple ailments, the most accurate method was CNN with deep architecture classification [14].

3. Methodology

When training machine learning models to do meaningful tasks, it is common practice to use basic models or features manually constructed from the raw data. Doing so ensures the highest quality outcomes. Deep learning bypasses this laborious and time-consuming step by automatically training computers to find relevant patterns and representations in raw data. Because of this, deep learning can bypass this stage. Although more deep learning models exist, ANNs and their variants are the most popular. Nonetheless, alternative models do exist. Feature learning, often called separately determining data illustrations, is the main emphasis of deep learning methods. This is the main thing that every one of them has in common. In this respect, deep learning differs the most from other "traditional" approaches to machine learning. The training session improves the capacity to locate traits and the ability to do tasks simultaneously because they are merged into a single challenge. Many people in the deep learning community, especially those in medical imaging, are interested in Convolutional Neural Networks (CNNs) because they can learn meaningful representations of pictures and other structured data. To make good use of convolutional neural networks (CNNs). Machine learning models with less experience or human coders produced earlier iterations of this content. It was common practice in the corporate world to discard many of the photographic assets created manually. In the past, characteristics could be learned directly from data and used. It all started when CNN realized the feature detectors weren't doing much. We can ascertain their efficacy by delving into the deep preferences encoded in CNNs.

To reduce the dimensionality of the feature maps before applying a 3x3 transformation, it is feasible to utilize 1x1 convolutions at specific network nodes. The combination of ResNets and the bottleneck block shown in Figure 2 allowed us to achieve this. Before conducting any analysis on a 256-level feature map, we gather all of the data into 64 feature maps. Following compression, we use our 3x3 convolution, which completes the process much more quickly with 64 feature maps compared to 256 feature maps and has proven to be as effective as, if not more so, utilizing conventional 3x3 stacks. It is possible to restore the original's 256-by-256 dimensions using the most current 1x1 map. In contrast to the pooling method used to acquire feature sum, CNN uses downsampling as we go deeper into the network. It is widely acknowledged that down sampling can yield more precise

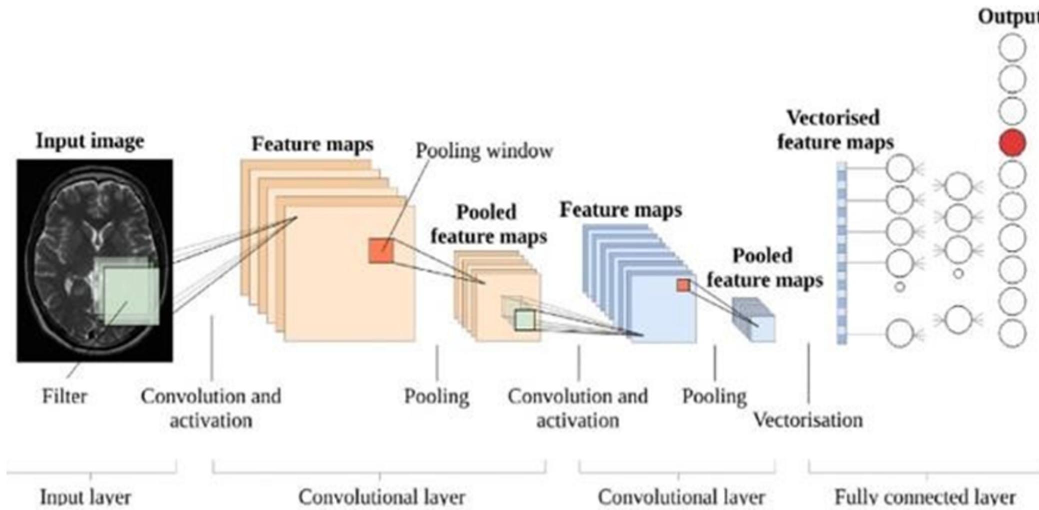

Figure 2. Proposed CNN architecture

results than pooling. Feel free to utilize any of these approaches to create a feature summary.

Reducing the sample size once each "stage" is finished will worsen our memory for spatial information. Finally, by combining our knowledge, we can ascertain its accuracy and provide a summary. When combining data, the two most common ways are an average and a maximum. The scientific community still does not agree on whether average or maximum pooling is the better approach. Honestly, I've learned from experience that there is absolutely no difference. It is standard procedure to implement network-wide max pooling before installing the last dense layer and passing control to the SoftMax function. Before installing the networking layer, this is accomplished. Then, we use an average pooling approach to provide you with a final vector depiction of your requirements. This process aims to preserve the most desired properties while making it considerably simpler to generate the final vector representation.

