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The worldwide methods of artificial intelligence for detection and diagnosis of COVID-19

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Key points

- Review of applications of AI on COVID-19
- AI Methods for virus detection and diagnosis
- AI applications on radiology
- Diagnosis by X-ray images and CT-Scan using AI methods
- Diagnosis of COVID-19 using text analytics and cough sound

7.1 Introduction

Artificial intelligence (AI) is known for its ability to have machines perform tasks that are associated with the human mind, and it has useful applications in many industries and fields including medicine and healthcare. The medicine continues to evolve as AI, machine learning and deep learning in technology become more accepted and used (Park et al., 2020). Machine learning, a subset of AI, has the potential to provide data-driven clinical decision support to physicians and hospital staff. As example, machine learning designed to identify patterns, uses algorithms, and data to give automated insights to healthcare providers using metagenomic datasets (Bzhalava et al., 2018).

Usually, diseases are not deadly, but late diagnosis may cause more damage to patients. Nowadays, diagnostic processes have become advanced and improved. However, sometimes, people have to undergo several tests, and doctors may not determine the exact health problems. As example, AI uses machine learning in making devices, which are of great assistance to pathologists; it helps make an immaculate diagnosis. AI has also enhanced other laboratory equipment, which is a breakthrough in diagnosing blood, lung, and heart illnesses (Liu et al., 2020). One example in radiology images, which help doctors in prescribing medicines and treatments.

Computed tomography (CT) scans, X-rays, and MRI machines give away nonaggressive functionality of the internal body. AI can enable the radiology tools to give more accurate and detailed images even for the recent pandemic of COVID-19 (Ory-Six, 2020). So that medical doctors can detect the damaged tissue and thus easily prescribe the replacement.

The coronavirus, SARS-CoV-2 (COVID-19), has caused a worldwide pandemic of respiratory illness, and now continuing in its third outbreak (Sauer, 2020). COVID-19 appeared in Wuhan, China, in December 2019. COVID-19 symptoms include cough, fever or chills, shortness of breath or difficulty breathing, muscle or body aches, sore throat, new loss of taste or smell, diarrhea, headache, new fatigue, nausea or vomiting, and congestion or runny nose. The COVID-19 can be spread from person to person, and it can be severe, and some cases have caused death. Diagnosis may be difficult with only a physical examination because mild cases of COVID-19 may appear similar to the flu or a bad cold, so that a laboratory test can confirm the diagnosis.

AI researches have improved medical diagnostics in a variety of ways, including predicting viral structures, reading X-ray and CT scan data, and predicting protein structures for the development of therapeutics (Agrebia and Larb, 2020). Diagnosing a case of a COVID-19-related pneumonia from X-ray and CT scan can, potentially, both shorten the time of diagnosis and enable better treatment. Reviews of some researches of using AI can be reached in these articles (Chen et al., 2020a,b; Ozsahin et al., 2020; Shi et al., 2020). Machine learning and deep learning on imaging can help lessen the burden. Learning how disease manifests itself in X-ray and CT scans can help provide more insight into the disease itself. Reviews of some researches of using machine learning and deep learning can be reached in these articles (Salehi et al., 2020; Shahid et al., 2020).

This chapter is about the applications of AI on the detection and diagnosis of COVID-19 virus, and it consists of three main sections. The Section 7.2 presents the general approach of using AI and its methods in the areas of the detection and diagnosis of viruses. It explains common methods of AI including the traditional work on expert systems, artificial neural networks (ANNs) and robots, and the recent approaches on machine learning and deep learning. This section also includes a quick survey on some examples of application of the previous methods on the detection and diagnosis of common viruses like influenza and hepatitis.

In Section 7.3, different approaches of using AI and its methods on the detection and diagnosis of COVID-19 virus are presented. It includes some early uses and trials of AI and its methods on the detection and diagnosis of COVID-19 as the early researches in China before the wide spread of the virus in other regions in the World. Then, a comprehensive survey on many examples of the application of the AI methods on the detection and diagnosis of COVID-19 is explained and cited, which covers most trials in all regions of the World including Asia, the United States, Canada, Europe, and Africa. In this section, some recent trials of AI and its methods on the detection and diagnosis of COVID-19 virus are stated and explained. Moreover, this section shows many comparisons of the previous explained approaches and trials of using AI methods on the detection/diagnosis of COVID-19 as presented in different tables. The comparisons are based on: type of applications (e.g., X-ray, CT scans, Cough Sound, and Text Data), Methods (e.g., deep learning, machine learning, or

other methods of AI), and locations (e.g., China, the United States, UK, and other regions in the world), beside the data source/size and main findings.

In the last Section 7.4, a brief view of the future and expected applications, trends, and concerns of AI in the area of detection and diagnosis of viruses and especially the COVID-19 are explained and discussed.

7.2 Artificial intelligence for virus detection and diagnosis

When any viruses make the infection to humans, time becomes very important factor. If disease outbreak is detected quickly, a fast move can be made to stop the spread and adequately treat the people. AI methods can provide better detection system for an unusual disease compared to the traditional disease reporting and detecting system (Liu et al., 2020). Due to the virus infection complex features such as duller skin, redder eyes, droopier mouth, and swollen face, AI systems can be trained to understand these features.

AI methods can be very useful in building detection system for viruses when there is too much of data which cannot be easily handled by the humans. One example is scanning system used at airport to scan multiple faces continuously. When trained with some data about the features of viruses, methods of AI can identify people who are sick without fevers. Many researchers and scientists are working on different methods like ANNs, machine learning, and deep learning that can analyze available big data to detect signs of illness before human can detect with better accuracy and efficiency (Agrebia and Larb, 2020; Salehi et al., 2020; Fatima and Pasha, 2017; Sweidan et al., 2016).

