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VISUAL QUALITATIVE ASSESSMENT OF CORONAVIRUS (COVID-19) USING DIGITAL WORLD

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ABSTRACT

World Health Organization (WHO) gave the name "Corona Disease of 2019 (COVID-19)", caused by the unique form of virus structure as SARS-COV-2. Medical authority registered the first case in Wuhan, China and afterwards it exponentially spreads among people globally. Till date, the WHO, UN and other worldwide organizations reported many deaths (in thousands and still counting) due to the unavailability of any cure as well as late detection. In addition, hospitals and government suffer from deficiency of general resources such as PPE kit, ventilators, masks, gloves, general medicines etc. that makes the condition more severe. Therefore, it becomes essential to implement an automatic detection model by using advanced image processing techniques, which deliver the instant diagnostic report in order to help in prevention from COVID-19 dispersion. This qualitative assessment offers the significant image processing techniques to detect the early symptoms of COVID-19 from X-ray reports or radiographs. For instance, Inception-ResNetV2, InceptionV3 and ResNet50 are some forms of Convolutional Neural Network schemes that have the potential to detect the COVID-19. This assessment report presents the other effective image processing schemes that can utilize to detect the spreading of virus in human body accurately within short duration. Such models needed the highest classification performance with authenticate datasets of patients. The best feature of advanced image processing is that it is highly compatible with other progressive techniques such as Machine Learning, Artificial Intelligence, Data Analytics, and Robotics etc. All such techniques are highly dependable on image processing procedures such as image detection, segmentation, and feature extraction for the analysis of images. Each detection process initiated with image acquisition step such as X-ray, Computed Tomography (CT) images etc. Therefore, each technology needs the help of advanced image processing schemes for further assessment of disease. Early phase detection is the most crucial stage in disease prevention. This article depicts the potential of the algorithms used in feature extraction such as Discrete Wavelet Transform (DWT), Grey-Level Size Zone Matrix (GLSZM), Grey Level Run Length Matrix (GLRLM), Local Direction Pattern (LDP), Grey Level Co-occurrence Matrix (GLCM), Support Vector Machines (SVM), etc. Some of the performance metrics of COVID-19 detection via image processing techniques are F-score, precision, accuracy, specificity and sensitivity. The existing work illustrates the highest classification accuracy of GLSZM feature extraction method among the others. Such image processing techniques can efficiently detect the minute spalls or cracks occurred in respiratory organs due to COVID-19.This study highlights the cost-effective methodologies to practice the medical treatments in spite of the others labor and time-consuming procedures. Image processing algorithms can extract the significant features from digital images due to the presence of projection integrals and steerable filters. Therefore, this assessment presents the correlation between imaging manifestations and medical practices on COVID-19.

Keywords: *Advanced Image Processing Techniques, CT Scan, X-ray, CNN, Image Classification.*

Introduction

COVID-19 started from an unknown cause of pneumonia. In Wuhan, Hubei province of China, doctors officially reported the first case of COVID-19 on December 31, 2019 and now become a pandemic [1–2]. The virus is termed asSevere Acute Respiratory Syndrome Coronavirus (SARS-CoV-2).

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Within 30 days, this new virus rapidly spread from Wuhan to almost all the regions of China [3]. On January 20, 2020, USA reported the first seven cases [4] that get exponentially risen beyond 300,000 by the April 5, 2020. Mostly the coronaviruses have zoonotic nature (transmitted to humans), but also influence the animals. Middle East respiratory syndrome Coronavirus (MERS-CoV) as well as SARS-CoVhave developed severe respiratory disease resulting as human deaths [5]. COVID-19 has the general symptoms as breath shortness, muscle pain, fatigue, headache, sore throat, cough and fever [6].Experts and doctors currently use Real-Time Reverse Transcription-Polymerase Chain Reaction (RT-PCR) test technique as the diagnosis tool for COVID-19. X-ray and Computed Tomography (CT) scan as the chest radiological imaging techniques haveplayed vital roles in the treatment as the early diagnosis of such virus [7]. Even if the obtained results are negative because of low RT-PCR sensitivity such as 60%–70%, radiological images of patients can examine the symptoms by easy detection technique [8]. Researchers proposed that CT is a screening tool with RT-PRC and is a sensitive process for COVID-19 pneumonia detection [8]. After the onset of symptoms, doctors monitor the CT findings over a long duration because the patients generally show the normal CT in initial 0–2 days [9]. Experts monitor the symptoms onsets of lung disease for at least ten days. The lung CT scan of those patients who survived COVID-19 pneumonia [10] shows such results.

