

AI Empowered Machine Learning and Deep Learning for Combating with Covid-19; State of the Art contributions, Available Datasets, Challenges and Future Directions

Sana Hameed¹, Farrukh Arslan², Munaza Iqbal³, Mubashir Ali⁴, Muhammad Umar Haroon⁵, Naveed Imran⁶

¹Department of Computer Science and Information Technology, University of Central Punjab, Lahore, Punjab

²Department of Electrical Engineering, University of Engineering and Technology, Lahore, Pakistan

³Department of Computer Science, GC University, Faisalabad (Sahiwal Campus), Sahiwal, Punjab, Pakistan

⁴Department of Software Engineering, Lahore Garrison University, Lahore, Pakistan

⁵Department of Software Engineering, National University of Modern Languages, Islamabad, Pakistan

⁶Department of Computer Science, University of Central Punjab, Lahore, Pakistan

*Corresponding author email: mubashirali@lgu.edu.pk

ABSTRACT

The brand-new coronavirus COVID-19 spread rapidly over the globe and killed plenty of people. The World Health Organization (WHO) has classified COVID-19 as a global pandemic and all possible efforts are made to save human lives. Various governments implement complete and smart lockdowns to reduce COVID-19. For the detection and diagnosis of COVID-19, the conventional Polymerase Chain Reaction (PCR) test is regarded as essential. But an examination of a PCR test is time-consuming, requires resources as well as reports a large number of false negative results. Artificial Intelligence is fast growing technology with unlimited successful implementation with remarkable results in all problematic sectors. There are already several examples of AI-enabled Machine Learning (ML) and Deep Learning (DL) being used successfully in the healthcare industry. We have evaluated the most recent and cutting-edge research in this paper. ML and DL-based work for combating COVID-19. We discussed the COVID-19 background with all essentials and presented ML and DL-based systems highlighted by a new hierarchy. Identification and diagnosis of COVID-19 by considering medical images, sound analysis, and textual and non-invasive technologies. Further, we have also tabularized the COVID-19 datasets with their possible implementation. In last, we have listed the current challenges which are faced by ML and DL while combating COVID-19 and future directions for research.

KEYWORDS

Machine Learning, Deep Learning, COVID-19, Detection, Diagnosis, Datasets, Medical Imaging, Sound Analysis

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1. INTRODUCTION

A virus known as Severe Acute Respiratory Syndrome Corona-Virus-2 was the culprit behind Covid-19 (SARS-CoV-2). It is now a significant infectious worldwide disease that was first noticed in Wuhan, China. World health organization (WHO) confirmed this infection as a public health emergency of international concerns (PHEIC) [1] and confirmed it as a pandemic. The disease spread worldwide and the death rate increased up to millions of confirmed cases. In these health crises, the health industry is looking for new tools, and technologies to control this pandemic. As Artificial Intelligence is a universal technology for combating all challenges. AI can identify the risk, and severity and can detect the growth rate of the virus. AI can predate the possibility of death by examining the patient's history. AI can help battle the virus by testing people, medical help, and recommendations concerning disease control, data, and information. AI covers a wide range of issues that arise in our complex daily lives. learning, looking, pondering, putting together, and representing. The subsets of AI known as machine learning (ML) and deep learning (DL) contain a

variety of techniques that produce intelligent models that can recognize particular tasks.

Some techniques for ML are Density Clustering (DS), Logistic Regression (LR), Decision Tree (DT), Naïve Bayes (NB), Artificial Neural Network (ANN), Restricted Boltzmann Machines (RBM) etc. The focus of DL is on building structural models that use feedforward and backpropagation algorithms to learn from the data. Deep Learning techniques use Deep Convolutional Neural Networks, Deep Neural Networks, and Deep Belief Networks (DBN) (Deep CNN).

ML and DL are massively used in public monitoring, covid-19 detection, patient diagnosis and pandemic protection. They are used in the safety check-ups at airports, tracing patients and epidemic revealing too.

The taxonomy of the survey, which we introduced in Figure 1 and which focuses on ML and DL research work on Covid-19 diagnostics and treatments as shown.



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2. COVID-19 BACKGROUND

The diameter of the circular positive sense RNA virus known as the corona virus ranges from 600A to 1400A. [2]. The epicenter for the outbreak of Covid-19 was a Wuhan's general market which is for sea-food and other uncommon animals such as, bats, snakes, marmots etc. Infected people serve themselves as the quiet transferors of the virus and contribute high generative number of Covid-19 virus.

2.1. CLINICAL FEATURES

The majority of Covid-19 patients displayed clinical traits such exhaustion, fever, sputum production, and dry cough, and other individuals displayed symptoms like headache, sore throat, and dyspnea. Hemoptysis, nasal congestion, diarrhea, nasal congestion, and nausea are extremely uncommon symptoms. People over 60 and those with pre-existing conditions like asthma, diabetes, cardiovascular disease, and high blood pressure were most at risk for developing serious diseases from COVID-19 [3].