4. Results and Discussion

A de-identified collection of 100,000 chest X-ray images is housed in the National Institutes of Health's (NIH) databases. In the storage system, the pictures are kept as individual PNG files. Obtaining the data is as simple as downloading it from the National Institutes of Health Clinical Center's website. Some photo expansion methods should be used to increase the size of the images, working out the dataset effectively. Image expansion improves the model's capacity to forecast new images by creating modified versions of the photos that make up the training set. The procedure is made possible by expanding and diversifying the dataset. Pixel values in digital photographs can be anywhere from zero to two hundred and fifty, with zero being black, two hundred and fifty being white, and all values in between. Digital photos contain microscopic things called pixels. To make their impact on the total loss more evenly distributed, it is suggested to rescale the array of unique image pixel standards to a range of [0,1]. A slower learning rate is recommended because it is possible that this is not the case. The opposite is true for photos with a lower pixel range; a higher learning rate is necessary to compensate for the more significant number of pixels that would be lost. The form of the picture clearly shows the effect of the shear. Figure 3 shows the "shear angle," which occurs at images stretched to a specific ratio. The image was stretched to achieve this angle. No change is made to the image along any of the specified axes throughout this operation.

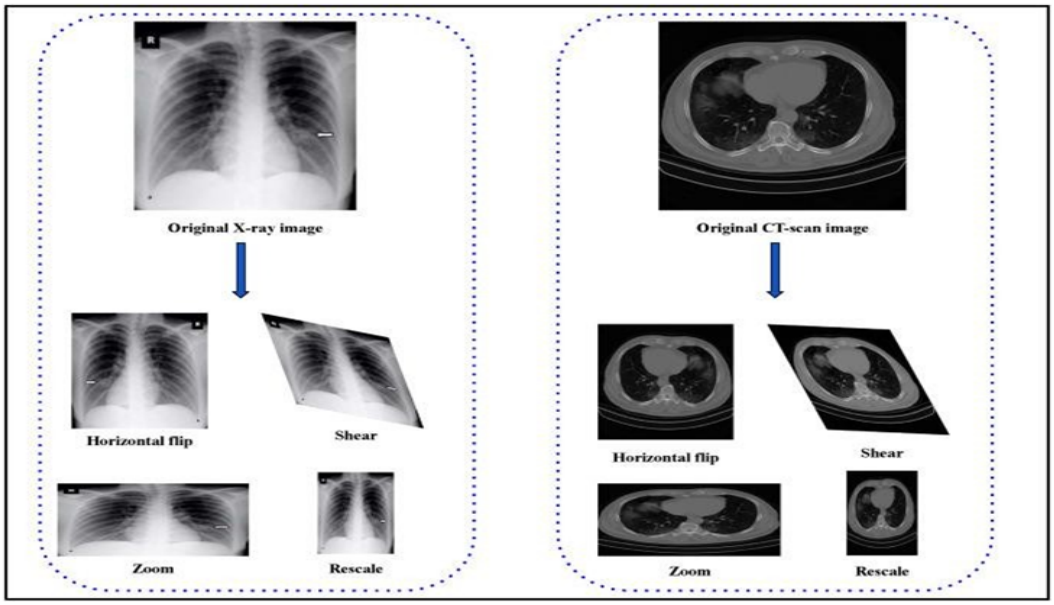

Figure 3. Zooming of the image

The convolutional layering technique is one of the basic building blocks of CNNs. After the convolution layers process the picture data, it is passed on to the next CNN layer for further processing. For this specific procedure, the term "convolutional operation" is employed. A certain number of filters must be present in every convolution layer. These filters scan various elements, such as colors, shapes, edges, forms, curves, and textures, for patterns. Deeper, more complex levels of items or patterns can be identified. An image kernel, the building block of a filter, is like a small 3x3 or 4x4 matrix when applied to the whole image. A low-dimensional input representation (image) will be utilized by employing the Pooling and Convolution layers. The next step is to lower the image sample frequency while keeping the active feature value in the subregion binding as high as possible. "stride" means the total number of pixels traversed in the input matrix. The stride becomes a pixel-by-pixel filter when it reaches 1. If we set the stride to 2, the filter will be advanced by two pixels every iteration. Applying filters and stages of varying sizes allows one to bring down a massive image to a more manageable size. Continuously start with a reduced value, like 32, and progressively grow the filter setting; only do it some at a time.

5. Conclusion

The primary emphasis of our research was placed on classifying medical images on massive datasets by applying Big Data technologies. The methods and classifications that use CNNs and are applied to large-scale X-ray pictures are the primary focus of this research. One additional service we provided was the development of a pipeline for classifying medical images. CNN approaches are superior to conventional model training in terms of artificial intelligence and traditional training of models due to the more excellent learning selection capabilities that CNN approaches possess. On the other hand, overfitting and the difficulty of training an excessively complicated network are both difficulties that are well-known throughout the industry. Alternatives that have not been tried and tested but have the potential to be fruitful include Resnetv2 and many CNN models working together. For this strategy, we utilized a Spark algorithm that extracts features. Even though we worked with enormous datasets, we discovered that our proposed model performed better and faster on GPU computers. The model stretched a score of 91.16% and an F1 score of 93.22% in terms of its accuracy scores.

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