7.2.1 Common methods of artificial intelligence

AI has entered our daily lives like never before. All technical companies such as Google, Microsoft, Facebook, Amazon, and IBM are competing in the race to lead the business and acquire the most innovative and promising AI researches. AI is already being used in everyday life with applications including smart vehicles, speech recognition, fraud detection, video recommendations, and virtual assistant such as Cortana and Siri (Liu et al., 2018). According to the father of AI, John McCarthy, it is "The science and engineering of making intelligent machines, especially intelligent computer programs." AI is a way of making a computer, a robot, or a software think intelligently, in the similar manner the intelligent humans think.

Machine learning is a subset of AI, in which machines take data and learn for themselves. It is currently the most promising tool. Machine learning systems can quickly apply knowledge and training from large datasets to excel many applications like speech recognition, facial recognition, and language translation (Jordan and Mitchell, 2015). Machine learning allows a system to learn to recognize patterns on its own and make predictions.

ANNs are computing systems that imitate the biological neural networks (Krogh, 2008). It is based on a collection of connected units called artificial neurons. An artificial neuron that receives a signal then processes it and can activate neurons connected to it. The activation at a connection is a real number, and the output of each neuron is computed by some

nonlinear function of the sum of its inputs. Neurons and connections typically have a weight that can be adjusted from learning process. ANNs can be composed into layers. Signals travel from the first layer (the input layer), to the last layer (the output layer), and via intermediate layers called hidden layers.

Deep learning is a subset of machine learning, and it is a special type of ANNs, which is a set of algorithms reaching new levels of accuracy for many important problems, such as image recognition, sound recognition, and recommender systems (LeCun et al., 2015). Deep learning can be costly and requires huge datasets to train itself, since it needs to understand a huge number of parameters by its learning algorithm.

7.2.2 Examples on using artificial intelligence for diagnosis of viruses

The first study, which we highlighted, proposed a diagnosis system based on ANNs for hepatitis virus. The proposed methodology has two stages: feature extraction, and reduction and classification stages. The classification accuracy of this ANN-based diagnosis system for the diagnosis of hepatitis virus was obtained. This accuracy was around 99.1% for training data and 100% for testing data (Jilani et al., 2011).

Another research presented a methodology to develop intelligent decision support systems in hepatitis diagnosis. The new approach includes two phases; the first phase is data preparation which analyzes hepatitis dataset from UCI repository. In addition, it added data mining techniques to handle data and solved missing values problems. The second phase was the reduction of data with rough set feature selection technique. Finally, classification phase was implemented by incremental back propagation neural networks (Mitra and Samanta, 2015).

Researchers in India performed a work to predict Arbovirus-Dengue disease. Machine learning algorithm that are used by these researchers are Support Vector Machine (SVM). Dataset for analysis is obtained from King Institute of Preventive Medicine and surveys of many hospitals and laboratories of Chennai and Tirunelveli from India. It contains 29 attributes and 5000 samples. Accuracy that was achieved by SVM is 0.9042 (Fathima and Manimeglai, 2012).

Another approach was proposed to detect infected patients by classification using vital signs like respiration rate, heart rate, and facial temperature. This new approach can successfully classify individuals at higher risk for influenza using neural network and fuzzy clustering method. Fuzzy clustering methods used the membership values, which are degree of belongness to a cluster based on edge and centroid position in the given cluster. This new way demonstrates the ability to develop effective methods for identifying populations at risk (Sun et al., 2015).

7.3 Artificial intelligence for detection and diagnosis of COVID-19

Many methods of AI can be used in the diagnosis and the detection of the disease caused by COVID-19. Reviews of using AI to tackle many areas of COVID-19, including the diagnosis

and the detection, can be reached in Naudé (2020), Mohammad and Tayarani (2020) and Lalmuanawma et al. (2020). Fast and accurate diagnosis of COVID-19 can save lives, limit the spread of the disease, and generate data on which to train models of AI. There are many efforts to train those models for diagnosis of COVID-19 using chest radiography images (CT and X-ray) and other approaches (Chen et al., 2020a,b; Ozsahin et al., 2020; Shi et al., 2020; Salehi et al., 2020; Shahid et al., 2020).

7.3.1 Early use of artificial intelligence

In the early days of the first outbreak, patients were overwhelming Chinese hospitals with pneumonia-like symptoms. Software from Infervision was deployed in 34 hospitals in China to speed diagnosis on more than 32,000 potential cases using AI (Wired, 2020). By mid-January, Infervision realized that existing customers were employing a little used feature in the software that looks for evidence of pneumonia. During the Lunar New Year holiday, the staff of company tuned their algorithm with more than 2000 images from COVID-19 patients. With this new dataset, hospitals were using Infervision's AI to diagnosis patients that may have the disease from CT images (Itn, 2020). Doctors would follow up with other examinations and lab tests to confirm diagnosis, with eliminating a significant bottleneck to quickly identify most at-risk patients.

In its early review of some trials of using applications of AI against COVID-19, study have shown that AI can be as accurate as humans, can save radiologists' time, and perform a diagnosis faster and cheaper than with standard tests for COVID-19 (Bullock et al., 2020). Both X-rays and CT scans can be used. Many early efforts have been presented. One example is a tutorial on how to use Deep Learning to diagnose COVID-19 using X-ray images (Rosebrock, 2020). Another effort has proposed a technique using mobile phones to scan CT images (Maghdid et al., 2020). In the next section some other worldwide initiatives and researches have been highlighted and reviewed.

7.3.2 Survey on methods of artificial intelligence on detection and diagnosis of COVID-19

X-ray and CT scans are widely used to provide evidences for radiologists. However, medical images contain hundreds of slices, which takes a long time for the specialists to diagnose. Diagnosis of COVID-19 has the same issues with various other types of pneumonia, which requires radiologists to gain many experiences for achieving a high diagnostic performance (Ory-Six, 2020; Shi et al., 2020). So that more automated-assisted approaches are needed especially of using tools and methods of AI to diagnosis X-ray and CT images.

However, there are other ways, far from radiology, can be used and adopted in the diagnosis of COVID-19 using also some methods from AIs. One way is using text processing, data analytics and natural language processing techniques. In another way, some recent researches have tried to build diagnosis system from symptoms such cough sound rather than the diagnosis of chest images.