2.2. TRANSMISSION MECHANISM

According to an analysis, the Covid-19 virus spreads between people when they sneeze or cough [4]. Every person who is close to the sick person is at risk since respiratory droplets have the ability to travel up to 6 feet. The Covid-19 transmission has also been linked to indirect contact with infected surfaces. According to some research, the virus can survive on copper surfaces for 4 hours, on cardboard for up to 24 hours, and on plastic and steel surfaces for up to 3 days. Through the nasal way, the virus enters the healthy body. The spikes on its surface breach the cell membrane, causing the cells to begin replicating and infecting other body cells. The lung air sacs are then damaged by the virus as it descends into the bronchial tubes.

2.3. PREVENTIVE MEASURES

- I. I. Use an alcohol-based hand sanitizer or wash your hands with soap and water to clean your hands.
- II. Without cleaning hands, avoid touching your nose, mouth and eyes.
- III. Cover your Cough or sneeze into a tissue or a cloth. If they are not available, sneezing into the elbow pit is suitable.
- IV. IV. It is recommended that people over 60, those with serious illnesses, and expectant mothers stay at home and refrain from social interaction.
- V. Keep yourself at a distance of 1 meter from others.
- VI. Sanitize the routinely touched surfaces including desks, phones, switches, laptops, and doorknobs.
- VII. Wear masks around the people and keep distance.

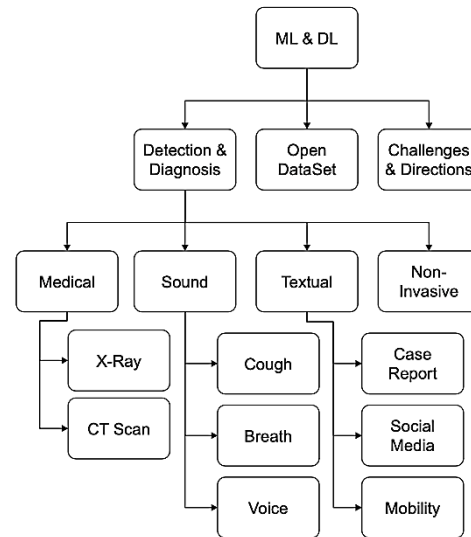


Figure. 1. ML and DL Hierarchy for COVID-19

3. COVID-19 DETECTION AND DIAGNOSIS WITH MEDICAL IMAGES

Medical imaging, including as computed tomography (CT), X-ray, and imaging, plays a crucial part in this global battle against Covid-19. Medical imaging research is used as a key tool against Covid-19 identification. Lung CT image and chest X-ray trials are commonly used in Covid-19 clinical imaging. In medical imaging testing AI has played a significant role. It has formed massive results in disease identification, geographic infection classification, organ recognition, and image classification. It reduces the image diagnostic time of the radiologist, as well as enhances the correctness and performance of the diagnosis. Through accurate diagnosis accuracy in X-ray and CT imaging, AI can enhance work performance. Test examination is fast and more accurate with AI. For the detection, observation, and forecasting of diseases, computer-aided networks are supporting the radiologists in building the clinical decisions. Revolutions of AI techniques are discussed below.

3.1. CHEST X-RAY IMAGE DETECTION

Chest X-rays is an extremely helpful process for testing and evaluating Covid-19 patients. Chest X-ray image is easy to attain in clinical radiology inspections as compared to CT images. CNN, nCOVnet, and U-Net++ are some mythologies of deep learning used to detect Covid-19 on X-ray images.

3.2. CHEST CT IMAGE DETECTION

Chest CT sensitivity is to identify the Covid-19 is prior to a viral positive lab test and the rate is considerably high. Covid-19 patients with severe and numerous respiratory symptoms are projected through Chest CT. The evaluation of AI may become the most important factor by decreasing the pressure on clinicians. As it takes up to 15 min to yourself understand a CT scan, images can be analyzed in 10s by using AI.

Table. 1. DL and ML Approaches for Detection and Diagnosis of COVID-19 Through Medical Imaging

