

# COVID-19 Pandemic Review: Future Directions on Detection of Coronavirus Using Imaging Modalities and Computational Intelligence



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## 1 Introduction

Coronavirus, an irresistible illness is brought about by serious intense respiratory condition (SARS-CoV-2) [1] and labeled COVID-19 because of visual appearance (under an electron magnifying lens) to sunlight-based corona (like a crown). The battle in opposition of COVID-19 has propelled scientists all over the world to investigate, comprehend, and devise new indicative and therapy strategies to complete this risk to our age. In this article, we look at how the PC vision network is battling with this peril by proposing new sorts of techniques, repairing viability, and acceleration of the current undertakings [2].

An easiest way to transmit COVID-19 is through the air and physical contact, such as hand contact with an infected person. The virus inserts itself into the lung cells through the respiratory system and replicates there, destroying these cells. COVID-19 comprises RNA and is very difficult to diagnose and treat due to its mutation characteristics. The most well-known indications of COVID-19 incorporate fever, hack, windedness, dazedness, migraine, and muscle throbs. The virus is so perilous and can provoke the death of people with weakened immune systems. Infectious disease specialists and physicians around the world are working to discover a treatment for the disease. COVID-19 is currently the leading cause of death for thousands of countries worldwide, including the USA, Spain, Italy, China, the United Kingdom, Iran, and others [3].

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## 2 Diagnostic Approaches for Corona Detection

The 2019 novel COVID named COVID-19 by World Health Organization is getting bunches of consideration as of late on the grounds that it is another sort of COVID that is exceptionally infectious and has not been seen among human previously.

The virus started in China and rapidly spread around countries [1, 2]. China adopted many technologies to suppress the spread of the virus, from applications that localize people who have the virus to unmanned vehicles that deliver medical supplies, sanitizer robots, food making robots, and delivery robots. Scientists are trying to tackle the pandemic by collecting databases and proposing algorithms that learn from them.

As per WHO, patients suffering from COVID-19 were categorized into symptomatic, pre-symptomatic, and asymptomatic. Once the person is suspected, then he/she needs to undergo the testing process for the confirmation whether the person was affected by the coronavirus or not. There are several diagnostic approaches that are available to test a person for the confirmation whether the person was affected or not as shown in Fig. 1.

These procedures utilize the fanatical changes in the tainted individual's organ by imaging like CT, or viral nucleic destructive like RT-PCR utilizing at least a quality, or resulting generation sequencing entire genome, immunological atoms created by the tainted individual, or by the infection in the patient's body-antigen-immunizer response-based tests like ELISA, and using of these end approaches is shown in Fig. 2.

Among the mentioned detection procedures, RT-PCR test is considered as reliable test for detection of coronavirus but still insufficient number of RT-PCR kits and also the delay in generating the results made the researchers and also government to look for other types of detection methods. Out of which, imaging approaches was considered as alternate answer to recognize if the individual was



**Fig. 1** Approaches for diagnosis of COVID-19

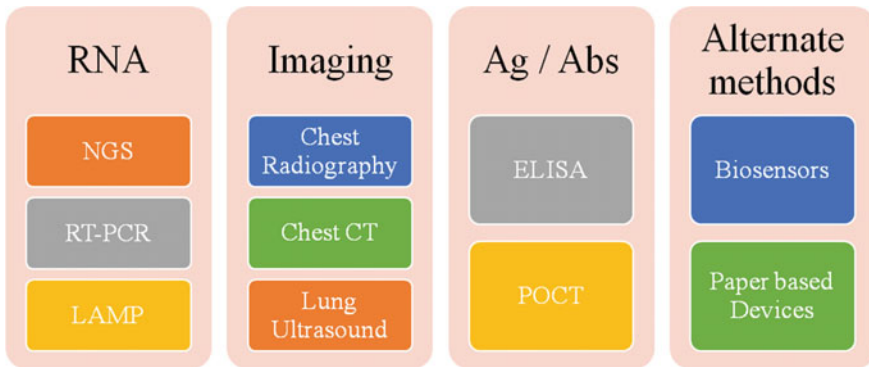


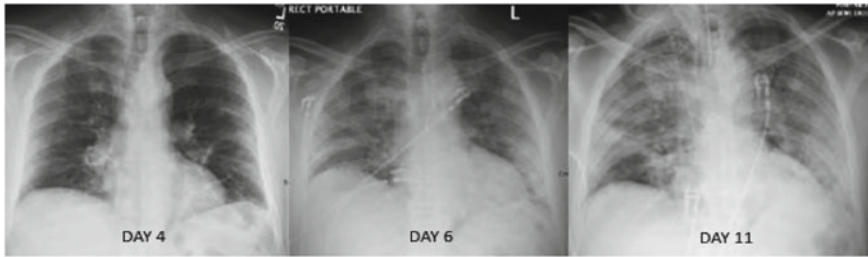
Fig. 2 COVID-19 detection methods using various approaches