In the following subsections, we will carry a detailed survey on some researches on X-ray images, CT scans, and other ways of the diagnosis of COVID-19, which were conducted in

Table 7–1   List and comparison of the researches based on X-ray.

Ref.	Type	AI methods	Data source/size	Main findings	Location/time
Zhang et al.	X-ray Images	DL (ResNet)	GitHub/ChestX-ray14 (1143 images)	Better on ResNet (96%)	China, Mar 20
El-Asnaoui et al.		DL (9 architectures)	Public (5856 images)	Accuracy (96%)	Morocco, Mar 20
Hemdan et al.		Pretrained DL (COVIDX-Net)	Public (50 images)	Better on VGG19 and DenseNet	Egypt, Mar 20
Narin, Kaya, and Pamuk		Pretrained DL (3 models)	Kaggle/GitHub (100 images)	Better on ResNet50 (98%)	Turkey, Mar 20
Wang and Wong		DL (COVID-Net)	Public (5941 images)	Accuracy (83%)	Canada, Apr 20
Apostolopoulos and Mpesiana		Transfer DL	Kaggle/GitHub (100 images)	Accuracy (ResNet50, 98%)	Greece, Apr 20
Sethy and Behera		Pretrained DL with SVM	Kaggle/GitHub (50 images)	Better on SVM + ResNet50	India, Apr 20
Hall et al.		Ensemble DL	Public (455 images)	Accuracy (91.2%)	USA, May 20
Panwar		Transfer DL (nCOVnet)	Public + Kaggle (282 images)	Accuracy (97.9%)	India, May 20
Borkowski et al.		DL (Software)	Kaggle/GitHub (1103 images)	Accuracy (97%)	USA, May 20
Sharma and Dyreson		Transfer DL (RAN)	Public (239 images)	Accuracy (98%)	USA, Jun 20
Misra et al.		Transfer DL	Public (6008 images)	Accuracy (94%)	Korea, Jul 20
Vinod and Prabaharan		DL + Decision Tree	Kaggle (18 images)	Accuracy (88%)	India, Jul 20
Ismael and Sengür		DL + SVM (2 strategies)	GitHub and Kaggle (380 images)	ResNet50 + SVM (94.7%)	Iraq, Sep 20
Ozsoz et al.		Transfer DL (AlexNet)	Different sources (11000 + images)	Testing accuracy (94.4%)	Cyprus, Sep 20
Zhang et al.		DL (COV19Net)	Henry Ford HS (over 10,000 images)	AUC (94%)	USA, Sep 20
Shiaelis et al.		CNN + imaging methods	Univ of Oxford (Size is unknown)	Good accuracy of 70%	UK, Oct 20
Wehbe et al.		Ensemble DL (DeepCOVID-XR)	NWM HS (Over 16,000 images)	Accuracy (83%)	USA, Nov 20
Narin		SVM + DL (ResNet50)	Kaggle (1905 images)	SVM-quadratic (96%)	Turkey, Dec 20

many worldwide locations using different methods of AI, along with comparisons as presented in Tables 7−1−7−3. The comparisons are based on type of applications, methods of AI, locations/time, data source/size, and main findings of researches.

7.3.2.1 Researches based on X-ray images

The research in Zhang et al. (2020a,b) proposed a deep learning model (ResNet) to detect COVID-19 from X-ray images. The proposed model has two tasks—one task for the classification between COVID-19 and non-COVID-19, and another task for anomaly detection. The anomaly detection task gives an anomaly score to optimize the COVID-19 score used for the classification. The dataset used in the research is 100 X-ray images from 70 COVID-19 patients and 1043 images from 1008 non-COVID-19 pneumonia patients obtained from

Table 7–2   List and comparison of the researches based on CT scans.

Ref.	Type	AI methods	Data source/size	Main findings	Location/time
Xu et al.	CT scans	General DL model	Many Hospitals, China (618 images)	Accuracy (87%)	China, Feb 20
Chen et al.		3D-DL (UNet++)	Hospital, China (106 subjects)	Accuracy (95%)	China, Feb 20
Barstugan, Ozkaya, and Ozturk, S.		SVM over five features	Med. authority, Turkey (150 images)	Accuracy (99%)	Turkey, Mar 20
Jin et al.		ResNet50 + 3D UNett++	Med. authority, China (1136 CT scans)	UNet++ (97%), ResNet50 (92%)	China, Mar 20
Shan et al.		3D VB-Net + Random Forest model	Multi centers, China (549 subjects)	Accuracy (88%)	China, Mar 20
Li et al.		3D-DL (COVNet)	6 Hospitals, China (4352 CT scans)	AUC (96% and other 95%)	China, Mar 20
Polsinelli et al.		Transfer CNN	2 sources (857 CT scans)	Accuracy (85%)	Italy, Apr 20
Wang et al.		General DL model	Hospital, China (1065 images)	Accuracy (73%)	China, Apr 20
Gifani et al.		Ensemble of 15 pretrained DLs	Public source (746 images)	Accuracy (85%)	Iran, May 20
Mei et al.		CNN + SVM + Random Forest + MLP	Many sources, China (905 subjects)	AUC (combined algorithms,92%)	USA, May 20
Jaiswal et al.		Pretrained DL (DenseNet201)	Kaggle (2492 images)	Accuracy (96.2%)	India, Jun 20
Jin et al.		Deeplab v1 + ResNet152	Multi Centers, China (1881 subjects)	AUC (97.9%)	China, Jun 20
Mishra et al.		Combine of five DL models	Two public sources (757 images)	Accuracy (86%)	India, July 20
Harmon et al.		3D-DL + DenseNet121	Public source (2724 CT scans)	Accuracy (90%), AUC (95%)	USA, Aug 20
Carlile et al.		General DL model	Special collection (1855 images)	Accuracy (81.6%)	USA, Sep 20
Loey, Manogaran and Khalifa		Three transfer DLs	Public source (307 images)	Medium accuracy (85%)	Egypt, Oct 20
Amyar et al.		UNet + CNN	Different sources (1369 subjects)	AUC (97%)	France, Nov 20

GitHub and ChestX-ray14 dataset. The sensitivity and specificity were 96.0% and 70.7%, respectively, along with an area under the curve (AUC) of 0.952.