Sr. No	ML or DL Approach	Data & Experimentation	Result or Matrices
1.	COV Net using pre-trained ResNet-50.	From 3322 patients, 4356 CT images were obtained from 6 clinics [5].	87% sensitivity, 92% specificity and 96% AUC.
2.	ResNet-18 and the location-attention network.	618 CT images of healthy individuals, patients with pneumonia, and Covid-19 patients [6].	86.7% accuracy.
3.	CNN	496 Covid-19 positive and 1385 Covid negative individuals underwent CT scans [7].	97% AUC, 95% specificity and 90% sensitivity.
4.	ResNet-50 and 3D UNet++	723 Covid-19 verified patients with 1136 CT scans from 5 hospitals [8].	97% sensitivity and 92% specificity.
5.	Pre-trained ResNet-50	50 chest X-rays of the healthy individuals and 50 of the Covid-19 patients. [9].	98% accuracy.
6.	Covid-Net	From 13,645 Covid patients, 16,756 chest X-ray scans were obtained [10].	92.4% accuracy and 91% sensitivity.
7.	ResNet-50	A significant number of CT scans were discovered from 157 Covid-19 patients in China and the US [11].	97% AUC, 98% sensitivity and 92% specificity.
8.	DenseNet201, AlexNet, SqueezeNet and ResNet-18	3487 CT scan images from normal, pneumonia and Covid-19 patients [12].	99% accuracy, 99% sensitivity and 99.5% specificity.
9.	Pre-trained AlexNet models and CNN	170 Covid-19 X-ray scans and 361 Covid-19 CT scan images [13].	CT scan accuracy is 94%, and X-ray scan accuracy is 98%. 100% sensitivity on X-ray scans and 90% sensitivity on CT scans.
10.	Pre-trained VGG-19	X-ray images of 1428 healthy individuals, Covid-19 patients, and pneumonia patients [14].	93.4% accuracy, 92% sensitivity and 98% specificity.
11.	SVM and ResNet-50	25 Covid-19 positive and 25 healthy individuals underwent CT X-ray scans [15].	93.28% accuracy, 93% specificity and 97% sensitivity.
12.	COVIDX-Net	CT X-ray scans of 25 Covid-19 patients and 25 healthy individuals [16].	90% accurate.
13.	M-Inception	258 healthy individuals and 195 patients with Covid-19 positivity had chest CT scans [17].	89.5% accurate, 87% sensitivity and 88% specificity.
14.	A 3D Deep Network and U-Net	229 patients without COVID-19 and 313 patients with COVID-19 had chest CT scans [18].	90% accuracy, 95% sensitivity and 95% specificity.
15.	Pre-trained ResNet-50	320 chest CT X-ray scans of viral and bacterial pneumonia patients and 135 of Covid-19 patients [19].	89.2% accuracy and 95% AUC.
16.	Deep CN	CT scan of 96 Covid-19 patients from 3 clinics of China [20].	73% accurate, 95% sensitivity and 95% specificity.
17.	MobileNet-v2	3905 X-ray scans of different diseases including Covid-19 [21].	99.1% accuracy, 97.3% sensitivity and 99.4% specificity.
18.	RF	CT images of 1658 patients with Covid-19 and 1027 patients with CAP from 3 hospitals [22].	87.9% accuracy, 90.7% sensitivity and 83.3% specificity.

19.	ResNet-18 pre-trained models, GAN with AlexNet and Google Net	Patients with Covid-19 bacterial pneumonia and healthy individuals underwent 307 CT X-ray scans [23].	80.56% accurate.
20.	Different convolutional support vector machines (CSVMs)	437 CT X-ray scans of healthy individuals, illnesses, and Covid-19 [24].	98.14% accuracy.

4. COVID-19 DETECTION AND DIAGNOSIS WITH COUGH AND RESPIRATION SOUND

Coughing is an indication of more than 30 diseases including Covid-19. Doctors use sound signals made by a human body such as breathing, digestion, moaning, vibrating and heartbeat sounds. They are the indicators to diagnose respiratory sounds. To investigate the sounds in Covid-19 suffers, Computer Audition (CA) and AI were used and it was

explored by Schullar et al [25]. They examined the CA in a variety of illnesses, including the flu, a dry or wet cough, sneezing, fatigue, and discomfort. To distinguish between Covid-19, asthmatic patients, and healthy people, speech sounds are used. Digital technologies will be used to capture the respiratory sounds and differentiate between the Covid-19 positive and a healthy person.

Table. 2. DL and ML Approaches for Detection and Diagnosis of COVID-19 Through Cough and Respiratory Sound Analysis

Sr. No	ML or DL Approach	Data & Experimentation	Result or Matrices
1.	MFCC, STFT with CN and MFB	1.8 million audio databases, free sound videos on YouTube with google audio datasets [26].	AUC is 94.6%
2.	INTERSPEECH 2013	A speech from 48 healthy and 47 asthmatic people [27].	48% accurate.
3.	Random separation, PCA on audio spectrograms, and FFT coefficients	People suffering Cough from different cough conditions, such as asthma, allergies, cold weather etc [28].	50% false positive rate and 92% true positive rates.
4.	MFCCs and ZCR with OV SVM separation.	Sleep measure using Watch PAT and 90 male speeches [29].	OSA detection is 54% and 50% detection of breath.
5.	Cepstrogram and support machine	Speeches recorded of 21-years old group of people [30].	89% of F1-measures.
6.	Pectrogram with RNN and CNN	Speech recordings using microphone of 20 healthy people, and two respiratory belts for breathing signals [31].	91% respiratory sensitivity
7.	Using OpenSmile with CNN and SVM separators, Functional characteristics and LLD are found.	Recordings of 312 emergency calls [32].	87.5% accurate with CNN and 87.9% accuracy with SVM.
8.	BI-ATGRU	Covid-19 detection using two classes and breathing patterns [33].	94.2% accurate.
9.	DTL-MC	Cough and waves from sounds of voice [34].	88.76% accurate.
10.	VGGish, SVM and PCA	Covid-19 patient’s cough, asthma patients cough and a healthy person’s cough [35].	82% accuracy
11.	LSTM	Cough sound of Covid-19 patient and Non-covid-19 patient [36].	97% accuracy
12.	MFCC	Difference between the Covid-19 patients cough sound and a Non-Covid-s19 patients cough sound, and a difference between the two Covid-19 patients cough sounds [37].	79% accurate voice, 65% cough and 58% breathe rate is accurate.
13.	BI-at-GRU mechanism	Detection of Covid-19 with the combination of thermal videos and breathe [38].	83.69% accurate.
14.	RF, LR, AB, DT, NL-SVM	ROC-AUC are the classifiers [39].	82.5% accuracy.