contaminated by infection. As of late, with the fast advancement of man-made reasoning [4], AI and profound learning-based frameworks can supplant people by giving a precise determination for the detection of various diseases. The ideal determination can spare radiologists’ time and can be practical than standard tests for COVID-19. Deep learning innovation has been broadly utilized in clinical image processing because of its ground-breaking highlight portrayal. A few strategies dependent on deep learning have distributed to identify COVID-19 pneumonia from CT images and X-ray imaging.

### 3 Different Imaging Modalities

#### 3.1 Chest Radiography

Chest radiography [5] is the most promptly accessible methodology for the identification of lung irregularities in numerous focuses. Contrasted with chest figured tomography (CT), chest radiographs are less expensive and are related with a lower radiation portion. Nonetheless, the absence of particularity, just as affectability for discovery of COVID-19, especially in patients with no or just minor manifestations, must be considered. The standard utilization of chest radiographs, be that as it may, is not viewed as shown in stable, incubated patients with COVID-19. The chest X-ray (CXR) commonly shows equal attacks yet might be typical in beginning illness. Sample chest radiograph images at different days of infection were shown below in Fig. 3.



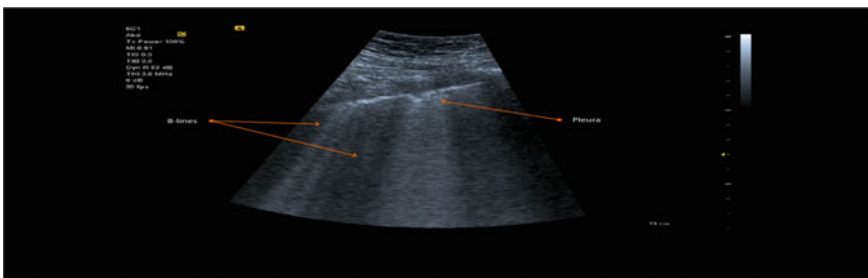
**Fig. 3** Sample chest X-ray images of COVID patient at different days of infection [Image Courtesy: Google Images]

### 3.2 Chest Ultrasound

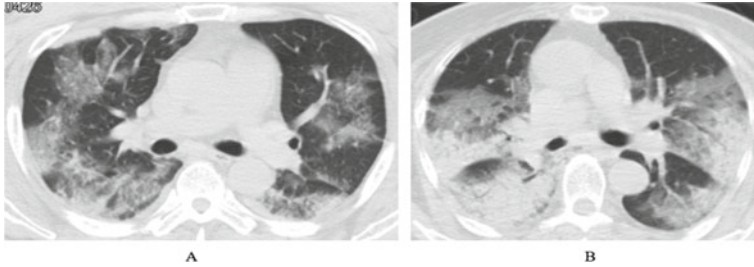
Chest ultrasound [5] is basically acted in certain focuses to emergency patients, to screen treatment impacts, and for diagnosing intricacies of COVID-19 pneumonias, for example, pleural effusions. Likewise, with all other imaging methodology in COVID-19 patients, ultrasound assessments ought to be kept to a base to maintain a strategic distance from the danger of disease of the clinical faculty. Chest ultrasound images are widely used to diagnosis the lesions and various chest diseases. With reference to COVID-19, the impressions of chest ultrasound is similar to chest CT. Sample chest ultrasound image is shown below in Fig. 4.

### 3.3 Chest CT

Contrasted with X-rays, CT screening is extensively preferred because of its legitimacy and three-dimensional perspective on the lung. In ongoing examinations [6], the normal indications of contamination can be seen from CT cuts, e.g., ground-glass haziness (GGO) in the beginning phase and pneumonic solidification in the final stage. Sample chest CT images with disease progression were shown in



**Fig. 4** Sample chest ultrasound image [Image Courtesy: Google Images]



**Fig. 5** Sample chest CT images of critically ill COVID-19 patient indicating the progression of disease [Image Courtesy: Google Images]

Fig. 5. The subjective assessment of contamination and longitudinal changes in CT cuts could along these lines give valuable and significant data in battling in opposition of COVID-19. Nonetheless, the manual framework of lung contaminations is monotonous and tedious process.