One study proposed automated techniques for classifying the X-Ray of chest into pneumonia and the class of disease-free by using nine architectures of deep learning (El-Asnaoui et al., 2020). Experiments have been conducted using dataset that includes 5856 images with 1583 normal and 4273 pneumonia, and the performance was evaluated using different performance metrics. The result presented that there are three architectures (MobileNet_V2, Inception_Resnet_V2, and Resnet50) have given more accurate results reach to 96%.

In the study of Hemdan et al. (2020), new approach of deep learning called COVIDX-Net was introduced to help radiologists to automatically diagnose patients with Coronavirus using X-ray images. The technique was built on seven Deep CNN classifiers. The study has

Table 7–3   List and comparison of the researches based on cough sound and text data.

Ref.	Type	AI methods	Data source/size	Main findings	Location/time
sImran et al.	Cough sound	AI app (AI4COVID-19)	Previous study (50 classes)	Accuracy (95%)	USA, May 20
Brown et al.		Linear ML models	Special collection, UK (491 samples)	AUC (all tasks, above 80%)	UK, Jun 20
Laguarta, Hueto, and Subirana		3 Pretrained DLs (ResNet50)	Collection pipeline, MIT (5320 subjects)	AUC (97%)	USA, Sep 20
Hassan, Shahin, and Alsabek		RNN (LSTM, six features)	Hospitals, UAE (240 samples)	Accuracy (Cough, 97%)	UAE, Oct 20
Fayyoumi, Idwan, and AboShindi	Text Data	ML (SVM, Logistic Regression, MLP)	Survey (105 subjects, 30 attributes)	Accuracy (MLP, 91.6%)	Jordan, May 20
Khanday et al.		ML (Logistic Regression, MNB, Ensemble)	GitHub (212 subjects, 25 attributes)	Accuracy (96.2%)	India, Jun 20
Obeid et al.		General CNN	Special collection (6813 subjects)	AUC (72.9%)	USA, Jul 20

successfully experimented and evaluated the result which is based on 80% training phase, 20% testing phase of X-ray images. The VGG19 and the DenseNet models have shown a better and similar functioning of automated classification of Coronavirus. X-ray images of the public dataset used in this work, which consists of 50 images, divided into two classes as normal cases of 25 and positive Coronavirus images of 25.

The early research of Narin et al. (2020) presented three different deep learning models (ResNet50, InceptionV3, and Inception-ResNetV2) to detect COVID-19 infection from X-ray images. Chest X-ray images of 50 COVID-19 patients from GitHub and 50 normal chest X-ray images from Kaggle are used. The evaluation results show that the ResNet50 model achieves the highest classification performance with 98.0% accuracy, compared to 97.0% accuracy by InceptionV3 and 87% accuracy by Inception-ResNetV2.

Another research of Wang and Wong (2020) proposed a deep convolutional neural network-based model (COVID-Net) to detect COVID-19 cases using X-ray images. The dataset includes 5941 chest X-ray images from 1203 healthy people, 931 patients with bacterial pneumonia, 660 patients with viral pneumonia, and 45 patients with COVID-19. The COVID-Net obtains the testing accuracy of 83.5%.

There is one research that has proposed a deep learning-based technique called deep transfer learning and detect patients with Coronavirus disease automatically (Apostolopoulos and Mpesiana, 2020). It used images of chest X-ray obtained from patients with Coronavirus and from a healthy person. Dataset of 50 patients, with Coronavirus, images of X-ray were taken from a shared GitHub repository, and 50 X-ray images of healthy humans have taken from a repository in Kaggle. The results showed that the pretrained model, ResNet50, yielded 98% accuracy among the other three models.

The research of Sethy and Behera (2020) presented different deep learning-based techniques for Coronavirus detection diseases by using X-ray images. The new approach has used different classification models, based on SVM, and using deep features of various deep

learning architectures for detecting the Coronavirus patients. In the experiment the study used an X-ray images dataset that includes 50 images with 25 Coronavirus cases from GitHub and 25 normal cases from Kaggle of X-ray Images of Pneumonia. The results reached that SVM + ResNet50 obtained high accuracy (FPR = 95.52%, F1-score = 95.52%, MCC = 91.41%, and Kappa = 90.76%) for detecting the Coronavirus patients as compared to the other models.

The new approach of Hall et al. (2020) handled the problem of COVID-19 detection with multiple DL model and using ensemble learning to obtain a high-accuracy classification using X-ray images. Ensemble of three pretrained models including Resnet50 and VGG16 and an own small CNN is applied for a dataset of 135 COVID-19 cases and 320 pneumonia cases. The overall accuracy achieved is of 91.24%.

In the paper of Panwar (2020), the researcher has proposed a deep learning neural network-based method called nCOVnet, as an alternative fast screening method that can be used for detecting the COVID-19 by analyzing the X-rays of patients. He used the VGG16 model as for feature extraction as a base model, then the researcher applied a transfer deep learning model. The dataset used in this work was from two sources—a public source consists of 142 XRayimages of COVID-19 positive patients and Kaggle's Chest X-Ray Images (Pneumonia) consisting of 142 images of normal cases. This approach was able to classify the COVID-19 patient correctly with 97.97% confidence and to provide the correct result with 98.68% confidence on normal cases.

Another initiative demonstrated the potential of using AI algorithms in assessing X-ray for COVID-19 by training the Microsoft CustomVision automated image classification and object detection system to differentiate cases of COVID-19 from pneumonia from other etiologies as well as normal lung X-ray images (Borkowski et al., 2020). One hundred and three images of COVID-19 were downloaded from GitHub, 500 images of non-COVID-19 pneumonia, and 500 images of the normal lung were downloaded from the Kaggle. When testing the model against known patients from their medical center, the researchers achieved 100% sensitivity (recall), 95% specificity, 97% accuracy, 91% positive predictive value (precision), and 100% negative predictive value in differentiating the three scenarios.