15.	Feature extraction, MFCC and spectrum	Differentiating between the negative and positive cough [40].	77% accurate.
16.	ResNet-50, MFCC	identifying the positive and negative cough noises in Covid-19 subjects [41].	97.1% accurate.
17.	SVM	Detecting sleep, fatigue and anxiety [42].	57% accuracy
18.	SVM	Differentiating between the positive Covid-19 speakers and negative Covid-19 speakers [43].	92.7% accuracy

5. COVID-19 DETECTION AND DIAGNOSIS WITH TEXTUAL DATA

Data is collected and updated by the WHO and DXY (a medical community) every 15 minutes. Health departments and other sources are used to gather reliable data. The purpose was to provide user-friendly tools and to examine the range of Covid-19 to health authorities, public and researchers. The data sets contain the daily infections, recoveries, deaths, collected recoveries and infections etc. Information regarding the age and sex of the cases, as well as information about the symptoms, date of hospital admission, and date of disease confirmation, are included in some data sets etc. Research was made to understand the public response on Covid-19 through social media, and many people participated and reported their feelings, how much disgust, fear, anger, relaxation, desire they felt. Worry and anxiety were the dominant emotions.

Mobility dataset of more than 150 countries is collected with the help of Google Location services. The privacy of users is ensured, and the personal information is not identifiable. It was done just to ensure the changes in workplaces, supermarkets, parks, residential visits.

6. COVID-19 DETECTION AND DIAGNOSIS WITH NON-INVASIVE METHODS

Smart phone sensors can help in detecting the Covid-19 in the invisible detection method. Finger recognition sensor can detect the body temperature and the sensors can detect the patient’s voice. As it takes so long to compare different CT pictures, so all the data collected from the sensors will be transferred to AI cloud and will diagnose it easily. The purpose of this work is to get accurate, high speed CT scan images and diagnose Covid-19. The sensitivity obtained by this method is 100%. During the comparison of images which were testing and trained images, 95% accuracy and 81.89% specificity was obtained [44].

7. AVAILABLE DATASETS FOR COVID-19 DETECTION AND DIAGNOSIS

The datasets that are available for COVID-19 detection and diagnosis are shown in Table 3.

Table 3. COVID-19 datasets

Sr. No.	Dataset Name
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1)	CT-EGFR dataset [45].
2)	Splitting Dataset [46].
3)	Domestic datasets [47].
4)	RSNA CXR dataset, pediatric CXR dataset [48].
5)	Lung CT scans using COVID-19 [49].
6)	Covid-19 Image Dataset [50].
7)	SARS-COV-2 Ct-Scan Dataset [51].
8)	Large COVID-19 CT scan slice dataset [52].
9)	COVID-CTset: A sizable dataset of COVID-19 CT scans [53]
10)	COVIDx CT [54]
11)	QaTa-COV19 Dataset [55].
12)	Chest Xray for covid-19 detection [56].
13)	COUGHVID [57].
14)	Covid-19 X-ray - Two proposed Databases [58].
15)	Consortium for Lung Image Data (LIDC) [59].
16)	Geneva's China University Hospitals (HUG) [60].
17)	Society for Italian Medical Radiology and Intervention [61].
18)	Generation of Candidate Points and Lung Segmentation [62].
19)	Dataset for COVID-19 CT segmentation [63].
20)	X-rays from COVID-19 [64].
21)	COVID-19+ BIMCV [65].
22)	
23)	chestxray data from COVID [66].
24)	Pneumonia-Related Chest X-Ray Images [67].

25)	Database for COVID-19 radiography [68].
26)	British Thoracic Society (BSTI) [69].
27)	Initiative for the COVID-19 Chest X-ray Dataset [71].
28)	Initiative for the ActualMed COVID-19 Chest X-ray Dataset [72].
29)	Collection of COVID-19 Image Data [73].
30)	OCT [74] stands for optical coherence tomography.

31)	X-ray data from COVID-19 (COVID-CAPS) [75].
32)	RSNA Pneumonia Detection Dataset from Kaggle [76].
33)	Chest X-ray Dataset from NIH [77].
34)	Classification of Pneumonia [78].
35)	COVID-19 [79].
36)	The COVIDGR-1.0 [80].

8. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Table. 4. Challenges and Future Research Directions

Sr.No.	Challenges	Future Research Directions
1.	Regulations to prevent any barriers in Covid-19 anticipation.	Detection of Non-contact disease.
2.	Unavailability of trained data.	AI-based DL and ML systems used in the biological researches to identify viral factors, proteins etc.
3.	Online rumors and loud data	Consultations and remote video diagnosis.
4.	Data protection and privacy.	Vaccination and drug development.
5.	lacking in the area where computer science and medicine meet.	Contact tracking of patients.
6.	Covid-19 early diagnosis with imaging technology.	Evaluation and impact assessment.
7.	Ambiguous information in text descriptions.	Screening and identification of fake information.
8.	To collect physical features and deal with unreliable data.	Using AI-based ML ad DL techniques for future work.