The computerized tomography is delicate and absolute [5]. CT imaging overall shows attack, area of increased attenuation in the lung on computed tomography, and sub fragmental mix. Here, comparably astounding in patients with no symptoms/patients with no medical proof of lower respiratory bundle thought or any infection in the lungs are considered as non-covid patients. As a general rule, weird CT investigates have been employed to separate corona virus in conjecture with negative sub-atomic finding cases; a tremendous part of these patients had positive sub-nuclear tests on keep testing.

Developing algorithms for CT image analysis is the current hot research aims to contribute to the automatic detection of the coronavirus and also for its progression of disease. It is also suggested that algorithms that were applied to identify lung cancer and lung collapse using X-ray images will also be useful for identifying abnormal cases from COVID-19 patients.

#### 4 Progression Stages of COVID-19 on Chest CT

A few examinations ordered COVID-19 CT discoveries into a few phases dependent on time since the beginning of symptoms [7–11]. Totally progression of COVID-19 was portrayed into four principal stages: initial, progression, advanced and final stage [9].

- Initial phase (0–2 days): The majority infected individual have negative chest CT (56%). The rest of the patients have dominantly 44% of ground-glass opacities and 17% of consolidation. Imaging disclosures when present were every now and again one sided [9]. Similar disclosures were portrayed in another examination, which displayed that in starting disorder 16.1% of cases

present with a solitary physical issue found in around 70% of cases in the right lower lobe of the lungs.

- Progression stage (3–5 days): As the infirmity propels, more ground-glass opacities and consolidations are identified in both the lung lobe. Around 9% of tested patients have negative chest CT [9].
- Advanced stage (6–12 days): A large portion of the patients in this stage have positive chest CT disclosures. More than 60% of patients have consolidation and GGO around 90%. The imaging revelations are corresponding in 88% and around 70% of cases were identified with peripheral predominant [9].
- Final stage (>14 days): Patients in this stage were observed nearer GGO and consolidation values similar to the advanced stage. The imaging revelations are individual in 88% and peripheral predominant in 72% of cases [12].

## 5 Related Work

This segment examines the sorts of works that are generally identified with division in chest CT, machine learning, and deep learning processes for the classification of corona virus infected patients.

### 5.1 Segmentation in Chest CT

CT imaging is a famous procedure for the detection of lung illness [13]. By and by, fragmenting various human parts and injuries from chest CT cuts can give critical data to specialists to analyze and measure lung illnesses. As of late, numerous works have been given and acquired promising exhibitions. These figurings consistently use a classifier with removed features for knob division in chest CT. For instance, Zhou et al. [14] did a novel deep learning calculation to solve the large-scene-small-object issue, which disintegrates the 3D division issue into three 2D ones, and accordingly diminishes the model unpredictability by a significant degree and, simultaneously, essentially improves the division accuracy. Shen et al. [15] introduced a robotized lung fragmenting framework reliant on bidirectional chain code to improve the presentation. Regardless, the near visual appearances of knobs and foundation make it hard for eliminating the knob regions. To defeat this hazardous circumstance, a couple of profound learning calculations have been proposed to pick up capability with pivotal visual depictions. Jin et al. [16] utilized GAN-consolidated data to raise the planning of a discriminative model for obsessive lung division. Jiang et al. [17] planned two deep networks to portion lung tumors from CT cuts by including different remaining floods of shifting goals. To boost the learning capacity and accomplish a better performance Fan et al. [18] utilizes lung infection segmentation deep network (Inf-Net) to subsequently

perceive corrupted territories from chest CT cuts and equivalent deficient decoder is employed to add up to the huge level features and produce a worldwide guide.

Coronavirus examination can be addressed as a picture fragmentation issue to eliminate the fundamental highlights of the illness. Guan et al. [19] initiated that CT check assessment inserted individual aspiratory parenchyma ground glass and consolidative pneumonic opacities, from time to time with a balanced morphology and a fringe lung conveyance. This fragmentation issue can be understood by building up an algorithm that can extricate the littler comparable areas that can show contamination with the COVID-19 infection.

Table 1 summarizes the performance of segmentation results of various architectures using CT scan images.