Chinese clinical centers suffered from the deficiency of test kits at the beginning of the pandemic. It also generates the high rate of false negative results. Therefore, doctors require to develop the diagnosis techniques that are only depending on the results of CT scans [10-11]. For instance, there is a wide utilization of CT scan forCOVID-19 diagnosis in other nations like Turkey, where there is the availability oftest kits in low numbers at pandemic onset. Investigators propose that integrating the laboratory results with clinical image characteristics may detect the COVID-19 at its initial stage [12–13]. COVID-19 cases can provide the significant information from radiologic images diagnosis. Few research works have to deal with alters in the CT images as well as X-ray of chest before the initiation of COVID-19 symptoms. Investigators in imaging COVID-19 studies have understood significant discoveries. Konget al. [14] suggested the diagnosis of COVID-19 patient as right infrahilar airspace opacities. Yoon et al. [15] proposed that one out of three patients consisted the single nodular opacity in the region of lower lung. On the other hand, the both lungs of other two contained4 and 5 irregular opacities. Zhao et al.[16] monitored the vascular as well as consolidation dilation present in the lesion. Furthermore, they stated that most of the patients had ground-glass opacities (GGO) or mixed GGO. Li and Xia [17] stated the common CT characteristics of COVIED-19 patients as consolidation as well as GGO, air bronchogram sign and interlobular septal thickening. Another observation shows the influence of 50%-70% lungs by multifocal or peripheral focal GGO [9].

Likewise, researchers found the rounded lung opacities in 33% of chest CTs. The applications of advanced image processing techniques in medical domain for automatic diagnosis have recently become the trend by adapting as an adjunct tool for clinicians [18–19]. Image processing is an essential part that can integrate with other advance techniques such as deep learning (DL), artificial intelligence (AI) and machine learning (ML) for the COVID-19 diagnosis. It initiates the process by developing the end-to-end systems to attain promised outcomes utilizing input datasets, excluding the requirement for manual feature extraction [20]. In previous cases, advance image processing methodologies have been successfully used in several problems such as lung segmentation [21], fund us image segmentation [22], pneumonia detection from the images of chest X-ray [23], brain disease classification [24], breast cancer detection [25], skin cancer classification [26] and arrhythmia detection [27]. It becomes necessary to find out the expertise due to the rapid rise in COVID-19 epidemic. Such has enhanced the interest of researchers in exploring the advanced image processing based automated detection systems. The limited number of radiologists makes to develop new techniques that fulfills the need of expert clinicians in every hospital. Thus, fast, precise and easy image processing systems can overcome such issue as well as offer the necessary assistance to patients in time. However, radiologists are the backbone of diagnosis system as they have the vast experience of this field, the image processing methodologies can be helpful to attain accurate diagnosis [28].

