A Review of COVID-19 Diagnosis and Detection Using Artificial Intelligence

Suhad Hussein Jasim

Department of Electrical Engineering, University of Technology, Baghdad, Iraq

Email: suhad.h.jasim@uotechnology.edu.iq

Abstract: Coronavirus has received widespread attention from the community of researchers and medical scientists in the past year. Deploying based on Artificial Intelligence (AI) networks and models in real world to learn about and diagnose COVID-19 is a critical mission for medical personnel to help preventing the rapid spread of this virus. This article is a brief review of recent papers concerning about detection of the virus; most of the schemes used to detect and diagnose COVID-19 rely on chest X-Ray, some on sounds of breathing, and by using electrocardiogram (ECG) trace images, all these schemes based on artificial neural network for early screening of COVID-19 and estimating human mobility to limit its spread. In some studies, an accuracy rate that was obtained exceeded 95%, which is an acceptable value and that can be relied upon in the diagnosis. Therefore, currently screening tests are better in terms accuracy and reliability for diagnosing patients with severe and acute respiratory syndrome coronavirus, frequently the most used test is the (RT-PCR).

Keywords: Neural network, Coronavirus, COVID-19.

الخلاصة: حظي فيروس كورونا باهتمام واسع من مجتمع الباحثين وعلماء الطب في العام الماضي. يعد النشر استنادًا إلى شبكات ونماذج الذكاء الاصطناعي (AI) في العالم للتعرف على COVID-19 وتشخيصه التي تعتبر مهمة حاسمة للعاملين في المجال الطبي وللمساعدة في منع الانتشار السريع لهذا الفيروس. هذه المقالة هي مراجعة موجزة للبحوث الحديثة المتعلقة بالكشف عن الفيروس ؛ تعتمد معظم المخططات المستخدمة لاكتشاف وتشخيص COVID-19 على بالأشعة السينية للصدر، وبعضها على أصوات التنفس ، وباستخدام صور تتبع مخطط القلب الكهربائي (ECG) ، كل هذه المخططات تعتمد على الشبكة العصبية الاصطناعية للفحص المبكر لـ COVID-19 وتقدير تنقل الإنسان للحد من انتشاره. في بعض الدراسات ، تجاوز معدل الدقة الذي تم الحصول عليه 95٪ وهي قيمة مقبولة ويمكن الاعتماد عليها في التشخيص. لذلك ، تعد اختبارات الفحص حاليًا أفضل من حيث الدقة والموثوقية لتشخيص المرضى المصابين بفيروس كورونا المتلازمة التنفسية الحادة, وغالبًا ما يكون الاختبار الأكثر استخدامًا هو(RT-PCR) .

1. Introduction

In recent years, the Coronavirus (COVID-19) has caused serious impacts on the health care system especially and the global economy in general. Doctors, researchers and experts are interested in finding alternative methods for rapid and accurate detection of this virus and are attempting to develop automatic detection systems for COVID-19. Detection methods play an important and dangerous role stopping its spread in treating patients. Subsequently, many medical scientists and researchers have looked for new techniques to detect diseases more accurately and quickly [1].

Advances in AI (artificial intelligence) in biomedical applications have helped in the development of networks trained to make reliable computer-aided diagnostic decisions and thus reduce stress from healthcare facilities (doctors, healthcare staff, etc.)[2].

Several literature studies have described the application of computer technique and Deep Learning (DL) in diagnosing disease based on medical images since COVID-19 has become widespread, with promising results.

The Computer-aided diagnosis (CAD) systems combine advanced technologies in computers hardware with modern image processing algorithms to perform diagnostic tasks, e.g. the segmentation of tumor and 3D imaging of vital organs[3][4].

Recently, AI has been widely used to obtain accurate diagnosis in many CAD systems fin the field of various medical applications such as brain tumor segmentation and classification [5][6], minimally invasive aortic valve implantation[7], and lung disease detection [8][9]. Deep learning approaches have become the most advanced approach in the studies that rely on AI. However, SC (Soft computing) technologies, such as; Fuzzy logic, genetics and neural networks have been proven to be as potential tools for detecting the disease [10][11]. These tools can support in decision-making, provide appropriate treatment for patients [12]. Although several mechanism have been suggested to diagnose COVID-19 infection; however, high accuracy has not yet been reached. Figure 1 shows the different diagnostic technique.