The research of Sharma and Dyreson (2020) proposed a novel method to detect COVID-19 with chest X-ray images using a Residual Attention Network (RAN) and data augmentation on the deep learning. The dataset used in this research was 239 images: 120 images of patients infected with COVID-19, and 119 images of non-COVID-19 patients obtained from public source. The Residual Attention Network to classify COVID-19 patients was compared with many pretrained deep learning models: VGG, DenseNet, NASNet, Xception, and Inception. The experiments resulted that the custom Residual Attention Network performed best among all of the models with 98% testing and 100% validation accuracy.

Multichannel transfer deep learning-based approach was proposed in Misra et al. (2020). In this research, multichannel pretrained ResNet model was used to perform the diagnosis of COVID-19. To classify the X-ray images on an one-against-all strategy, three ResNet models have been retrained. These three models were ensembled and fine-tuned using X-rays from 1579 normal, 4245 pneumonia, and 184 COVID-19 individuals to classify normal,

pneumonia, and COVID-19 cases in an one-against-one framework. The method achieved an accuracy of 94%.

In the paper of Vinod and Prabaharan (2020), a framework dependent on deep learning was produced for the recognizable of COVID-19 as a characterization task. Deep learning element extraction depends on the extraction of highlights procured from a pretrained CNN. The deep features highlights were extricated from completely associated layer and feed to the classifier for training and testing. The profound highlights obtained from each CNN systems were utilized by Decision tree classifier. The proposed model applied for the dataset of Chest X-ray images contains nine number of Covid-19 positive and nine number normal images gathered from Kaggle repository. This recommended analysis model for identification of Covid-19 accomplished the accuracy of 88% of precision score in chest X-ray images.

Two strategies have been conducted to accurately classify Chest X-ray images into positive of negative COVID-19 including fine-tuning strategy and end-to-end training in the research of Ismael and Sengür (2020). In ResNet101, VGG19, ResNet50, ResNet18, and VGG16, SVM is used for ML-based classification, whereas a new CNN model is used for the fine-tuning strategy. End-to-end training with a dataset of 180 COVID-19 and 200 normal is carried out as a third strategy. The accuracy of using ResNet50 model and SVM classifier is 94.7%, where fine-tuned strategy with ResNet50 model achieved 92.6%. The end-to-end training strategy of the developed CNN model realized a 91.6% result. (Iraq, Sept)

The work of Ozsoz et al. (2020) presented the utilization of Deep Neural Network based on Transfer Learning approach (Pretrained AlexNet Model) for automatic detection of COVID-19 pneumonia, non-COVID-19 viral pneumonia and bacterial pneumonia. The models were trained based on two classes and multiclass. For two classes, the models were trained based on each of COVID-19, non-COVID-19 viral pneumonia, and bacterial pneumonia with healthy CXR Images, COVID-19, and non-COVID-19 viral pneumonia. The datasets used in this work were obtained from different resources—373 COVID-19 pneumonia, 4237 Non-COVID-19 viral pneumonia, 4078 Bacterial pneumonia, and 2882 normal cases. The models achieved 94.43% testing accuracy, 98.19% sensitivity, and 95.78% specificity for non-COVID-19 viral pneumonia and healthy datasets. For bacterial pneumonia and healthy datasets, the model achieved 91.43% testing accuracy, 91.94% sensitivity, and 100% specificity.

In the retrospective study of Zhang et al. (2020a,b), a deep neural network, CV19-Net, was trained, validated, and tested on X-ray images from patients with and without COVID-19 pneumonia. A total of 2060 patients (5806 X-ray images) with COVID-19 pneumonia and 3148 patients (5300 X-ray images) with non-COVID-19 pneumonia were included in this study and obtained from Henry Ford Health System, which includes five hospitals and more than 30 clinics. Over a set of 500 randomly selected test X-ray images, the AI algorithm achieved an AUC of 0.94, compared to an AUC of 0.85 from three experienced thoracic radiologists.

To demonstrate how single-particle fluorescence microscopy combined with deep learning can help to rapidly detect and classify coronaviruses, the new approach presented in Shiaelis et al. (2020) used the process of instantaneous labeling, rapid automated imaging, preprocessing, and deep learning. Dataset of X-ray images were collected and confirmed as

SARS-CoV-2-positive or negative using kit either from the Public Health England or Altona diagnostics. The trained network was able to distinguish between SARS-CoV-2-positive and negative with good accuracy of 70%. The decrease in accuracy reflected the greater heterogeneity and complexity of clinical samples (e.g., varied storage conditions, wide range of virus concentrations, the presence of residual cellular material, different sampling techniques).

DeepCOVID-XR is an ensemble of convolutional neural networks to detect COVID-19 on X-ray images as presented in Wehbe et al. (2020). The algorithm was trained and validated on 14,788 images (4253 COVID-19 positive) from sites across the Northwestern Memorial Healthcare System from February 2020 to April 2020, then tested on 2214 images (1192 COVID-19 positive) from a single hold-out institution. Performance of the algorithm was compared with interpretations from five experienced thoracic radiologists on 300 random test images. On the entire test set, DeepCOVID-XR's accuracy was 83% with an AUC of 0.90. On 300 random test images (134 COVID-19 positive), DeepCOVID-XR's accuracy was 82% compared to individual radiologists (76%−81%) and the consensus of all five radiologists (81%).

In another study of Narin (2020), classification performances with SVM were obtained by using the features extracted with residual networks (ResNet50), one of the convolutional neural network models, on X-ray images of COVID-19. In this study, 3-class datasets are used from Kaggle, which consists of 219 "Covid-19," 1341 "Normal," and 1345 "Viral Pneumonia." While Covid-19 detection was resulted with SVM-quadratic with the highest sensitivity value of 96.35% with the fivefold cross-validation method, the highest overall performance value has been detected with both SVM-quadratic and SVM-cubic above 99%.