Furthermore, image-processing methods can also be helpful in eradicating the limitations e.g. waiting time of test results, test costs and deficiency of existing RT-PCR test kits. In recent times, several radiology images have been broadly utilized in the diagnosis of COVID-19. Hemdan et al. [29] utilized DL for COVID-19 diagnosis via X-ray images and suggested a COVIDX-Net system consisting of seven Convolutional Neural Network (CNN) models. Wang and Wong [30] suggested another deep model for as COVID-Net that attain the accuracy of 92.4% in characterizing the COVID-19, non-COVID pneumonia and normal classes. Ioannis et al. [31] proposed a model utilizing the assured COVID-19 images. The success rate of their model are 98.75% and93.48% with2 and 3 classes, respectively. Narin et al.[32] utilized the images of chest X-rays along with ResNet50 model and attained the accuracy of 98% in COVID-19 detection. Sethy and Behera [33] used the images of X-ray and characterized the features achieved from several CNN systems with support vector machine (SVM) classifier. They claimed to acquire the best performance by their designed model. In last, recent studies show the development of numerous different models for COVID-19 diagnosis consisting the CT or X-ray images examined by advance image processing techniques [34].

Several studies involve the utilizing with or without feature extraction approaches to develop end-to-end architecture for the automatic diagnosis of COVID-19. These processes need the images of raw chest X-ray to return the diagnosis. Such process includes a fix amount of patients and has the training datasets of chest X-ray images (obtained hastily or not in regular form). The positive recovery of patients observed by conducting the diagnostic tests after 5–13 days[35]. However, such critical discovery depicts the continuous spreading of virus by recovered patients. Thus, there is the requirement for highly precise diagnosis techniques. The chest radiography assessment has one of the crucial limitation as the inability to diagnose the COVID-19 at the preliminary stage, as they consist the inadequate sensitivity inGGO recognition. Nevertheless, advanced image processing models can target to the regions that are unrecognizable to human eye, and may change this perception.

Diagnosis

Clinicians have conducted the medical diagnosis with wide meaningful ranges of COVID-19 in order to recognize the confirmed virus cases [8]. Such process can contribute in detecting the new confirmed cases on daily basis by utilizing electronic health records (EHR). These methodologies for medical recognition of COVID-19 involve the both radiologist's diagnosis as well as clinical characteristics. Clinical features contain RT-PCR and human temperature monitoring [9]. The body temperature of patient should be in between 36.5–38.8°C depending on the human body temperature standards [36]. Based on that the instantaneous data has been collected through existing thermal images or thermal sensors to examine the capable COVID-19 [37]. RT-PCR is a clinical methodology used for COVID-19 examination including blood sample of the case. The actual number of confirmed cases can be detected by using real time RT-PCR test globally [38]. Furthermore, the other techniques to detect the infected cases are antibodies detection, Immunoglobulin M (IgM) and point-of-care testing [39].

COVID-19 detection has a gold standard test to confirm the cases named as quantitative reverse transcriptase PCR (qRT-PCR). Although, such process requires the sample collection according to CDC guide, presence of skilled microbiology specialists and continuous observation from 4hrs up to 6hrs duration. Thus, COVID-19 cases must involve the screening as medical imaging as the necessity [40]. Radiologist's diagnosis consists the chest X-ray (CXR) radiographs as well as computed tomography (CT) scans [10]. The symptoms of this disease can be efficiently recognized by X-ray or CT images. Radiologists can detect the pneumonia of COVID-19 by observing the chest CT scan with the deterioration or recovery stage of patient. Advanced image processing techniques can precisely perform the COVID-19 diagnosis and deliver early detection of disease by showing the preliminary signs of lung damage via images. A research performed on the healthy as well as infected persons by gathering 1,119 CT images with the help of artificial neural networks (ANNs) [41]. This process involves internal validation datasets and performs the binary classification by Inception transfer-learning model. It generates the result with the accuracy of 89.5% with 0.87 and 0.88 for sensitivity as well as specificity, respectively. In second test, examiners consider external validation dataset on which the system generated the accuracy of 79.3% with 0.67 and 0.83 for sensitivity and specificity, respectively. Thus, the outcomes validate the potential of image processing to discover the radiological characteristics of COVID-19 depending on the terms of accuracy and time.