The lack of accurate diagnosis or preventive measures led to an increment in the number of infections of infection and an increase in the cost of hospitalization. This was to urge medical industries and scientists around the world to find accurate COVID-19 detection for early preservation, screening, diagnosis, drug improvement and tracing the contact to provide more time for the medical scientific community and health care cadres to reduce the death rate of COVID-19.

Recent reviews showed that the use of new technology in along with AI and machine learning (ML) technologies greatly speeds up diagnosis, screening, tracking, prediction, and progression of vaccines with high reliability.

The field of medical imaging has particularly emerged in recent years in providing reliable automated methods for clinical decision-making and has been widely accepted by scientists and personals in the medical field. In diagnostic case of COVID-19, CT scan and X-ray can have an essential and important function in early detection for the disease. Where X-ray is an effective screening and classification method; it is quick to pick up, less expensive than RT-PCR and widely available worldwide. Additionally, CT scans can be obtained faster and more accurately with an efficient algorithm (particularly deep learning algorithms) to accurately identify affected patients [13].

CT and X-ray imaging have seen wider application in detecting COVID-19 while RT-PCR tests have low sensitivity in medical and clinical examinations. Various studies demonstrated the avail of using CT or CXR by improving the outcome of COVID-19 detection in a clinical scenario. Because of the limited sensitivity of the RT-PCR technology, it necessitates refined negative tests, leads to kit shortages or unobtainable in certain parts of the world [14]. Furthermore, detection of the disease in its early stages can lead to false-negative results from CT scan. Although CT can become the modality of choice for COVID-19 detection [15], lung US has recently received attention due to the fact that US machines are widely available and comparatively inexpensive, with the enhancing benefit of being safe and disinfected easily in busy centers with lung ultrasound (US).

Although, recent studies recommended avoiding the use of diagnostic images or ruling out COVID-19 because it produces false cases both positive and negative [14]. For the limitations of the X-rays to be overcome, CAD systems have provided a practical solution by assisting the radiologists to detect the potential diseases accurately in low-resolution X-ray images [16].

Additionally, classifying the respiratory sounds have received decent interest by scientists in medical area and research community last year to diagnose COVID-19 virus based on AI models from patient's sounds such as speech, breathes and cough).

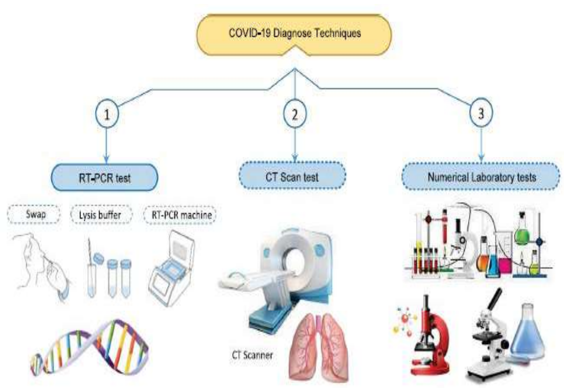

Fig. 1. Diagnosis techniques of Covid-19[17].

2. Literature review

J. Sharma et al. [18] Obtained highly accurate model by classifying the sounds from US8K and ECS-10 datasets using DCNN with channels including ;(multi-feature (MFCC), Chroma gram, GFCC, QCT (Constant Q-Transform)). The proposed model for classifying lung sounds, which was implemented on grouped respiratory sounds by using a digital stethoscope and achieved accuracy, is about 80% for classified sound on the respiratory system and 62% for classifications by audio. The proposed model was improved to achieve better accuracy by using the CNN model and channels multiple features including; (De-noising Auto Encoder, GFCC, and IMFCC) to provide an accurate diagnosis based on a sound crowdsourced dataset.

Kranthi Kumar et al,[19] a DCNN model was proposed to classify the signs of respiratory sound specifically into normal and abnormal cases depends on voice, cough, and sounds of breathing to detect COVID-19 infection. The implemented system obtains the depth features of respiratory voice/sounds by using IMFCC (Improved Multi-frequency Cepstral Coefficients), (DAE) De-noising Auto Encoder technique, and (GFCC) Gamma-tone Frequency Cepstral Coefficients. DCNN transforms the DAE input features; pooling activity is carried out using IMFCC, and GFCC techniques. The processed signal is categorized by using (Softmax) classifier. The DAE is used to extract features of patients voice signals by remove the mummer sounds from background, the IMFCC extracts important features from sounds of respiratory, and the GFCC extracts the transient features from the respiratory sound. Thus the utility of the fundamental function for that study is thus demonstrated. The implemented model approaches around 95.45% accuracy which is better than that of previous work.

