Review Article

A Narrative Review Of Machine Learning Systems In The Diagnosis Of Ct Scan

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Abstract:

Clinicians rely on their knowledge and experience, as well as the results of complex and time-consuming clinical trials, despite the inevitable human error, to diagnose and treat diseases. The application of machine learning sheds light on the ability of these techniques to help correctly diagnose some diseases. Nowadays, with the emergence of the COVID-19 pandemic, the mass number of COVID-19 cases who refer to medical centers increased through the last two years of the pandemic, leading to a large number of patient records being collected in the medical database; while these resources not being used properly in some cases. In this regard, data mining and machine learning approaches have attracted researchers to help to predict and diagnosing disease. Through the literature, machine learning is applied to extract patients' characteristics and their correct classification to help diagnose suspicious cases. Due to the need for sufficient experience to diagnose the COVID-19 based on the imaging methods of the lung, researchers have thought of using intelligent diagnostic methods by modeling the knowledge of skilled radiologists using machine learning algorithms. Our study showed how machine learning-based analysis of lung imaging can lighten the burden on radiologists, as they must review and prioritize the growing number of imaging findings in a pandemic peak. Also, there is a need for big datasets for better training of Machine learning algorithms; while literature review shows the possibility of statistical errors like duplication of images in public imagining repositories of COVID-19. But yet it is unlikely that these machine learning algorithms will be used instead of standard nucleic acid tests as the primary tool for detecting COVID-19; while broad application of these inexpensive systems could occasion opportunistic screening of COVID-19 in lung scans.

Keywords: COVID-19, imaging, CT scan, chest X-ray, machine learning.

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Background:

The new coronavirus (SARS-COV-2) is part of a large family of viruses that have been identified and spread over the past two years, and almost the entire world has shown a mass number of infection cases, also known as COVID-19 (1). Over time, strategies and methods have been developed to detect SARS-COV-2 that can prevent the spread of the COVID-19. The high transmissibility of SARS-COV-2 makes the necessity of quick detection of infected cases (2-4). Real-time PCR (RT-PCR) genetic testing has been proposed by the World Health Organization and the Center for Infectious Disease Control as the most accurate diagnostic method for SARS-CoV-2 or COVID-19 (5-8). COVID-19 RT-PCR is usually necessary for people with symptoms of Covid-19 disease such as high fever, dry cough, chest pain, and respiratory problems such as shortness of breath or dyspnea. Because the number of patients with COVID-19 is increasing worldwide, it is essential to identify patients with COVID-19 in its early stages to provide appropriate treatments. chest X-ray (CXR) is very important in diagnosing lung lesions caused by COVID-19. However, its sensitivity and specificity are relatively low for patients with mild COVID-19 (9). For this reason, it is not recommended for the diagnosis of patients in the early stages of Covid-19 disease. But a CT scan of the lung can show almost any abnormality, including premature exudative lesions. As shown in some studies, computed tomography (CT) scan seems to be a promising and effective method in the diagnosis of COVID-19. High-resolution CT (HRCT) scan is necessary to examine the lungs to diagnose the disease in its early stages and to assess the severity of Covid-19 infection in patients (10). Typical CT scans in Covid-19 patients show images of Bilateral pulmonary parenchymal ground-glass and stabilized pulmonary opacities (Consolidation Pulmonary opacities) and in some cases as Circular shapes that extend to the outside of the lung tissue are seen. a large number of patients in COVID-19 peaks may make it difficult for diagnosticians to properly interpret numerous CT scan records; So, some researchers have tried to get computer-based technologies to help to diagnose COVID-19 in CT scans (10-13). Artificial intelligence techniques can support medical diagnostic procedures and help increase diagnostic accuracy. Human factors such as fatigue, lack of knowledge, etc. are involved in the diagnosis of the disease and cause the error to be diagnosed. The accuracy of COVID-19 diagnosis always depends on the level of expertise and knowledge of the doctors requesting the graphs, the correct sampling method for PCR examination, and the quality of PCR diagnostic kits. Diagnosis of COVID-19 disease with the help of chest radiography and CT scan also requires expert radiologists, which is a major limitation, which in many epidemic conditions and high prevalence of these specialists is not enough. Artificial intelligence techniques can be used to design appropriate models to identify people and predict disease. Researches in the field of tuberculosis diagnosis with artificial intelligence of input variables examined different data sets and algorithms.