CONCLUSION:

As the COVID-19 becomes global pandemic and drastically impact on world population. All available technologies are considered for combating with COVID-19. AI is one of the leading technologies with proven results in healthcare. Initially we discussed the COVID-19 background by highlight its clinical features, symptoms transmission mechanism and preventive measure. Then we proposed a novel hierarchy to elaborate the contributions of DL and ML for combating with COVID-19. We discussed medical images such as CT-Scans and X-rays. Sound analysis via cough, breath and voice, textual data analysis and non-invasive technologies with DL and ML for detection and diagnosis of COVID-19. We tabularized the recent research and contributions which are made by ML and DL.

Furthermore, we presented the available datasets for the detection and diagnosis of COVID-19. Finally, we have list down the current research challenges which needs to be address along with future research directions.

CREDIT AUTHOR STATEMENT

Sana Hameed: Data Curation, Writing- Original Draft Preparation, Visualization, **Farrukh Arslan:** Conceptualization, Methodology, Validation, **Munaza Iqbal:** Writing, Investigation, Visualization, **Mubashir Ali:** Conceptualization, Supervision, Visualization, Reviewing, Validation, **Muhammad Umar Haroon:** Writing- Reviewing, Editing, **Naveed Imran:** Data curation, Reviewing, Editing

COMPLIANCE WITH ETHICAL STANDARDS

It is said that there are no conflicts of interest among any of the authors. Furthermore, each participant who took part in the study gave their free, informed consent.

REFERENCES:

- [1] M. A. Soghaier, K. M.I. Saeed, and K. K. Zaman, "Public Health Emergency of International Concern (PHEIC) has Declared Twice in 2014; Polio and Ebola at the Top," *AIMS Public Heal.*, vol. 2, no. 2, pp. 218–222, 2015.
- [2] "Coronavirus disease (COVID-19)." [Online]. Available: https://www.who.int/emergencies/diseases/novel-coronavirus-2019?gclid=CjwKCAjwqcKFBhAhEiwAfEr7zbuo7QNqJyiHHFa37tKsznVsdYAR6MI3YX-QSp54g35beJo2EnWwuxoChIcQAvD_BwE. [Accessed: 29-May-2021].
- [3] "Health Programs." [Online]. Available: https://www.cartercenter.org/health/index.html?s_src=health&s_subsrc=search&gclid=CjwKCAjwqcKFBhAhEiwAfEr7zaB6bZfmWGKKiLXbeepe-63HdxZ6a8jkMIN3b2k031Tcc1jDO-0xjhoC4sgQAvD_BwE. [Accessed: 29-May-2021].
- [4] "Mythbusters." [Online]. Available: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/advice-for-public/mythbusters?gclid=CjwKCAjwqcKFBhAhEiwAfEr7zZkZ0MMtTQ1T8e14fXV_kaDWu0Gmtli-4aDgaOYdnlNp8FYK6m1oWxoCgDMQAvD_BwE#virus. [Accessed: 29-May-2021].
- [5] L. Li *et al.*, "Using Artificial Intelligence to Detect COVID-19 and Community-acquired Pneumonia Based on Pulmonary CT: Evaluation of the Diagnostic Accuracy," *Radiology*, vol. 296, no. 2, pp. E65–E71, Aug. 2020.
- [6] X. Xu *et al.*, "Deep Learning System to Screen Coronavirus Disease 2019 Pneumonia," *Engineering*, vol. 6, no. 10, pp. 1122–1129, Feb. 2020.
- [7] C. Jin *et al.*, "Development and evaluation of an artificial intelligence system for COVID-19 diagnosis," *Nat. Commun.*, vol. 11, no. 1, pp. 1–14, Dec. 2020.
- [8] S. Jin *et al.*, "AI-assisted CT imaging analysis for COVID-19 screening: Building and deploying a medical AI system in four weeks," *medRxiv*, p. 2020.03.19.20039354, Mar. 2020.
- [9] A. Narin, C. Kaya, and Z. Pamuk, "Automatic Detection of Coronavirus Disease (COVID-19) Using X-ray Images and Deep Convolutional Neural Networks," *Pattern Anal. Appl.*, Mar. 2020.
- [10] L. Wang, Z. Q. Lin, and A. Wong, "COVID-Net: a tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images," *Sci. Rep.*, vol. 10, no. 1, pp. 1–12, Dec. 2020.
- [11] 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," Mar. 2020.
- [12] M. E. H. Chowdhury *et al.*, "Can AI help in screening Viral and COVID-19 pneumonia?," *IEEE Access*, vol. 8, pp. 132665–132676, Mar. 2020.
- [13] H. S. Maghdid, A. T. Asaad, K. Z. Ghafoor, A. S. Sadiq, and M. Khurram Khan, "Diagnosing COVID-19 Pneumonia from X-Ray and CT Images using Deep Learning and Transfer Learning Algorithms."
- [14] I. D. Apostolopoulos and T. A. Mpesiana, "Covid-19: automatic detection from X-ray images utilizing transfer learning with convolutional neural networks," *Phys. Eng. Sci. Med.*, vol. 43, no. 2, pp. 635–640, Jun. 2020.
- [15] P. Kumar Sethy, S. Kumari Behera, P. Kumar Ratha, and P. Biswas, "Detection of coronavirus Disease (COVID-19) based on Deep Features and Support Vector Machine," Preprints, Apr. 2020.
- [16] E. E.-D. Hemdan, M. A. Shouman, and M. E. Karar, "COVIDX-Net: A Framework of Deep Learning Classifiers to Diagnose COVID-19 in X-Ray Images," Mar. 2020.
- [17] S. Wang *et al.*, "A deep learning algorithm using CT images to screen for Corona virus disease (COVID-19)," *Eur. Radiol.*, pp. 1–9, Feb. 2021.
- [18] C. Zheng *et al.*, "Deep Learning-based Detection for COVID-19 from Chest CT using Weak Label."
- [19] L. O. Hall, R. Paul, D. B. Goldgof, and G. M. Goldgof, "Finding Covid-19 from Chest X-rays using Deep Learning on a Small Dataset," Apr. 2020.
- [20] Q. Ni *et al.*, "A deep learning approach to characterize 2019 coronavirus disease (COVID-19) pneumonia in chest CT images," *Eur. Radiol.*, vol. 30, no. 12, pp. 6517–6527, Dec. 2020.
- [21] I. D. Apostolopoulos, · Sokratis, I. Aznaouridis, · Mpesiana, and A. Tzani, "Extracting Possibly Representative COVID-19 Biomarkers from X-ray Images with Deep Learning Approach and Image Data Related to Pulmonary Diseases," *J. Med. Biol. Eng.*, vol. 40, pp. 462–469, 1234.
- [22] F. Shi *et al.*, "Large-scale screening to distinguish between COVID-19 and community-acquired pneumonia using infection size-aware classification," *Phys. Med. Biol.*, vol. 66, no. 6, p. 065031, Mar. 2021.
- [23] M. Loey, F. Smarandache, and N. E. M. Khalifa, "Within the lack of chest COVID-19 X-ray dataset: A novel detection model based on GAN and deep transfer learning," *Symmetry (Basel)*, vol. 12, no. 4, p. 651, Apr. 2020.
- [24] M. Maia, J. S. Pimentel, I. S. Pereira, J. Gondim, M. E. Barreto, and A. Ara, "Convolutional support vector models: Prediction of coronavirus disease using chest x-rays," *Inf.*, vol. 11, no. 12, pp. 1–19, Dec. 2020.
- [25] B. W. Schuller, D. M. Schuller, K. Qian, J. Liu, H. Zheng, and X. Li, "COVID-19 and Computer Audition: An Overview on What Speech & Sound Analysis Could Contribute in the SARS-CoV-2 Corona Crisis," *Front. Digit. Heal.*, vol. 3, Mar. 2020.
- [26] I. D. S. Miranda, A. H. Diacon, and T. R. Niesler, "A Comparative Study of Features for Acoustic Cough Detection Using Deep Architectures*," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2019, pp. 2601–2605.
- [27] S. Yadav, M. Keerthana, D. Gope, K. Uma Maheswari, and P. Kumar Ghosh, "Analysis of Acoustic Features for Speech Sound Based Classification of Asthmatic and Healthy Subjects," in *ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings*, 2020, vol. 2020-May, pp. 6789–6793.
- [28] E. C. Larson, T. Lee, S. Liu, M. Rosenfeld, and S. N. Patel, "Accurate and privacy preserving cough sensing using a low-cost microphone," in *UbiComp'11 - Proceedings of the 2011 ACM Conference on Ubiquitous Computing*, 2011, pp. 375–384.