Tawsifur Rahman, et al. [20] was the first study explores the ability of using electrocardiogram (ECG) trace images to detect COVID-19 infection using DCNN models. The study used a generic dataset of ECG scans that included 1937 images divided into five divisions: normal, COVID-19, Myocardial Infarction (MI), Abnormal Heartbeat (AHB), and Recovered Myocardial Infarction (RMI). Alternative categorization strategies investigated using six various DCNN models (ResNet18, ResNet50, ResNet101, InceptionV3, DenseNet201, and MobileNetv2. Schemes of divisions classified into five-classes (normal, COVID-19, MI, AHB, and RMI), two classifying classes (normal vs COVID-19), in addition to three classifying classes (normal, COVID-19, and other CVDs). For each categorization scheme, six CNN models had been trained and tested to improve its validation and to identify irregularity for various ECG images. Figure 2 shows an overview of this methodology. The two and three classification networks reached accuracy about 99.1%, and 97.36%; while the accuracy of five classification network 97.83% was achieved.

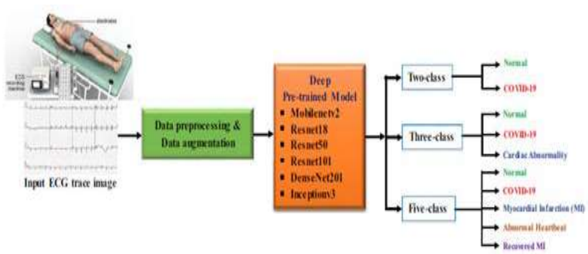

Fig. 2. An overview of ECG based methodology [20].

For CAD based on lung computed tomography (CT) images, many CNN-based approaches were developed. However, the appearances, sizes, and positions of pneumonia lesions in CT scans vary widely; in addition symptoms for COVID-19 in CT scan are likewise comparable to different kinds of viral pneumonia, preventing further advancement of CNN-based approaches. Manual delineation of infection areas is a solution to this problem, however due to the heavy workload of medical staff and physicians through the epidemic, manual delineation is challenging. Bin Xiao et al. [21] suggested a CNN termed PAM-Dense Net (Parallel Attention Module with dense connection network), that can implement coarse label well without requiring to delimit the infected zones manually. The PAM learned to simultaneously reinforce the characteristics informality from both channel and spatial perspectives allowing the network paying greater attention to infected zones without needing manual segmentation. The model provides direct connections between previous layers and all subsequent layers; the dense connectivity structure performs feature map reuse, allowing for extracting exemplary features from fewer number of CT slices. To obtain a suitable model for slice wise prediction, the proposed network was trained firstly using 3530 CT images for lung picked from 382 COVID-19 CT images, 372 lungs CT scan with infections by deferent pneumonia, and 200 normal lungs CT scan. Then researchers applied the pre-trained model to a CT scans dataset contained 93 normal lung scans, 93 other pneumonia CT scans, 94 COVID-19 CT scan and achieved a patient wise predicting using polling mechanism. The suggested network obtained 94.29% impressive accuracy, about 93.75% of precision, 95.74% of sensitivity, and about 96.77% of specificity, that is equivalent to techniques based on manual drawn of infected regions. The appearances, sizes, and positions of pneumonia lesions in CT scan vary widely and the presentation of COVID-19 using CT images is similarly comparable to other various species of viral pneumonia, hampering future advancement of CNN-based approaches. The module is based on a self-learning mechanism which allows the network to improve extracting the informative characteristic. The suggested attention module in this paper is PAM, which is able to learn to both strengthen and suppress features from channels at the same time spatially. The PAM instructs the network to pay more awareness to infected regions in lung CT images, improving performance without the need for manual demarcation.