Machine learning:

Inspired by pattern learning and computational learning theory, machine learning studies and builds algorithms that can learn and predict based on data. Such algorithms do not follow program instructions and make predictions or decisions by modeling sample input data. Machine learning is used in computational tasks in which designing and programming explicit algorithms with proper performance is difficult or impossible (14).

With the expansion of information technology applications in various fields, the need for automation of decision-making processes has increased (15). Artificial intelligence knowledge as one of the main solutions to meet these needs uses machine learning methods. Machine learning is closely related to and often overlaps with computational statistics. The focus of this branch is computer prediction, and

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it is strongly linked to mathematical optimization, which also introduces methods, theories, and applications (16). Machine learning is sometimes integrated with data mining; The focus of this sub-category is on exploratory data analysis and is known as unsupervised learning. Machine learning can also be unsupervised and can be used to learn and recognize the basic form of the behavior of different organisms and then to find a significant anomaly (16-18).

In the field of data analysis, machine learning is a method for designing complex algorithms and models that are used for prediction; In industry, this is known as predictive analytics. These analytical models allow researchers, data science researchers, engineers, and analysts. Achieve reliable and repeatable decisions and results, and expose hidden frustrations by learning about past relationships and trends. Effective implementation of machine learning is difficult because modeling is difficult and often, not enough training data is available, resulting in machine learning programs often failing (19).

Machine learning methods enable different systems to learn, review, and make practical suggestions. These systems become smarter over time as they interact with data, networks, and people. Using machine learning and artificial intelligence approaches, these systems are able to help people solve important, practical, and everyday problems. This is often done using data that is not very useful to humans due to its large size or incomprehensible nature (20).

So far, humans have experienced many applications of artificial intelligence and machine learning in everyday life. Email services use machine learning algorithms to detect spam. Suggestion systems, search engine results sorting, smiling face recognition for self-portrait photography are all other examples of machine learning applications. Machine learning tools and methods, unlike other human inventions, are not intended to overcome physical limitations and needs, but to build systems that learn and teach instead of human beings (18-21).

Machine learning in image process:

The field of medicine and health is one of the important sectors in industrial societies. Extracting knowledge from the large volume of data related to disease records and medical records of individuals using the machine learning process can lead to the identification of laws governing the creation, growth, and spread of disease and provide valuable information to identify the causes of disease. The result of this could be an increased life expectancy (22).

One of the most important fields of machine learning is the extraction of classification rules in the field of medical sciences. By using machine learning algorithms, intelligent systems can be developed that are able to automatically understand and interpret the medical properties of individuals without the need for physician supervision, or to discover useful information that helps experts make sound judgments. In the machine learning literature, a very diverse set of methods has been presented so far, each of which has its own strengths and weaknesses, the performance of which varies depending on the type of data and the prevailing conditions, so it cannot be considered the best method alone (23-25).

The first impetus for this learning structure was inspired by the study of the neural structure in the human brain, in which nerve cells make sense by sending messages to each other (26). Depending on the various hypotheses about how these neurons connect, different models and structures have been proposed and studied in this field, although these models do not exist naturally in the human brain and the human brain is more complex (27). These models, such as deep neural networks, complex neural networks, and deep belief networks, have made good progress in the areas of natural language processing, and image processing (28).

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Machine learning algorithms mainly extract features from the data, such as patient "features" and preferred medical outcomes. For a long time, artificial intelligence in health care dominated by logistic regression was the simplest and most common algorithm when it needed to be classified. It was easy to use, quick to finish, and easy to interpret (29).