7.3.2.2 Researches based on computed tomography scans

The early initiative of Xu et al. (2020) established a deep learning paradigm for the screening of Coronavirus patients at an early stage. The main aim of this research is to distinguish Coronavirus from Influenza-A viral pneumonia and normal cases with the use of CT images. CT samples were taken from three hospitals designated to Coronavirus from China, Zhejiang Province. The total number of 618 samples was collected, which includes 219 from 110 Coronavirus patients, 224 samples of CT from patients with the viral pneumonia Influenza-A and CT samples of 175 healthy people. The experiments result of this study shown an overall 87% accuracy from the viewpoint of CT cases as a whole. The researchers demonstrated that it can be a promising accompanying diagnostic tool for the clinical frontline doctors.

Another early study predicted the final label (COVID-19 or non-COVID-19) based on the appearance of segmented lesions using a 3D deep learning approach of UNet++ based segmentation model (Chen et al., 2020a,b). The researchers employed chest CT images of 51 COVID-19 patients and 55 patients with other diseases from Renmin Hospital of Wuhan University. The proposed model could identify all the viral pneumonia patients from non-pneumonia patients with accuracy of 95%. The reading time of radiologists is shortened by 65% with the help of AI results.

In another study, Barstugan et al. (2020) presented earlier detection of Coronavirus using CT Scan images by using machine learning methods. The dataset was taken from public

medical authority in Turkey, which belongs to the 53 Coronavirus cases and data involving 150 CT images. Then, patch regions of the images were cropped, and four different subsets of the patch were created. The feature extraction techniques used in this study are: Grey-Level Cooccurrence Matrix, Local Directional Pattern, Grey-Level Size-Zone Matrix, Grey-Level Run-Length Matrix, and Last-Discrete Wavelet Transform. The SVM classifier was applied to classify the extracted features and the best classification outcomes were obtained from GLSZM future extraction techniques with an accuracy rate of 99.68%.

Similarly, the research in Jin et al. (2020a,b) also proposed a UNet++ based segmentation model for locating lesions and a ResNet50 based classification model for diagnosis. The study includes chest CT images of 1136 cases (i.e., 723 COVID-19 positives and 413 COVID-19 negatives) from medical authority in China. In the experiment the sensitivity and specificity using the proposed UNet++ and ResNet50 combined model are 97.4% and 92.2%, respectively.

In another research of Shan et al. (2020), a 3D VB-Net was adopted to segment the image into the left/right lung, 5 lung lobes, and 18 pulmonary segments in the preprocessing phase. A number of hand-crafted features were calculated and used to train the random forest (RF) model. Dataset included chest CT images of 249 COVID-19 patients of training, and 300 new COVID-19 patients for validating obtained from two medical hospitals in China. Experimental results presented a sensitivity of 91%, specificity of 83%, and accuracy of 88% of differentiating COVID-19.

The retrospective and multicenter study of Li et al. (2020) proposed a 3D deep learning model, the COVID-19 detection neural network (COVNet), to extract visual features from volumetric chest CT scans for the detection of COVID-19. The datasets were collected from six hospitals and consisted of 4352 chest CT scans from 3322 patients including 1292 COVID-19 CT scans, 1735 CAP, and 1325 nonpneumonia CT scans. The deep learning method was able to identify coronavirus disease 2019 on chest CT scans (AUC, 0.96) and also community-acquired pneumonia on chest CT scans (AUC, 0.95).

While in another study, Polsinelli et al. (2020) proposed a conventional neural network (CNN) design, starting from the model of the SqueezeNet CNN, to discriminate between COVID-19 and other CT images. The datasets obtained from two different sources—one from previous research and other from medical authority in Italy. The first is composed by 360 CT scans of COVID-19 subjects and 397 CT scans of other kinds of illnesses and/or healthy subjects, whereas the Italian dataset is composed of 100 CT scans of COVID-19. On both dataset arrangements, the proposed CNN outperforms the original SqueezeNet. In particular, CNN achieved 85.03% of accuracy, 87.55% of sensitivity, 81.95% of specificity, 85.01% of precision, and 86.20% of F1-Score.

A 2D CNN model was proposed by Wang et al. (2020) on manually delineated region patches to classify between COVID-19 and typical viral pneumonia. The researchers collected 1065 CT images of pathogen-confirmed COVID-19 cases (325 images) along with those previously diagnosed with typical viral pneumonia (740 images) from hospital in china. The testing dataset shows a total accuracy of 73.1% along with a specificity of 67.0% and a sensitivity of 74.0%.

The new approach presented by Gifani et al. (2020) proposed an ensemble deep transfer learning system with 15 pretrained CNN architectures: EfficientNets(B0-B5), NasNetLarge, NasNetMobile, InceptionV3, ResNet50, SeResnet 50, Xception, DenseNet121, ResNext50, and Inception_resnet_v2 are used and then fine-tuned on the target task. An ensemble method based on majority voting of the best combination of deep transfer learning outputs to further improve the recognition performance was built. Dataset was obtained from publicly source, which consists of 349 CT scans labeled as being positive for COVID-19 and 397 negative COVID-19 CT scans that are normal or contain other types of lung diseases. The researchers obtained the results: accuracy (85%), precision (85.7%), and recall (85.2%).

In the paper by Mei et al. (2020), the researchers developed a deep CNN to learn the imaging characteristics of patients with COVID-19 on the initial CT scan, and then they used SVM, RF, and multilayer perceptron (MLP) classifiers to classify patients with COVID-19 according to clinical information. Finally, they created a neural network model combining radiological data and clinical to predict COVID-19 status. A dataset of chest CT scans from 905 patients (419 patients tested positive and 486 tested negative) was acquired from different places in China. The proposed joint AI algorithm combining CT images and clinical history achieved an AUC of 0.92 and performed equally well in sensitivity (84.3%) as compared to a senior thoracic radiologist (74.6%) when applied to a test set of 279 cases.