A novel Hybrid Diagnostic Strategy (HDS) based on laboratory findings of the patient was introduced in Warda M. Shaban et al. [17] employed an unprecedented method based project the ranking features into a virtual Patient Space (PS). A Feature Connectivity Graph (FCG) was created to obtain the weight and the degree for each feature as related to other features. A feature's rank is determined by two factors: the weight of the feature and its degree of binding to its neighbors in PS. The elements after being ranked were employed to develop a classifying model which can identify new persons and determine whether they were infected before or not. The classifying model was mix of two classifiers: the Deep Neural Network (DNN) and the fuzzy inference engine. Recent techniques have been compared to the planned HDS. The HDS model that was proposed outperforms the competitors related to many parameters such as its accuracy, precision, recall, and F-measure. According to experimental data, the model provided an accuracy of 97.658%, precision of 96.756%, recall of 96.55%, and F-score of 96.615%. Furthermore, HDS had 2.342% an error rate which is the lowest. Statistically, the results were confirmed by the use of two tests Wilcoxon Signed Rank and Friedman. To implement the proposed diagnostic model, Fuzzy Logic (FL) was chosen as the soft computing approach for the many reasons, first fuzzy algorithms are reliable and simple allowing saving computing power, second reason the fuzzy techniques typically take less time to develop than traditional methods especially for online diagnoses detection applications. Third, the FL is simple and flexible to implement ML approaches. Alternatively in FL, it is difficult to specify the values for the membership of fuzzy systems and to store abase storage since it requires a considerable amount of memory. Additionally, FL needs to be carried out with a complete guide of experts.

Address the latest global forecasts for the COVID-19 pandemic. Every country around the world faced this epidemic differently, which was dependent on the statistical number of confirmed cases and deaths. Forecasting the number of confirmed infected cases and deaths may anticipate the future number of infections and provide each country with requisite information to help make decisions depends on expectations. Patricia Melin, et al, [22] built a Firefly Algorithm (FA) that ensemble the architecture of the neural networks for each of the 26 countries. The proposed FA optimized to ensemble NN that applied to time-series prediction of COVID-19 using FL (type two) based on weighted mean integration method. That method determines the number of ANNs required forming a collective neural network and its architecture based on type two FL inference systems to integrate the individual responses of ANNs to make a latest accurate prediction. The type two weighted mean integration approaches has benefits over the traditional method type one weighted mean integration.

Lung ultrasound (US) is properly an effective test for detecting COVID-19, due to easily operation with least protective equipment and ease of disinfection. New, based DL COVID-19 diagnostic model are not easy to be deployed for common use mobile platform. Navchetan Awasthi, et al, [23] researchers developed an easy to use mobile technology, functional DL algorithm for COVID-19 diagnosis by the use of lung US images included three specified classification (COVID-19, healthy , and pneumonia). The developed network, called Mini-COVID Net, was distinguished from other lightweight NN models. The achieved accuracy by the implemented network was 83.2% the time of training required is only 24 minutes. The Mini-COVID Net had fewer network parameters by 4.39 times comparable to next best performing network and required only 51.29MB of memory, which makes diagnostic model using US lung imaging feasible on mobile platform. The developed lightweight network (Mini-COVID Net) can be deployed on embedded platforms; it is versatile, offers optimum resolution performance and having frequent response for the same order. Developed Mini-COVID Net model is available on (https://github.com/navchetan-awasthi/Mini-COVIDNet.).

Aayush Kumar et al. [24] introduced SARS-Net, CADx system for COVID-19 recognition using chest X -ray (CXR) images that combine Graph Convolutional Network and CNN. Extensive testing revealed the suggested SARS-Net model outperforms state-of-art methodologies and achieves the best outcomes among all other proposed networks. The SARSI-Net is a hybrid method that incorporates the SARSI-Net CNN model with the 2L-GCNI model. SARS-Net CNN assists in the extraction of image-level features, while GCN assists in the extraction of relation-awareness features. The proposed model achieved 97.60% accuracy and 92.90% sensitivity in the validation set. Implementing automatic detection of COVID-19 enables faster treatments and enhances the recovery rate, and as a result improves people's overall health. CAD-X systems able to help medical care services and decrease the refrain from physicians and radiologist to develop countries having restricted health care services.