- [29] R. M. Simply, E. Dafna, and Y. Zigel, "Obstructive Sleep Apnea (OSA) classification using analysis of breathing sounds during speech," in *European Signal Processing Conference*, 2018, vol. 2018-September, pp. 1132–1136.
- [30] K. Mohamed Ismail Yasar Arafath and A. Routray, "Automatic measurement of speech breathing rate," in *European Signal Processing Conference*, 2019, vol. 2019-September.
- [31] V. Srikanth Nallanthighal, A. Härmä, and H. Strik, "Deep sensing of breathing signal during conversational speech," 2019.
- [32] P. Partila, J. Tovarek, J. Rozhon, and J. Jalowiczor, "Human stress detection from the speech in danger situation," 2019, vol. 10993, p. 31.
- [33] Y. Wang, M. Hu, Q. Li, X.-P. Zhang, G. Zhai, and N. Yao, "Abnormal respiratory patterns classifier may contribute to large-scale screening of people infected with COVID-19 in an accurate and unobtrusive manner," Feb. 2020.
- [34] A. Imran *et al.*, "AI4COVID-19: AI enabled preliminary diagnosis for COVID-19 from cough samples via an app," *Informatics Med. Unlocked*, vol. 20, p. 100378, Jan. 2020.
- [35] C. Brown *et al.*, "Exploring Automatic Diagnosis of COVID-19 from Crowd-sourced Respiratory Sound Data," in *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 2020, vol. 11.
- [36] A. Hassan, I. Shahin, and M. B. Alsabek, "COVID-19 Detection System using Recurrent Neural Networks," in *Proceedings of the 2020 IEEE International Conference on Communications, Computing, Cybersecurity, and Informatics, CCCI 2020*, 2020.
- [37] M. Bader, I. Shahin, and A. Hassan, "Studying the Similarity of COVID-19 Sounds based on Correlation Analysis of MFCC," Oct. 2020.
- [38] Z. Jiang *et al.*, "Combining Visible Light and Infrared Imaging for Efficient Detection of Respiratory Infections such as COVID-19 on Portable Device," Apr. 2020.
- [39] M. Al Ismail, S. Deshmukh, and R. Singh, "Detection of Covid-19 Through the Analysis of Vocal Fold Oscillations," 2021, pp. 1035–1039.
- [40] G. Chaudhari *et al.*, "Virufy: Global Applicability of Crowdsourced and Clinical Datasets for AI Detection of COVID-19 from Cough," Nov. 2020.
- [41] J. Laguarda, 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, Sep. 2020.
- [42] J. Han *et al.*, "An Early Study on Intelligent Analysis of Speech under COVID-19: Severity, Sleep Quality, Fatigue, and Anxiety," *Proc. Annu. Conf. Int. Speech Commun. Assoc. INTERSPEECH*, vol. 2020-October, pp. 4946–4950, Apr. 2020.
- [43] K. V. S. Ritwik, S. B. Kalluri, and D. Vijayasenan, "COVID-19 Patient Detection from Telephone Quality Speech Data," Nov. 2020.
- [44] N. R. Raajan, V. S. R. Lakshmi, and N. Prabakaran, "Non-Invasive Technique-Based Novel Corona(COVID-19) Virus Detection Using CNN," *Natl. Acad. Sci. Lett.*, p. 1, 2020.
- [45] S. Wang *et al.*, "A fully automatic deep learning system for COVID-19 diagnostic and prognostic analysis," *Eur. Respir. J.*, vol. 56, no. 2, Aug. 2020.
- [46] N. F. Omran, S. F. Abd-El Ghany, H. Saleh, A. A. Ali, A. Gumaci, and M. Al-Rakhami, "Applying Deep Learning Methods on Time-Series Data for Forecasting COVID-19 in Egypt, Kuwait, and Saudi Arabia," *Complexity*, vol. 2021, 2021.
- [47] M. Ghaderzadeh and F. Asadi, "Deep Learning in the Detection and Diagnosis of COVID-19 Using Radiology Modalities: A Systematic Review," *Journal of Healthcare Engineering*, vol. 2021. Hindawi Limited, 2021.
- [48] J. Nayak, B. Naik, P. Dinesh, K. Vakula, P. B. Dash, and D. Pelusi, "Significance of deep learning for Covid-19: state-of-the-art review," *Research on Biomedical Engineering*. Springer Science and Business Media Deutschland GmbH, pp. 1–24, 20-Mar-2021.
- [49] "COVID-19 Lung CT Scans | Kaggle." [Online]. Available: <https://www.kaggle.com/luisblanche/covidct>. [Accessed: 29-May-2021].
- [50] "Covid-19 Image Dataset | Kaggle." [Online]. Available: <https://www.kaggle.com/pranavraikokte/covid19-image-dataset>. [Accessed: 29-May-2021].
- [51] P. (Universidade de L. Soares, Eduardo (Universidade de Lancaster); Angelov, "SARS-COV-2 Ct-Scan Dataset," *June*, 2020. [Online]. Available: <https://www.kaggle.com/plameneduardo/sarscov2-ctscan-dataset>. [Accessed: 29-May-2021].
- [52] X. Yang, X. He, J. Zhao, Y. Zhang, S. Zhang, and P. Xie, "COVID-CT-Dataset: A CT Scan Dataset about COVID-19," Mar. 2020.
- [53] M. Rahimzadeh, A. Attar, and S. M. Sakhaei, "A Fully Automated Deep Learning-based Network For Detecting COVID-19 from a New And Large Lung CT Scan Dataset," 2020.
- [54] H. Gunraj, A. Sabri, D. Koff, and A. Wong, "COVID-Net CT-2: Enhanced Deep Neural Networks for Detection of COVID-19 from Chest CT Images Through Bigger, More Diverse Learning," Jan. 2021.
- [55] A. Degerli, M. Ahishali, S. Kiranyaz, M. E. H. Chowdhury, and M. Gabbouj, "Reliable COVID-19 Detection Using Chest X-ray Images," Jan. 2021.
- [56] "Chest Xray for covid-19 detection | Kaggle." [Online]. Available: <https://www.kaggle.com/fusicfenta/chest-xray-for-covid19-detection>. [Accessed: 29-May-2021].
- [57] L. Orlandic, T. Teijeiro, and D. Atienza, "The COUGHVID crowdsourcing dataset: A corpus for the study of large-scale cough analysis algorithms," Sep. 2020.
- [58] E. Vantaggiato, E. Paladini, F. Bougourzi, C. Distante, A. Hadid, and A. Taleb-Ahmed, "Covid-19 recognition using ensemble-cnns in two new chest x-ray databases," *Sensors*, vol. 21, no. 5, pp. 1–20, Mar. 2021.
- [59] S. G. Armato *et al.*, "The Lung Image Database Consortium (LIDC) and Image Database Resource Initiative (IDRI): A completed reference database of lung nodules on CT scans," *Med. Phys.*, vol. 38, no. 2, pp. 915–931, Feb. 2011.
- [60] O. Gozes, M. Frid-Adar, N. Sagie, H. Zhang, W. Ji, and H. Greenspan, "Coronavirus Detection and Analysis on Chest CT with Deep Learning."
- [61] "SIRM - Società Italiana di Radiologia Medica e Interventistica." [Online]. Available: <https://sirm.org/>. [Accessed: 29-May-2021].
- [62] "Lung Segmentation and Candidate Points Generation | Kaggle." [Online]. Available: <https://www.kaggle.com/arturscussel/lung-segmentation-and-candidate-points-generation>. [Accessed: 29-May-2021].
- [63] "COVID-19 - Medical segmentation." [Online].