COVID-19 Imaging Databases:

It is important that we all share our methods and data so that we can complement each other. Accordingly, many important efforts are being made to collect large repositories and image data and accompanying data from hospitals and communities around the world. Currently, many databases around the world have been published of chest radiographs and lung CT scans of new coronavirus patients, which have been used by various researchers to investigate automatic diagnostic methods. The study by Afshar et al. (30) introduced a new CT-scan dataset, called COVID-CT-MD, which included COVID-19 cases and community-acquired pneumonia. This database contains information on lobe level, incision level, and patient information. RICORD includes 240 chest CT scans and 1,000 chest radiographs from four international sites (31). The COVID-19 CT segmentation, which contains 829 CT scans of the lungs of coronary arteries, was made available to the public by Jiang et al. (32). LIDC database containing 1018 CT scan images (33), CC-19 Dataset containing 34006 CT scan images (34) have been published. However, the number of CXR datasets is innumerable. One of the problems with this large number of free COVID-19 imaging databases is the possibility of duplicate images. There is no limitation for a supporter of transfer COVID-19 CT scans to upload images to any public archive, so, there is a high probability of duplication of images across these sources and no affirmation that the cases remembered for these datasets are affirmed COVID-19 (35). This issue definitely prompts problems with calculations being prepared and tried on indistinguishable or covering datasets while trusting them to be from particular sources.

Processing units

Fragmentation of chest X-ray images is a key process and is the first and most important step in many applications and some cases of COVID-19. Due to the uneven and uncoordinated structure of the lungs and the use of different imaging devices with different protocols, segmentation of the lung area has always been a challenging issue. Some existing segmentation methods are semi-automated and depend on the human factor. Another problem with these methods is the high level of false positives (36).

Computed tomography (CT) was developed in 1972 by Godfrey Hansfield. Computed tomography or computed tomography imaging using X-rays is used in conjunction with computer algorithms and calculations to create an image of the body. In CT, an X-ray tube is placed in front of a radiation detector, and a cross-sectional computer image is made with the help of a loop that rotates around the patient in the form of a device. CT images have a wide variety of gray colors that follow the scale based on the amount of damping in each tissue of the human body. Following the inventor of CT, this scale is called the Hansfield scale and shows the values -1000 to 1000 and is expressed in units (HU), where zero is the damping value for water and 1000 is for the air damping value (37).

Machine learning in COVID-19 imaging

In the study of Elaziz et al. in the differentiation of COVID-19 and non-COVID-19 cases, Characteristics extracted from chest X-ray images using Fractional Multichannel Exponent Moments (FrMEMs) and Manta-Ray Foraging were used to differentiate chest images. their proposed method had an accuracy of 96-98% (38). Kadry et al. (39) performed a similar study on CT scans. They developed the Naive Bayes (NB), k-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF), and Support Vector Machine with linear

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kernel (SVM) algorithms to differentiate lung images of Covid-19 from healthy individuals, and the results showed that their model was about 89.80% accurate. Naive Bayes classifiers are a set of classification algorithms based on Bayes theory. Naive Bayes is not a single algorithm but a family of algorithms that share a common principle. Each pair of properties classified in Bayesian algorithms is independent of each other (40). Simple Bayesian algorithm is one of the supervised learning methods and data mining in artificial intelligence. This algorithm is a probabilistic and statistical classification that was introduced in 1950 and is based on the Bayesian theorem. The simple Bayesian algorithm is called naive because it assumes that the input variables are independent. This assumption is strong but not always true for real data; However, this technique is very effective in most complex issues (40).

Hussain et al. (41), using 5 machine learning algorithms including XGB-L, XGB-Tree, CART, KNN, and Naïve Bayes, achieved 100% sensitivity in detecting COVID-19 based on CXRs images. COVID-19 detection neural network (COVNet) achieved a sensitivity of more than 90% in the detection of COVID-19 cases based on CT scan images of the lungs (42). A similar system called Covid-net was developed by Wang et al. based on CXRs using the neural network (43).

state-of-the-art convolutional neural network architectures in the study of Apostolopoulos et al (44). in the study of Gozes et al., Deep Learning CT Image Analysis was used, which reached 98.2% sensitivity (45). Hurt et al. in a retrospective study using U-net (CNN) pixel potential maps achieved a sensitivity of 82.8 (46). In recent years, networks based on deep learning in medical image segmentation have achieved advanced performance. Among the existing networks, U-Net has achieved great success in this field (47).