## 5.2 *Classification of COVID 19*

As of late, deep learning systems have been proposed to distinguish patients contaminated with COVID-19 by means of radiological imaging. For instance, a practical and effective deep learning-based chest radiograph classification (DL-CRC) structure to recognize the COVID-19 cases with good precision from other odd and normal cases. An unprecedented dataset is set up from four straightforwardly open sources including the posteroanterior (PA) chest perspective on X-ray information for COVID-19, pneumonia, and standard cases [20]. Sethi et al. [21] proposed four unmistakable profound CNN models were inspected on pictures of chest X-rays for finding of COVID-19. These models have been pre-arranged on the ImageNet information base as such reducing the necessity for huge preparing sets as they have pre-prepared loads.

Convolutional neural networks have a high computational unpredictability just as a huge memory necessity to actualize with the goal that Gozes et al. [22] introduced a framework that uses 2D and 3D deep learning models, changed and adjusted current deep network representative and consolidated them with medical comprehension. A feebly regulated deep learning system for recognizing and ordering COVID-19 disease from CT images is introduced by Hu et al. [23] that can limit the necessities of manual labeling of CT images yet at the same time have the option to get exact contamination identification and recognize COVID-19 from non-COVID-19 cases.

Oh et al. [24] presents a patch-based convolution neural organization technique with a generally modest number of teachable boundaries for COVID-19 detection. This technique is roused by our measurable examination of the potential imaging biomarkers of the CXR radiographs. While Rajaraman et al. [25] shows the usage of iteratively pruned deep learning model social affairs for identifying aspiratory indication of COVID-19 with chest X-rays. A custom convolutional neural organization and an assurance of ImageNet pre-prepared models are arranged and surveyed at quiet level on freely accessible CXR assortments to learn methodology explicit element portrayals.

**Table 1** Summary of the performance of segmentation results of various architectures using CT scan images

Reference	Dataset used	Methods proposed	2/3D	Automated (Y/N)	Performance
Zhou et al. [14]	Harbin Riyadh	Machine-agnostic segmentation	2.5D	Y	Proposed method exhibits a sensitivity of 77.6%, dice similarity coefficient (DSC) of 78.3%, and the worst case performance of dice is 55.7%. Proposed method was compared with other architectures such as 2D U-NET, H-DU Net, MPU net, 3D U-Net and 3D V-net
Shen et al. [15]	LIDC	Bidirectional coding method combined with SVM classifier	2D	Y	Proposed method presents an average of overlap as 97.3%, average of over segmentation as 0.3%, average of under segmentation as 2.4%, and re-inclusion rate as 92.6%
Jiang et al. [17]	TCIA MSKCC LIDC	Incremental MRRN Dense MRRN (multiple resolution residually connected network)	2D	–	Incremental MRRN exhibits superiority over dense MRRN in terms of DSC, HD95, and sensitivity except for precision. <b>DSC:</b> TCIA: 70%, MSKCC: 75%, LIDC: 68%. <b>HD95:</b> TCIA: 7.94 mm, MSKCC: 5.85 mm, LIDC: 2.60 mm. <b>Sensitivity:</b> TCIA: 80%, MSKCC: 82%, LIDC: 85%. <b>Precision:</b> TCIA: 73%, MSKCC: 72%, LIDC: 70%. Proposed methods were compared with other architectures such as U-Net, Segnet, RF + fCRF and FRRN

(continued)



**Table 1** (continued)

Reference	Dataset used	Methods proposed	2/3D	Automated (Y/N)	Performance
Fan et al. [18]	COVID-19 segmentation dataset	Inf-Net Semi-Inf-Net	2D	Y	Semi-Inf-Net exhibits the precedence over Inf-Net in terms of dice (73.9%), sensitivity (72.5%), specificity (96%), structure measure (80%), enhanced alignment measure (89.4%), and mean absolute error (6.4%). Proposed methods are compared with U-Net, attention—U-Net, Gated U-Net, Dense U-Net, U-Net++

The primary advantage of these AI-based platforms is to quicken the cycle of finding and treatment of the COVID-19 disease. Barabas et al. [26] presents device prototype which can help in two different ways—through automatic assessment of bodily temperature at different checkpoints and by authorizing appropriate cleanliness norms identified with face covers.

Wang et al. [27] model spotlights on transfer learning, model integration, and arrange chest X-ray pictures as demonstrated by three marks: ordinary, COVID-19, and viral pneumonia. According to the exactness and hardship regard, pick the models ResNet-101 and ResNet-152 with extraordinary effect for mix and intensely improve their weight extent during the arrangement cycle. Subsequent to preparing, the model can achieve 96.1% of the sorts of chest X-ray pictures exactness on the test set. This development has higher affectability than radiologists in the screening and finding of lung nodules. El-kenawy et al. [28] proposes a system for COVID-19 characterization with three fell stages.