Prottoy Saha et al. [25] by analyzing chest X-ray images, an automated detection mechanism called EMC Net proposed to identify COVID-19 patients. To extract the high level features from X-ray images of patients infected with COVID-19, a CNN was formed with a focus on model naivety. COVID-19 was detected using ML classifiers including (randomly forest, support vectors machine, decision trees, and Ada Boost). The outputs of these classifiers merged to create a crew of classifiers; results improved for varying sizes and different resolutions dataset. EMC Net performed better compared to DL based systems, its precision is 98.91 %; its recall is 97.82 %, and its F1-score is 98.89 %.

Murukessan Perumal et al. [26] inception Nasnet (INASNET) is a proposed model that can divide and categorize X-ray pictures into (normal, infected, and infected pneumonia) classes. The testing technique cheaper compared to testing kits used for diagnosing the disease by the healthcare workers. INASNET is built on a platform that combines Inception Net and NN Architecture; searching would result in more accurate and faster-predictions. INASNET efficient and achieved an accuracy rate of 0.943 compared with DL models. The INASNET model trained with complicated datasets and was optimized using batch normalization and a dense layer which improved the efficiency of detection.

Muhammad Umer et al. [27] presented the usage of a CNN for prognosis using features extracted from X-ray images of the chest. The model used three extracting filters which aid in obtaining the segmented target with the contaminated X-ray area. Ten thousand augmented photos generated by using Keras' Image Data Generator class to overcome decreased amount of training dataset. Classification was done with two, three, and four classes, with X-ray images for people diagnosed with COVID-19, normal, viral-pneumonia, and bacterial-pneumonia. The results showed that the CNN model is capable of accurately predict COVID-19 cases. The accuracy of the implemented two, three, and four classification classes were 0.97, 0.90, and 0.85, respectively. Figure 3 shows the architecture of the proposed approach.

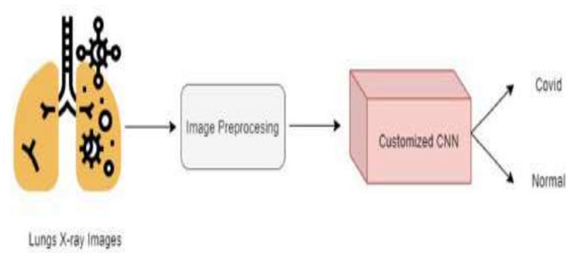

Fig. 3. Architecture of the model. [27]

Kamal KC et al. [28] a comprehensive evaluation provided for eight previously trained models. Training and testing of these models were applied on chest X-ray images belong to five various classes, contains 760 images. The finely tuned models, which were previously trained in the ImageNet dataset, were functional and computationally accurate. Controlled Dense Net121 had a 98.69% of accuracy and a 0.99 of F1 score for four classifying classes. Only 62 % parameters were retrained to obtain such accuracy, according to the data. The work created and compared the performance of various deep learning models and transfer learning approaches on CXR pictures for COVID-19 classification while keeping computational demands low.

Mohamed Esmail Karar et al. [16] used three cascaded DL classifiers to offer a new framework for the automatic CAD to diagnose COVID-19, viral, and bacterial pneumonia on CXR images. In comparison to prior studies, the implemented cascaded classifiers make promised results when used with the VGG16 model to confirm affirmative COVID-19 cases. The ResNet50V2 and DenseNet169 models correctly detected both viral and bacterial diseases. The major object of that study is to automate the segmentation of COVID-19 infections on chest X-ray scan. Segmentation task would be greatly assisting the clinician in monitoring disease progression in infected patients' lungs. The VGG16 and ResNet50V2 models showed classification and performance accuracy of 99.9% in identifying COVID-19 cases.

Qiuchen Xie et al. [29] a DL model trained with 563 chest CT scan for 380 patients (227 out of 380 cases diagnosed with COVID-19), the CT images collected from five hospitals. Firstly, extracting Lung regions using U-net, then these regions transformed to be fit with ResNet-50 based on IDAN1-Net (Identification and Analysis of Network). Five validation cross points were used to verify the accuracy of the model results. Additionally 318 scan from 316 patients (243 out of 316 with COVID-19 cases) were included prospectively scanned as RWDs to indicate the performance of DL model and compare with three experienced radiologists from two other hospitals. As a Result a three-dimensional DL model was formed. The diagnosing accuracy of COVID-19 infection was 95 %.