The deep convolutional neural networks (DCNN) was used in the study by Asif et al. Wang et al. presented a model of machine learning based on the Xception + SVM algorithm, which was associated with more than 99% sensitivity in detecting COVID-19 in CXR images (48). Deep Convolution neural networks (CNN) were also used in the study of Purkayastha et al. to diagnose COVID-19 in CT scan images of the lungs along with clinical data that were able to predict the severity and prognosis of the disease (49). CNN is one of the most important deep learning methods in which several layers are taught in a powerful way. This method is very efficient and is one of the most common methods in various applications of computer vision. In each convolution neural network, there are two steps for training. Feedforward stage and backpropagation stage. In the first stage, the input image is fed to the network and this action is nothing but multiplying the point between the input and the parameters of each neuron and finally applying convolution operation in each layer. Then network output is then calculated. After repeating a good number of these steps, the network training ends. So, there is a need for big datasets for better training of Machine learning algorithms (50-51).

The most important advantage of using CNN is its ability to automatically extract image features using the concept of deep learning (52). Because of this very important advantage, in recent years, the use of CNNs to diagnose diseases in various medical applications has been considered by researchers. For example, in the diagnosis of diabetic retinopathy (DR) with ocular diabetes, in which the retinal arteries are deformed and widened for better blood supply due to diabetes in this group of patients, from CNN networks to extract the features of retinal images. With the help of the group learning method, segmented retinal blood vessels are located (53). CNNs are also used for automatic detection of pulmonary edema in CT scans [54], detection of lymph nodes in CT images [55], Categorization of pulmonary diseases [56].

In the study of Wang et al. in a deep learning algorithm for COVID-19 diagnosis, the

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Alexnet network was used to determine whether the lung CT images are infected with Covid19 (57). This method accelerated the Pre-training process. AlexNet is a remarkable convolution neural network architecture that consists of 5 convolutional layers and three fully connected layers. This architecture receives 224x224x3 images as input and then processes the input image by performing sequential convolution and pooling operations and finally sending the results to the fully connected layers. This network is trained on the ImageNet data set and uses various regularization techniques such as data augmentation and dropout. Pre-training means preparing (initializing) a network with pre-trained parameters instead of random parameters. This method is very popular in CNN-based models because it speeds up the learning process as well as improves generalizability (58).

Limitations:

All things considered, this study has specific limitations. One of them is the absence of studies that analyze the exhibition of machine learning models between CXR and CT scan images. Regardless of the force of machine learning in COVID-19 exploration, the absence of huge informational collections is a critical issue confronting specialists when creating machine learning calculations for COVID-19 identification. Nonetheless, these models should be additionally approved on enormous informational collections. Additionally, assess the models utilizing an outer approval informational index to feature generalizability to other differed information sources.

Conclusion:

Today, the methods of artificial intelligence and machine learning are used in medical sciences, especially in the diagnosis of diseases. Since COVID-19 has a relatively high prevalence and early diagnosis of this disease plays an important role in its treatment, therefore, rapid and accurate development of new diagnostic tools and techniques is necessary for early diagnosis of coronary heart disease. In this study, coronary heart disease diagnosis algorithms were reviewed and high accuracy was observed in studies using this technology. According to the results of this study, the performance of machine learning models for COVID-19 detection has high accuracy. Therefore, the proposed diagnostic system can lead to timely and appropriate measures to control COVID-19 in other individuals and accelerate the recovery of the disease and reduce the costs associated with the disease. Although the findings of this study are justified, it is suggested that this system be examined in other settings with different data sets, in other medical centers, or at other time points. The creation and development of mobile telephony software programs are also recommended for the initial diagnosis or confirmation of COVID-19. Future studies may include the use of a larger database or the addition of features, the development of new models based on different techniques and approaches, especially models based on good techniques.

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