In the main stage, the progressive element portrayal is consequently removed from the preparation CT pictures by the CNN model of AlexNet. A short time later, the proposed highlight choice calculation, utilizing SFS and Guided WOA strategies, is implemented to choose highlights in the subsequent stage. Wang et al. [29] presents a deep learning-based model for COVID-19 classification on chest CT is valuable to counter the episode of SARS-CoV-2. 3D CT volumes were obtained by using weakly supervised deep learning structure for COVID-19 plan and injury restriction. Yang et al. [30] presents the LSTM algorithm from the start to anticipate the tainted populace in China. Notwithstanding, it does not clarify the elements of diffusion process, and the drawn out forecast mistake is excessively enormous. Han et al. [31] presents another endeavor of pitifully managed screening of COVID-19 using deep 3D multiple instance learning (AD3D-MIL). Proposed method for the

screening of COVID-19 with delicate marks has yet high interpretability. AD3D-MIL joins a deep model generator to make deep 3D events thusly.

Sun et al. [32] presents a versatile element choice guided deep timberland for COVID-19 versus CAP classification by utilizing the chest CT images. In particular, the AFS-DF utilizes the deep backwoods to get familiar with the significant level representation dependent on the area explicit features. In the interim, a versatile feature selection operation is utilized to decrease the repetition of features dependent on the trained forest. Vrbancic et al. [33] utilize another adjusted characterization technique that can identify COVID-19 patient's dependent on a chest X-ray, and afterward receive a nearby interpretable model—agnostic clarifications way to provide the insights. The characterization technique utilizes a dark wolf optimizer algorithm to upgrade hyperparameter esteems inside transfer learning tuning of a CNN. Rahimzadeh and Attar [34] deep convolution networks with introduced preparing strategies for ordering X-ray images into three categories, which are COVID-19, customary, and pneumonia, by using two available datasets. The maker presents some preparation systems that help the organization learn better when we have an unbalanced dataset. Samiappan and Chakrapani [35] proposed an ANN classifier for an ultrasound images. It is a feed forward multilayer back-propagation Network (BPN) using Levenberg–Marquardt training to overcome the problem of local minima in the back propagation network. Latha et al. [36] have summarized various segmentation and classification methods which are suitable for ultrasound images. Bridge et al. [37] proposed initiation work on an openly accessible dataset and remotely favor on a dataset containing 1909 strong chest X-rays and 84 COVID-19 X-beams. The technique presented brings an improved locale under the beneficiary working trademark (DeLong's  $p$ -value  $<0.05$ ) contrasted and the sigmoid initiation.

## 6 Some Performance Metrics Used

Performance of any machine learning and deep learning networks was analyzed through a confusion matrix. Using the confusion matrix, the following metrics such as sensitivity, specificity, F1 score, and accuracy are computed as shown below [24, 28, 32, 34, 36]:

$$\text{Accuracy (A)} = \frac{(\text{TN} + \text{TP})}{(\text{TN} + \text{TP} + \text{FN} + \text{FP})} \quad (1)$$

$$\text{Sensitivity (Sn)} = \frac{(\text{TP})}{(\text{TP} + \text{FN})} \quad (2)$$

$$\text{Specificity (Sp)} = \frac{(\text{TN})}{(\text{TN} + \text{FP})} \quad (3)$$

$$\text{Precision } (P) = \frac{(\text{TP})}{(\text{TP} + \text{FP})} \quad (4)$$

$$F1 \text{ score}(F1) = \frac{2(P \times \text{Sn})}{(P + \text{Sn})} \quad (5)$$

$$\text{Area Under the ROC Curve (AUC)} = \frac{(\text{Sn} + \text{Sp})}{2} \quad (6)$$

where

TP True positive value

TN True negative value

FP False positive value

FN False negative value.

Most of the cases, the above-mentioned parameters are compared among various networks to check the performance of the proposed works. Table 2 summarizes the performance metrics of different classification architecture proposed by various researchers.

## 7 Future Directions

By observing the above literature, it is evident that most of the work was carried out using both X-ray and as well as CT images for the purpose of two class (i.e., COVID or non-COVID) or three class (i.e., normal, pneumonia, COVID). So, still there is a necessity to explore in the direction of developing classifiers indicating the disease progression stages. Also, there is a possibility of developing a classifier such that it detects the infected person by feeding the input image of the person under testing in the form of either chest X-ray or chest CT. And also, there is other possibility of investigation the long-term effects of COVID-19 patients using the imaging modalities.