The neural network model with image processing technique such as U-Net++ can process over 6000 CT scans for COVID-19 classification in between infected or not infected persons [42]. Such model generated the accuracy of 100% and 93.55% for sensitivity and specificity, respectively. Furthermore, the developed model illustrated the positive value (PPV) of 84.62% and negative positive value (NPV) of 100%, with the overall accuracy of 95.24%. Such model can reduce the monitoring duration of CT scans by 65% and has a great help to radiologists [42]. Xu et al. (2020) and Song et al. (2020) developed a 3-category classification system for COVID-19 characterization. They utilized numerous fully connected layers and Feature Pyramids as the feature extraction for cases characterization [43]. This model generates an adequate overall accuracy of 86.7% utilizing CT scans. The COVID-19 detection by using fully-connected layers model generates the sensitivity of 0.93 and Area Under the Curve(AUC) of 0.99.

The COVID-19 diagnosis depends on primarily on the existence of clinical symptoms related with respiratory systems. More precisely the signs of pneumonia such as dyspnea, fever, myalgia, fatigue and dry cough. A wide range of COVID-19 means in the confirmed cases with the recent history (two weeks apart) of exposure including the medical diagnostics as point of care (POCT) as the screening of this pandemic outbreak. Many of the cases involve the most advance techniques for screening as radiological imaging, CRISPR-cas13 lateral flow (CASLFA), Nucleic acid lateral flow (NALF) and lateral flow (lateral immunochromatographic assay) of IgM/IgG. However, expert radiologists found X-ray imaging and CT scans very exhaustive and time consuming. Furthermore, such techniques are categorized as the highest sensitivity diagnostic process with respect to gold standard (qRT-PCR) and other rapid diagnostics. Therefore, it is meaningful to depend on the radiological imaging for the diagnosis as well as screening COVID-19.Therefore, image processing tools can provide the automated and accurate results, early detection and less tiresome for medical imaging workers. It also well differentiate between the COVID-19 cases with the radiological images of influences lung from other diseases such as SARS which caused by (SARS-CoV-1) and MERS which caused by (MERS-CoV). Such viruses belong from the same family and have some mutual clinical symptoms. However, these viruses have some uniqueness or differences even if influenced lung radiological with similar image patterns.

In case of confirmed COVID-19, a radiological imaging generally illustrates either diffuse or patchy asymmetric airspace opacities, same as the MERS or SARS related pneumonia. The first few days of COVID-19, infection contains the bilateral lung affection in 98% of cases. In most of the cases, the patients outside intensive care units (ICUs)depicted the ground glass predominant patterns, while patients inside ICUs presented consolidation pattern. Furthermore, in case of 21 confirmed COVID-19 cases, examination exhibited the radiological images of chest as the influence on their lungs as 86% of patients having the majority of 89% consist bilateral lung affections [44]. Multifocal ground-glass predominant opacities or peripheral lung affection with consolidation was stated in 57% and 29% of cases, respectively. Some other diagnosis shows the chest radiological images of older people have more visible bilateral patchy ground-glass predominant opacities as compared to the young people. However, there is the huge similarities between imaging features of COVID-19 with MERS and SARS. Moreover, COVID-19 has the involvement of bilateral lungs involvement on early diagnosis, while MERS/SARS are more predominantly unilateral.

Current Existing Techniques

Nowadays, it becomes a necessity to fight against the wide spread of COVID- 19 disease with accurate patient's screening as well as and quick clinical reaction by contaminated patients. RT-PCR examination on respiratory specimen is the highest quality level strategy for the screening of COVID- 19 testing [45]. Such process has the most commonly used testing procedure for COVID- 19 detection, although is a time consuming, relentless, complex and manual system with just 63% of positivity rate[45]. Some other investigating tools forCOVID- 19 diagnosis are positive pathogenic testing, positive radiographic images (such as Chestoradiograph (CXR) or computed tomography (CT)), epidemiological history and clinical symptomsinvestigation. The serious cases of COVID-19 contamination include several clinical attributes related with bronchopneumonia such as acute respiratory distress syndrome (ARDS), respiratory failure, dyspnea, hack and fever [46]. The key symptomatic tool for COVID-19 are radiological imaging with promptly accessible features.