Saeed Sani et al. [1] Used chest CT images to diagnose and treat lung disorders, such as viral-pneumonia. The advantages of CT scanning as compared with molecular diagnostic tests are several indications including shorter turnaround time; includes more details about pathology information and quantification of lesion size and lung involvement, which have substantial consequences for prognosis. A novel neural network was introduced for COVID-19 data and detection methods utilizing chest CT to distinguish the symptoms. To enhance the accuracy, a mathematical model was applied, and high-precision Hopfield Neural Network (HNN) was used to identify symptoms. The HNN was trained on a dataset which includes 12 patterns of CT scan, and it was evaluated with 295 CT images from three separate datasets. The model's sensitivity and specificity were 97.4 % and 98.6 %. In addition, the model was able to diagnose the community acquired pneumonia with sensitivity of 97.3 % and specificity of 9.5 %, while its ability to diagnose non pneumonia patients with sensitivity of 100% and specificity of 98.5%.

Amiya Kumar Dash, et al. [30] Also presented a new diagnostic framework of COVID-19 by replacing the proven previous model VGG-16 with fully connected layers with weights initiated randomly based on DCNN. The model learned the discriminatory features, colors, geometric changes, namely, objects and shapes. The VGG-16 was considered as a source base model to classify the patients for training the deep convolutional neural network. The suggested model produces an accuracy of 97.12%, sensitivity of 99.2% and specificity of 99.6%. A fine-tuned model VGG-16 framework also recommended providing a complete solution that is, the input is a CT scan image and the output is a COVID-19 or non-COVID-19 diagnosis with a highly sensitive rate. The benefits of this model that there are no technical requirements to extract the features from CT scan, inexpensive, and can be a useful tool for assisting radiologists with diagnosis.

3. Discussion

Generally, most of studies focused on two known images, X-ray and CT scan. The most favorably is X-ray because of it is availability; its low memory space, easily accessing public databases and high accuracy results which encouraged researchers to use it. CT images provide many cross-sections for the chest area therefore radiologists can simply recognize patients but CT images are more complicated than X-ray images. It's highly necessary to compare the results for the studies associated with data acquired from several various centers; otherwise, produced sensitivity and accuracy for these studies would be misleading.

Alternative approaches are vital in diagnosis of COVID-19, that it is possible to save more patients' morbidity and mortality real-time systems of diagnosis and detection based on online scanning systems installed on computers or mobiles.

ML algorithms also used by extracting part of the features of deep learning models that improves the performance of the approach.

Despite various studies based on DL approach, it is difficult to provide sufficient and reliable models. Accordingly, many factors affect the results.

Alternatively, diagnosing COVID-19 is now being performed on the coughing sounds and breathing sounds of the patient instead of relying on computed tomography and X-Ray or CT imaging.

Because of all these methods of diagnosing and exanimating voices, it is predicted that detecting COVID-19 patients will highly accurate and stable. Many researchers have achieved a high level of reliability with accuracy crossed 98% and thusly can be dependent in helping healthcare workers and this will open a new broad employing of using AI in the medical sector.

4. Conclusion

Early detection and diagnosis of COVID-19 is vital in the process of preventing spread of the disease, for that a lot of researches conducted to find the fastest and the cheapest method to detect Covid-19. This review covered three main kinds of researches dealing with cardio diagnosis using electrocardiogram (ECG) trace images, chest X-ray diagnosis, and sound diagnosis. Most of researches were concentrating on chest x-ray since it is relatively an effective screening method; it is pick up fastely, cheaper as compared to RT-PCR test and available widely worldwide.

Ultimately, the lack of sufficient information about COVID-19 and the speed of its spread made analyzing the severity of the disease are difficult. The accuracy of the data can be useful and important for categorizing the severity of COVID-19, working more efficient and choosing more suitable and appropriate treatments.

5. References

[1] S. Sani and H. E. Shermeh, “A novel algorithm for detection of COVID-19 by analysis of chest CT images using Hopfield neural network,” Expert Syst. Appl., vol. 197, no. May 2020, p. 116740, 2022, doi: 10.1016/j.eswa.2022.116740.

[2] M. Dahmani et al., “An intelligent and low-cost eye-tracking system for motorized wheelchair control,” Sensors (Switzerland), vol. 20, no. 14, pp. 1–27, 2020, doi: 10.3390/s20143936.