- Available:<http://medicalsegmentation.com/COVID19/>. [Accessed: 29-May-2021].
- [64] F. Song *et al.*, “Emerging 2019 novel coronavirus (2019-NCoV) pneumonia,” *Radiology*, vol. 295, no. 1, pp. 210–217, 2020.
- [65] “BIMCV-COVID19 – BIMCV.” [Online]. Available: <https://bimcv.cipf.es/bimcv-projects/bimcv-covid19/>. [Accessed: 29-May-2021].
- [66] J. P. Cohen, P. Morrison, and L. Dao, “COVID-19 Image Data Collection,” Mar. 2020.
- [67] “Chest X-Ray Images (Pneumonia) | Kaggle.” [Online]. Available: <https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia>. [Accessed: 29-May-2021].
- [68] T. Rahman *et al.*, “Exploring the effect of image enhancement techniques on COVID-19 detection using chest X-ray images,” *Comput. Biol. Med.*, vol. 132, p. 104319, May 2021.
- [69] “COVID-19 British Society of Thoracic Imaging Database | The British Society of Thoracic Imaging.” [Online]. Available: <https://www.bsti.org.uk/training-and-education/covid-19-bsti-imaging-database/>. [Accessed: 29-May-2021].
- [70] “Normal chest imaging examples | Radiology Reference Article | Radiopaedia.org.” [Online]. Available: <https://radiopaedia.org/articles/normal-chest-imaging-examples?lang=gb>. [Accessed: 29-May-2021].
- [71] “GitHub - agchung/figure1-COVID-chestxray-dataset: Figure 1 COVID-19 Chest X-ray Dataset Initiative.” [Online]. Available: <https://github.com/agchung/figure1-COVID-chestxray-dataset>. [Accessed: 29-May-2021].
- [72] “GitHub - agchung/Actualmed-COVID-chestxray-dataset: Actualmed COVID-19 Chest X-ray Dataset Initiative.” [Online]. Available: <https://github.com/agchung/Actualmed-COVID-chestxray-dataset>. [Accessed: 29-May-2021].
- [73] J. P. Cohen, P. Morrison, and L. Dao, “COVID-19 Image Data Collection,” Mar. 2020.
- [74] J. M. Schmitt, “Optical Coherence Tomography (OCT): a review,” *IEEE J. Sel. Top. Quantum Electron.*, vol. 5, no. 4, pp. 1205–1215, Jul. 1999.
- [75] P. Afshar, S. Heidarian, F. Naderkhani, A. Oikonomou, K. N. Plataniotis, and A. Mohammadi, “COVID-CAPS: A capsule network-based framework for identification of COVID-19 cases from X-ray images,” *Pattern Recognition Letters*, vol. 138. Elsevier B.V., pp. 638–643, 01-Oct-2020.
- [76] “RSNA Pneumonia Detection Challenge | Kaggle.” [Online]. Available: <https://www.kaggle.com/c/rsna-pneumonia-detection-challenge>. [Accessed: 29-May-2021].
- [77] “NIH Chest X-rays | Kaggle.” [Online]. Available: <https://www.kaggle.com/nih-chest-xrays/data>. [Accessed: 29-May-2021].
- [78] “Folder - Google Drive.” [Online]. Available: <https://drive.google.com/drive/folders/1J9I-pPtPflRGHJ42or4pKO2QASHzLkkj>. [Accessed: 29-May-2021].
- [79] T. Ozturk, M. Talo, E. A. Yildirim, U. B. Baloglu, O. Yildirim, and U. Rajendra Acharya, “Automated detection of COVID-19 cases using deep neural networks with X-ray images,” *Comput. Biol. Med.*, vol. 121, Jun. 2020.
- [80] “GitHub - ari-dasci/OD-covidgr: Datasets of X-Ray imaging for detection of COVID-19.” [Online]. Available: <https://github.com/ari-dasci/OD-covidgr>. [Accessed: 29-May-2021].