There have been comparable outlines on radiographic images in most of COVID- 19 cases such as ground glass, multi-focal, reciprocal opacities along with a back/fringe dissemination, mainly in the lower projections, at the initial stage and the occurrence of pulmonary consolidation at the late stage [47]. However, general CXR pictures may perform the primary screening of suspected cases. The different images taken from several viral pneumonia cases are comparative, where some signs are mutual with other inflammatory as well as infectious lung sicknesses. Thus, radiologists found this difficult to detect or differentiate the COVID- 19 from other viral pneumonia. It can cause the side effects of COVID- 19 as the confusion with other viral pneumonia can mislead the entire process under such lacking of medical services. In current time, there is the nonstop working environment due to which medical clinics are over-burden. Thus, wrong diagnosis of non- COVID viral Pneumonia with the COVID-19 can change the complete treatment procedure with danger, risks, exertion and resulting costs. Nowadays, several biomedical complications (such as breast cancer/brain tumor detection etc.) are utilizing the advanced image processing based solutions. Table-1 highlights some of the significant researches based on image processing techniques for COVID-19 detection.

Table1: Literature Review on role of advanced image processing on COVID-19 detection [48]

Literature	Task	Subjects	Modality	Method	Result
Tang *et al.*	Severity assessment	176 COVID-19	CT	RF	87.5% (Acc.) 93.3% (TPR) 74.5% (TNR)
Shi *et al.*	Classification: COVID-19/CAP	1658 COVID-19 1027 CAP	CT	RF	87.9% (Acc.) 90.7% (Sens.) 83.3% (Spec.)
Li *et al.*	Classification: COVID-19/ CAP/ Non-pneu.	468 COVID-19 1551 CAP 1445 Non-pneu.	CT	ResNet-50	90.0% (Sens.) 96.0% (Spec.)
Ghoshal*et al.*	Classification: COVID-19/ Others	70 COVID-19	X-Ray	CNN	92.9% (Acc.)
Xu *et al.*	Classification: COVID-19/ Influ.-A/ Normal	219 COVID-19 224 Influ.-A 175 Normal	CT	CNN	86.7% (Acc.)
Narin*et al.*	Classification: COVID-19/ Normal	50 COVID-19 50 Normal	X-Ray	ResNet50	98.0% (Acc.)
Ying *et al.*	Classification: COVID-19/ Bac. Pneu./ Normal	88 COVID-19 100 Bac. Pneu. 86 Normal	CT	ResNet-50	86.0% (Acc.)
Zhang et al.	Classification: COVID-19/ Others	70 COVID-19 1008 Others	X-Ray	ResNet	96.0% (Sens.) 70.7% (Spec.) 0.952 (AUC)
Wang *et al.*	Classification: COVID-19/ Vir. Pneu.	44 COVID-19 55 Vir. Pneu.	CT	CNN	82.9% (Acc.)
Wang *et al.*	Classification: COVID-19/ Bac. Pneu./ Vir. Pneu./ Normal	45 COVID-19 931 Bac. Pneu. 660 Vir. Pneu. 1203 Normal	X-Ray	CNN	83.5% (Acc.)
Jin *et al.*	Classification: COVID-19/ Others	723 COVID-19 413 Others	CT	UNet++ CNN	97.4% (Sens.) 92.2% (Spec.)
Chen *et al.*	Classification: COVID-19/ Others	51 COVID-19 55 Others	CT	UNet++	95.2% (Acc.) 100% (Sens.) 93.6% (Spec.)
Jin *et al.*	Classification: COVID-19/ Others	496 COVID-19 1385 Others	CT	CNN	94.1% (Sens.) 95.5% (Spec.)
Zheng *et al.*	Classification: COVID-19/ Others	313 COVID-19 229 Others	CT	U-Net CNN	90.7% (Sens.) 91.1% (Spec.) 0.959 (AUC)