The study in Jaiswal et al. (2020) implemented a pretrained network DenseNet201-based deep model on classifying COVID-19 using CT scans. The dataset contained 2492 CT- scans (1262 positive for COVID-19, and the rest 1230 are negative) as positive or negative obtained from Kaggle. The researchers compared their results with VGG16, ResNet152V2, and Inception-ResNetV2. They concluded that their model outperformed other considered models and achieved an overall accuracy of 96.25%.

While the research of Jin et al. (2020a,b) employed a 2D Deeplab v1 model for segmentation the lung and a 2D ResNet152 model for lung-mask slice based identification of positive COVID-19 cases. The researchers used a dataset of chest CT images from 496 COVID-19 positive cases and 1385 negative cases. Experimental results presented that the proposed model achieves sensitivity of 94.1%, specificity of 95.5%, and AUC of 0.979.

In the new approach of Mishra et al. (2020), various Deep CNN-based approaches were explored for detecting the presence of COVID-19 from chest CT images. A decision fusion-based approach was also proposed, which combines predictions from multiple individual models, to produce a final prediction. These baseline models include VGG16, InceptionV3, ResNet50, DenseNet121, and DenseNet201. The COVID-CT dataset contained 360 positive COVID-19 cases and 397 negative Chest CT images obtained from two public sources. Experimental results presented that the proposed decision fusion-based approach was able to achieve above 86% results across all the performance metrics under consideration, with average AUROC and F1-Score being 0.883 and 0.867, respectively.

The study of Harmon et al. (2020) considered 2724 CT scans from 2617 patients. Lung regions were segmented by using 3d anisotropic hybrid network architecture (AH-Net), and the classification of segmented 3D lung regions was performed by using pretrained model

DenseNet121. The proposed algorithm achieved an accuracy, specificity, and AUC score of 0.908, 0.930, and 0.949, respectively.

The researchers in another study deployed a previously developed and validated deep learning algorithm for assisted interpretation of chest radio-graphs for use by physicians at an academic health system in Southern California (Carlile et al., 2020). Physicians were surveyed in real time regarding ease of use and impact on clinical decision making, and collecting of 1855 CT images were analyzed by the algorithm. Overall area under the receiver operating curve for the convolutional neural network was 0.854. At the optimal operating point (Youden J-index threshold), this corresponded to an accuracy of 81.6%, sensitivity of 82.8%, and specificity of 72.6%.

While Loey et al. (2020) proposed classical data augmentation techniques along with Conditional GAN (CGAN) on the basis of a deep transfer learning model for COVID-19 detection using CT images of COVID-19, normal, pneumonia bacterial, and pneumonia virus. To do so, the authors have used a dataset of 307 images from public source. Three deep transfer models are then carried out in this work for investigation—Googlenet, Alexnet, and Restnet18. Three strategies have been conducted; in each strategy the authors applied a different deep TL using the three pretrained models. The testing accuracies achieved by the Googlenet, Alexnet, and Restnet18 are 80.6%, 85.2%, and 100%, respectively.

The research of Amyar et al. (2020) developed another model architecture that included image segmentation, reconstruction, and classification tasks, which was based on the encoder and convolutional layer using UNet and CNN models. The experiments were performed on three datasets from three difference sources consisted on 1369 patients including 449 patients with COVID-19, 425 normal ones, 98 with lung cancer, and 397 of different kinds of pathology. The obtained results presented very encouraging performance of this approach with a dice coefficient higher than 0.88 for the segmentation and an area under the ROC curve higher than 97% for the classification.

7.3.2.3 Researches based on other ways (cough sound and text data)

Some researchers affirm that cough sounds generated by the respiratory system can also be diagnosed and analyzed to decide whether the patient is infected or not by COVID-19 in many initiatives and studies, so that methods of AI can supply useful ways enabling the development of the diagnostic instruments and applications using this approach (Hariri and Narin, 2020).

The initiative by Imran et al. (2020) proposed a smartphone application using cough-based diagnosis for COVID-19. The application was based on an AI-powered screening solution called AI4COVID-19. The main principle is to send three 3 seconds cough sounds to an AI engine running in the cloud, and give a result during two minutes. To overcome the lack of COVID-19 cough training data, the authors applied transfer learning using ESC-50 dataset from previous study that contains 50 classes of cough and noncough sounds acquired using a smartphone. The results presented high overall accuracy of 95.60%, a sensitivity of 96.01%, a specificity of 95.19%, and precision of 95.22%.

In order to diagnose the disease via coughs and breathing, a binary machine learning classifier is used in Brown et al. (2020). The refined records of cough and breaths consist of 141 samples of patients who declared having tested positive of COVID-19 and the control sets of non-COVID-19 consist of 298 samples (reported no symptoms), 32 samples (declared a cough as symptom), and 20 (asthma with cough). The results presented that even a simple binary machine learning classifier was able to classify correctly healthy and COVID-19 sounds. The researchers also provided how their model can distinguish a user who tested positive for COVID-19 and has a cough from a healthy user with a cough, and users who tested positive for COVID-19 and have a cough from users with asthma and a cough. This model achieved AUC of above 80% across all tasks.

Researchers in MIT developed an AI speech processing framework that leverages acoustic biomarker feature extractors to prescreen for COVID-19 from cough recordings (Laguarta et al., 2020). The model used in this study was CNN-based architecture made up of one Poisson biomarker layer and three pretrained ResNet50 in parallel, outputting a binary prescreening diagnostic. The dataset was obtained from data collection pipeline of COVID-19 cough recordings through MIT website, which consisted of 4256 subjects for training and 1064 subjects for testing the model. This model achieved COVID-19 sensitivity of 98.5% with a specificity of 94.2% (AUC: 0.97). For asymptomatic subjects, it achieved sensitivity of 100% with a specificity of 83.2%.