## 8 Conclusion

Coronavirus is a rising pandemic infection that, in a brief timeframe, can seriously imperil the soundness of numerous individuals all through the world. It legitimately influences the lung cells, and if not precisely analyzed early, can cause irreversible harm, including passing. The nitty-gritty synopses of primer agent work, including accessible assets to encourage further research and development is talked about.

**Table 2** The performance metrics of different classification architectures

Reference	Image modality	Image dataset used	Methods	Accuracy (%)	AUC (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1 score (%)
Sethi et al. [21]	X-ray	Non-COVID-5928 COVID-320	Inception V3	98.1	-	81.1	99.2	85.9	83.4
			ResNet50	82.5		24.2	99.7	95.6	38.6
			MobileNet	98.6		87.8	99.3	87.8	87.8
			Xception	97.4		62.2	99.5	88.9	73.2
Gozes et al. [22]	CT	Normal-150 COVID-120	DL with 2D slice and 3D volume analysis	-	99.6	98.2	92.2	-	-
			U-Net	85.9		84	95.3	82.3	82.5
Oh et al. [24]	X-ray	Bacterial-54 TB-57 Viral-20 COVID-180	FC-Dense Net 67	81.8		76.6	91.5	73.1	74.3
			FC-Dense Net 103	88.9		85.9	96.4	83.4	84.4
			VGG16-U	97.02	99.77	97.02	-	97.09	97.02
			VGG-16-P	97.22	99.38	97.22		97.25	97.22
Rajaraman et al. [25]	X-ray	Pediatric RSNA Twitter COVID-19 Montreal COVID-19	VGG19-U	95.63	99.36	95.63		95.88	95.63
			VGG-19-P	97.62	99.72	97.62		97.67	97.62
			IncV3-U	97.42	99.69	97.42		97.46	97.42
			IncV3 -P	98.41	99.62	98.41		98.41	98.41
			Alex Net	79.00	-	81.00	77.31	75.00	77.88
			VGG 16	58.21		95.08	28.44	51.75	67.02
EL-Kenawy et al. [28]	CT	Normal-794 COVID-334	VGG 19	77.17		62.00	89.92	83.78	71.26
			Google Net	73.06		50.00	92.44	84.75	62.89
			ResNet50	77.17		62.50	88.62	81.08	70.59
			C3D	89.7	97.1	85.0	-	88.2	
Han et al. [31]	CT	COVID Pneumonia Non-COVID	DeCovNet	90.6	97.5	84.1		93.7	
			AD3DMIL	94.3	98.8	90.5		95.9	

(continued)

**Table 2** (continued)

Reference	Image modality	Image dataset used	Methods	Accuracy (%)	AUC (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1 score (%)
Sun et al. [32]	CT	COVID-1495 Community Acquired Pneumonia-1027	Logistic Regression	89.81	95.52	91.64	87.10	91.22	91.42
			SVM	89.97	95.62	91.51	87.70	91.38	91.43
			Random Forest	89.41	95.40	90.51	87.85	91.21	90.85
				89.96	95.73	92.66	86.04	90.65	91.64
Vrbancic et al. [33]	X-ray	COVID-182 Other-660	VGG-19	76.73	50.00	100	-	76.73	86.83
Transfer Learning(TL)			91.56	85.64	96.76	-	92.71	94.62	
Grey wolf Optimizer for TL tuning			94.76	93.47	95.83	-	97.42	96.52	
Rahim zadeh and Attar [34]	X-ray	COVID-180 Pneumonia-6054 Normal-8851	Xception	91.31	-	73.35	99.55	-	-
			ResNet50 V2	89.79	-	74.02	99.33	-	-
			Xception + ResNet50 V2	91.40	-	80.53	99.56	-	-

This paper means to diagram the as of late created frameworks dependent on deep learning strategies utilizing distinctive clinical imaging modalities like computer tomography (CT) and X-ray. This survey explicitly talks about the frameworks created for COVID-19 analysis utilizing deep learning techniques and gives insights on notable datasets used to prepare these networks and the techniques utilized for segmentation of lung images. Deep learning-based methodologies are helpful for the programmed discovery of corona infected patients utilizing X-rays and CT images. CT images are likewise useful in discovering the illness seriousness which should be mulled over so as to lessen the casualty rate over the globe. The significant point is to build the quantity of datasets for corona infected patients and utilizing advance deep learning algorithms to accomplish better execution for the detection and prediction of corona virus.

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