Advanced image processing techniques can disclose the features of a picture that are not possible visually. Specifically, feature extraction or segmentation with CNN can exhibit amazingly the assessment of images by learning and extraction, thus broadly accepted by research community. CNN can enhance the quality of picture taken as low- light images from a high- speed video endoscopy. Furthermore, it can discriminate the idea of aspiratory knobs by cryptoscopic image acknowledgement extraction from recordings; robotized marking of polyps at the time of colonoscopy recordings pediatric pneumonia conclusion by means of chest X-ray images and CT images. Image processing methods on chest X- Rays becomes the trend due to simple utilization along with low- cost imaging processes. In addition, there is a huge volume of information exists for training different image processing models. Vikash et al. [49] used transfer-learning concept in image processing with DL framework for pneumonia detection using pre- trained Image Net systems with their assemblages.

Xianghong et al. [50] used a customized VGG16 model for several sorts of pneumonia classification as well as lung regions detection. Ronneburger et al. [51] utilized image augmentation integrated with CNN to exhibit the signs of enhanced results through little preparation of pictures arrangement and Wang et al. [52] utilized a high volume of training dataset. Rajpurkar et al. [53] worked on the chest X-rays as proposed a 121- layer CNNto detect 14 different pathologies, involving pneumonia using the arrangement of several networks. The precise detection of 14 thoracic diseases can be conducted by feature extraction techniques and a pre- trained DenseNet- 121[54]. Sundaram et al. [55] utilized image augmentation with GoogLeNet and AlexNetto achieve an AUC of 0.95 in pneumonia detection.

COVID-19 test becomes a difficult task due to the lacking of diagnosis test kits universally leading to develop panic. Experts need to rely on other determination measure due to the limited accessibility of COVID-19 testing kits. Experts can use the X-rays to examine the patient's lungs strength as COVID-19 attacks on epithelial cells (respiratory tract lining). The clinicians often utilizes the X-ray images to assess enlarged lymph nodes, abscesses, lung inflammation and pneumonia. Furthermore, nearly all hospitals contains the imaging tools as X-ray machines, so that, it can be used as the diagnostic tool for COVID-19 excluding the test kits. However, X-ray has a limitation as the process needs a radiology expert and consume a huge time that is crucial during the vast spreading of this disease. Thus, it becomes essential to create an automated assessment model to save the precious time of medical professionals. In recent time, numerous communities have explained image-processing techniques with DL to detect the COVID- 19 pneumonia [56]. Shuai et al. [57] utilized a model on CT images for preliminary screening of the disease with the sensitivity, specificity and accuracy 87%, 88% and 89.5% respectively. Linda et al. [56] exhibited another model named as DCNN or COVID- Net utilizing chest X-ray images for the identification of cases with 83.5% of accuracy.

Methodology

- **Case Selection**

Several medical experts have conducted a single-center and retrospective research of SARS-CoV-2 laboratory- in between a particular duration at a certain region by investigating on the confirmed cases as a sample size [58].rRT-PCR and high throughput sequencing can define the confirmed cases via pharyngeal and nasal swab specimens [59]. For instance, Shanghai Zhijiang Biotechnology Co. manufactures the rRT-PCR test kits utilized on patients. Afterwards, several ethics committee such as Sun Yatsen University as Fifth Affiliated Hospital approved the investigation where they monitor the risk, adverse impact with subjects' welfare or rights. There is no exclusion criteria in selecting the patient for suchstudy.