In another study, Hassan et al. (2020) highlighted the importance of speech signal processing in the process of early screening and diagnosing the COVID-19 virus by utilizing the Recurrent Neural Network (RNN) and specifically its significant well-known architecture, the Long Short-Term Memory (LSTM) for analyzing the acoustic features of cough, breathing, and voice of the patients. The total number of acoustic data used in this study was 240 of 180 recordings from 60 healthy participants and 60 recordings from 20 COVID-19 participants. Samples of COVID-19 patients were recorded in different United Arab Emirates hospitals. The results were obtained based on cough sounds, breath sounds, and voices. When comparing the three types of sounds, the best accuracy was achieved for breathing sound, reaching up to 98.2%. Then, for cough sounds, an accuracy of 97% was attained. When it comes to voices, the accuracy of the system was only 88.2%.

Actually, a lot of data describing the diseases are stored in the form of text data and to exploit them text processing and data analytics algorithms should be adopted. Therefore some researchers worked in a new way to detect the patients of COVID-19 using text processing and data analytics through some methods of AI.

The early initiative by Fayyoumi et al. (2020) developed an online questionnaire to collect data about COVID-19 patients. The data were then fed to some machine learning prediction algorithms including SVM, Logistic Regression, and MLP to predict potential COVID-19 patients based on their signs and symptoms. The collected dataset consists of 30 attributes of one class attribute and 12 test feature attributes that present the signs and symptoms of the candidate patient for novel COVID-19, which was obtained from 105 subjects (64 of non-COVID-19 patients and 41 of COVID-19 patients). These models were utilized to predict potential patients of COVID-19 based on their signs and symptoms. The MLP has shown the

best accuracy (91.62%) compared to the other models. Meanwhile, the SVM has shown the best precision 91.67%.

In another example by Khanday et al. (2020), textual clinical reports were collected and feature extraction tools like term frequency and inverse document frequency (TF/IDF), bag of words (BOW), and report length were then used to collect data. Then some traditional end ensemble machine learning algorithms like Logistic Regression (LR) and Multinomial Naive Bayes (MNB) have been used to classify the data. The researchers collected their dataset from GitHub, in which about 212 patient's data were stored which have shown symptoms of coronavirus and other viruses. Data consists of about 24 attributes. Logistic regression and Multinomial Naïve Bayes showed better results than other ML algorithms by having 96.2% testing accuracy.

After segmenting and parsing documents, Obeid et al. (2020) conducted analysis of over-represented words in patient symptoms. Then they developed a word embedding−based convolutional neural network for detecting the COVID-19 test results based on patients' self-reported symptoms. Text analytics revealed that concepts such as smell and taste were more prevalent than expected in patients testing positive. Therefore screening algorithms were adapted to include these symptoms. The total number of patients included in this analysis was 6813, 498 of whom tested positive and 6315 of whom tested negative. The deep learning model yielded an area under the receiver-operating characteristic curve of 0.729 for the positive results and was subsequently applied to prioritize testing appointment scheduling.

7.4 Concluding remarks and future trends and concerns

Application of methods of AI to X-ray and CT scans are being actively investigated and show promising results in many locations in the world. However, many countries are offering many benefits like a point-of-care method and no ionizing radiation beside X-ray and CT scans. Investigating the ability of the modality of AI to support the early diagnosis of COVID-19 would therefore most certainly be interesting as we presented many examples of initiatives, researches and applications in this chapter in many regions worldwide and also as presented in this recent review (Hariri and Narin, 2020).

Moreover, the current situation and especially in the third worldwide outbreak requires fast, widely accessible diagnostic tools which would preferably have been available in hand. Developing certified radiology software using some methods of AI usually takes long time, so medical imaging using those methods does not seem ideally suited for the immediate sup-port that is much needed in the current situation.

Furthermore, the accuracy of the presented methods of AI will be improved with increas-ing care and adopt, and so that they will be of more relevance in real-world settings and usage. As example, one initiative showed that the deep learning model for diagnostic imag-ing could be augmented by having a radiologist stationed at key checkpoints where the algorithm has difficulty, and the researchers called "human in the loop" AI may represent medicine's near future (Patel et al., 2019).

However, the ethical and societal implications of the AI technologies must also be considered and especially during the spread of the recent pandemic of COVID-19. So that more systematic examination is required like issues around security, privacy, and confidentiality as described in (Davenport and Kalakota, 2019). Overall, AI is still in its early stage with regard to wide spread applications across the medicine and healthcare industries.

Review questions

Q1. Artificial intelligence (AI) methods can be very useful in building detection system for viruses when there is too much of data which cannot be easily handled by the humans. Mention two examples of detection system using AI.

Q2. What is machine learning? What is artificial neural network? What is deep learning?

Q3. What is Infervision's AI and how did scientists use it against COVID-19?

Q4. Some methods of artificial intelligence to diagnosis COVID-19 by X-ray and CT images were presented in the chapter. Describe two other ways, far from radiology, presented in chapter to diagnosis COVID-19 using AI methods.

Q5. Briefly describe two early initiatives, which used AI methods to diagnosis COVID-19 by X-ray images.

Q6. Mention two early researches used CT scans to diagnosis COVID-19 by means of AI methods.

Q7. Briefly describe two early studies—one used cough sound and another used text analysis to diagnosis COVID-19 using AI methods.

Discussion questions

Q1. From your understanding of this chapter, can you briefly describe the differences between artificial neural network and deep learning, and especially in the applications of AI in the medicine field?

Q2. Some researchers called "human in the loop" AI may represent medicine's near future. Discuss the possibility of this statement, and especially in the expected-worldwide treatment and control of any pandemic in the future.

Problem statements

P1. As mentioned in some studies in this chapter, researchers have used some public data from open sources like Kaggle and GitHub. Search those sources for any suitable small datasets of X-ray images or CT scans. Using your background of any AI method, try to put a short research plan to use a small dataset for the diagnosis of COVID-19. Your research plan will be same as any research proposal including: introduction, problem statement, proposed methodology, and expected results.

P2. Use your plan from P1 to prepare a small project in the diagnosis of COVID-19 using X-rays images or CT scans. Try to follow the same way as you can see in some research papers presented in this chapter in Sections 7.3.2.1 or 7.3.2.2. In your project report, you need to describe the dataset, your adopted methodology, the results and finding, and your conclusion and any recommended remarks.

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