[3] T. He, J. Hu, Y. Song, J. Guo, and Z. Yi, “Multi-task learning for the segmentation of organs at risk with label dependence,” Med. Image Anal., vol. 61, 2020, doi: 10.1016/j.media.2020.101666.

[4] R. Hannan, M. Free, V. Arora, R. Harle, and P. Harvie, “Accuracy of computer navigation in total knee arthroplasty: A prospective computed tomography-based study,” Med. Eng. Phys., vol. 79, pp. 52–59, 2020, doi: 10.1016/j.medengphy.2020.02.003.

[5] B. Pirouz, S. S. Haghshenas, S. S. Haghshenas, and P. Piro, “Investigating a serious challenge in the sustainable development process: Analysis of confirmed cases of COVID-19 (new type of Coronavirus) through a binary classification using artificial intelligence and regression analysis,” Sustain. (United States), vol. 12, no. 6, 2020, doi: 10.3390/su12062427.

[6] A. Hamed, A. Sobhy, and H. Nassar, “Accurate Classification of COVID-19 Based on Incomplete Heterogeneous Data using a KNN Variant Algorithm,” Arab. J. Sci. Eng., vol. 46, no. 9, pp. 8261–8272, 2021, doi: 10.1007/s13369-020-05212-z.

[7] M. Z. Islam, M. M. Islam, and A. Asraf, “A combined deep CNN-LSTM network for the detection of novel coronavirus (COVID-19) using X-ray images,” Informatics Med. Unlocked, vol. 20, p. 100412, 2020, doi: 10.1016/j.imu.2020.100412.

[8] O. Gozes et al., “Rapid AI Development Cycle for the Coronavirus (COVID-19) Pandemic: Initial Results for Automated Detection & Patient Monitoring using Deep Learning CT Image Analysis,” 2020, [Online]. Available: http://arxiv.org/abs/2003.05037

[9] G. Marques, D. Agarwal, and I. de la Torre Díez, “Automated medical diagnosis of COVID-19 through EfficientNet convolutional neural network,” Appl. Soft Comput. J., vol. 96, p. 106691, 2020, doi: 10.1016/j.asoc.2020.106691.

[10] N. Aydin and G. Yurdakul, “Assessing countries’ performances against COVID-19 via WSIDEA and machine learning algorithms,” Appl. Soft Comput. J., vol. 97, p. 106792, 2020, doi: 10.1016/j.asoc.2020.106792.

[11] Gayathri, G.V., Satapathy, S.C. (2020). A Survey on Techniques for Prediction of Asthma. In: Satapathy, S., Bhateja, V., Mohanty, J., Udgata, S. (eds) Smart Intelligent Computing and Applications. Smart Innovation, Systems and Technologies, vol 159. Springer, Singapore. https://doi.org/10.1007/978-981-13-9282-5_72

[12] F. Pegoraro, E. A. Portela Santos, E. de Freitas Rocha Loures, and F. W. Laus, “A hybrid model to support decision making in emergency department management,” Knowledge-Based Syst., vol. 203, p. 106148, 2020, doi: 10.1016/j.knosys.2020.106148.

[13] W. Hariri and A. Narin, “Deep neural networks for COVID-19 detection and diagnosis using images and acoustic-based techniques: a recent review,” Soft Comput., vol. 25, no. 24, pp. 15345–15362, 2021, doi: 10.1007/s00500-021-06137-x.

[14] O. Reyad, “Novel Coronavirus COVID-19 Strike on Arab Countries and Territories: A Situation Report I,” pp. 1–3, 2020, [Online]. Available: http://arxiv.org/abs/2003.09501

[15] H. Liu, F. Liu, J. Li, T. Zhang, D. Wang, and W. Lan, “Clinical and CT imaging features of the COVID-19 pneumonia: Focus on pregnant women and children,” J. Infect., vol. 80, no. 5, pp. e7–e13, 2020, doi: 10.1016/j.jinf.2020.03.007.

[16] M. E. Karar, E. E.-D. Hemdan, and M. A. Shouman, “Cascaded deep learning classifiers for computer-aided diagnosis of COVID-19 and pneumonia diseases in X-ray scans,” Complex Intell. Syst., vol. 7, no. 1, pp. 235–247, 2021, doi: 10.1007/s40747-020-00199-4.

[17] W. M. Shaban, A. H. Rabie, A. I. Saleh, and M. A. Abo-Elsoud, “Detecting COVID-19 patients based on fuzzy inference engine and Deep Neural Network,” Appl. Soft Comput., vol. 99, p. 106906, 2021, doi: 10.1016/j.asoc.2020.106906.

[18] J. Laguarta, F. Hueto, and B. Subirana, “COVID-19 Artificial Intelligence Diagnosis Using only Cough Recordings,” IEEE Open J. Eng. Med. Biol., vol. 1, pp. 275–281, 2020, doi: 10.1109/OJEMB.2020.3026928.

[19] K. K. Lella and A. Pja, “Automatic diagnosis of COVID-19 disease using deep convolutional neural network with multi-feature channel from respiratory sound data: Cough, voice, and breath,” Alexandria Eng. J., vol. 61, no. 2, pp. 1319–1334, 2022, doi: 10.1016/j.aej.2021.06.024.

[20] T. Rahman et al., “COV-ECGNET: COVID-19 detection using ECG trace images with deep convolutional neural network,” Heal. Inf. Sci. Syst., vol. 10, no. 1, pp. 1–17, 2022, doi: 10.1007/s13755-021-00169-1.

[21] B. Xiao et al., “PAM-DenseNet : A Deep Convolutional Neural Network for Computer-Aided COVID-19 Diagnosis,” pp. 1–12, 2021.

[22] P. Melin, D. Sánchez, J. C. Monica, and O. Castillo, Optimization using the firefly algorithm of ensemble neural networks with type-2 fuzzy integration for COVID-19 time series prediction, vol. 5, no. 2020. 2021. doi: 10.1007/s00500-020-05549-5.

[23] N. Awasthi, A. Dayal, L. R. Cenkeramaddi, and P. K. Yalavarthy, "Mini-COVIDNet: Efficient Lightweight Deep Neural Network for Ultrasound Based Point-of-Care Detection of COVID-19," IEEE Trans. Ultrason. Ferroelectr. Freq. Control, vol. 68, no. 6, pp. 2023–2037, 2021, doi: 10.1109/TUFFC.2021.3068190.

[24] A. Kumar, A. R. Tripathi, S. C. Satapathy, and Y. D. Zhang, "SARS-Net: COVID-19 detection from chest x-rays by combining graph convolutional network and convolutional neural network," Pattern Recognit., vol. 122, p. 108255, 2022, doi: 10.1016/j.patcog.2021.108255.

[25] P. Saha, M. S. Sadi, and M. M. Islam, "EMCNet: Automated COVID-19 diagnosis from X-ray images using convolutional neural network and ensemble of machine learning classifiers," Informatics Med. Unlocked, vol. 22, p. 100505, 2021, doi: 10.1016/j.imu.2020.100505.

[26] M. Perumal, A. Nayak, R. P. Sree, and M. Srinivas, "INASNET: Automatic identification of coronavirus disease (COVID-19) based on chest X-ray using deep neural network," ISA Trans., no. xxxx, 2022, doi: 10.1016/j.isatra.2022.02.033.

[27] M. Umer, I. Ashraf, S. Ullah, A. Mehmood, and G. S. Choi, "COVINet: a convolutional neural network approach for predicting COVID-19 from chest X-ray images," J. Ambient Intell. Humaniz. Comput., vol. 13, no. 1, pp. 535–547, 2022, doi: 10.1007/s12652-021-02917-3.

[28] K. Kc, Z. Yin, M. Wu, and Z. Wu, "Evaluation of deep learning-based approaches for COVID-19 classification based on chest X-ray images," Signal, Image Video Process., vol. 15, no. 5, pp. 959–966, 2021, doi: 10.1007/s11760-020-01820-2.

[29] Q. Xie et al., "The usage of deep neural network improves distinguishing COVID-19 from other suspected viral pneumonia by clinicians on chest CT: a real-world study," Eur. Radiol., vol. 31, no. 6, pp. 3864–3873, 2021, doi: 10.1007/s00330-020-07553-7.

[30] A. K. Dash and P. Mohapatra, "A Fine-tuned deep convolutional neural network for chest radiography image classification on COVID-19 cases," Multimed. Tools Appl., vol. 81, no. 1, pp. 1055–1075, 2022, doi: 10.1007/s11042-021-11388-9.