- **CT image or Chest X-Ray acquisition**

Most of the datasets are acquired from the chest X-rays or CT scan images conducted on patient. It includes majorly the supine position at the time of end-inspiration excluding intravenous contrast e.g. uMI 780 and uCT 760 scanners type of CT scanners (UnitedImaging). Usually, images consist the data of apex to lung base from scanning. Scanning protocol can provide the based on standard dose. It is important to set the lung window setting at the window level for Hounsfield units (HU).

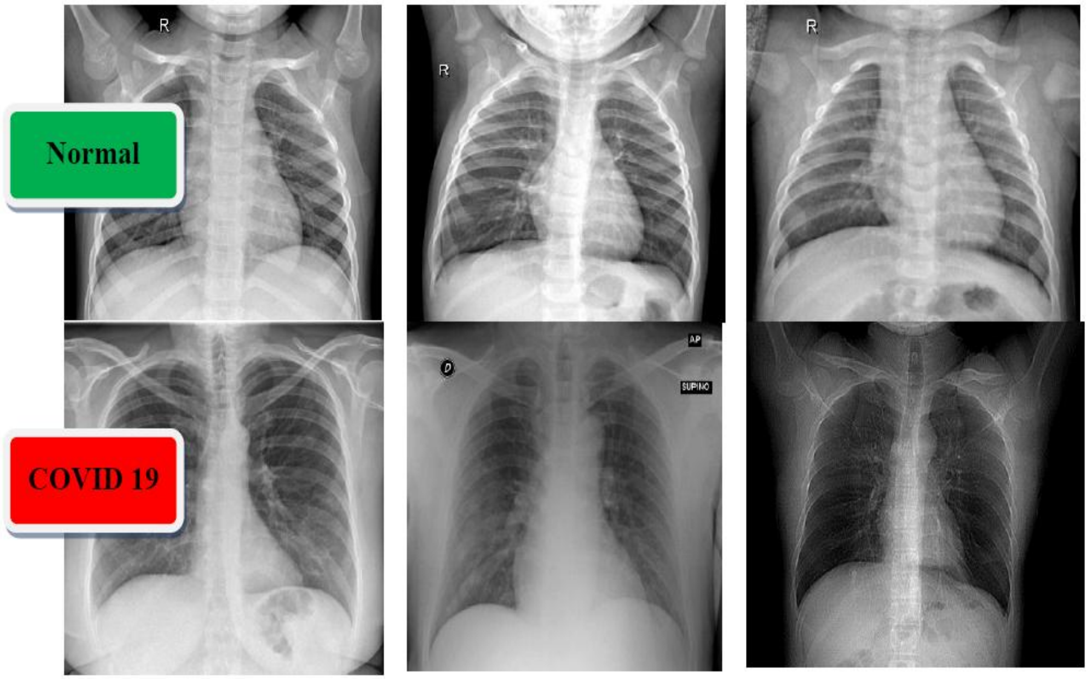

Fig. 1: Dataset representation of X-ray images as normal cases and COVID-19 cases [23].

- **Image Interpretation**

Organizational digital database system (such as Neusoft V5.5.4.50720) can conduct the image assessment. It is important the availability of radiologists having good experience for reviewing the CT images. They reviewed independently the imaging and made final decisions after lot of discussion. If there is any disagreement in between the committee, then the process include another expert that provide the interpretations and then reach up to the final decision. If the process included the CT scan for investigation, then some significant characteristics are:

- Existence of a pleural effusion;
- Existence of centrilobular nodules;
- Existence of fibrotic lesions;
- Lobe number: Influenced by consolidative or ground glass opacities;
- Internal structures: Existence of cavitation, interlobular septal thickening and air bronchogram;
- Density: Existence of consolidation, mixed ground glass opacities and ground-glass opacities;
- Distribution: Existence of peribronchovascular or peripheral;
- Existence of outlining lung disease like interstitial lung disease, emphysema or tuberculosis.
- Existence of thoracic lymphadenopathy (referredfor short-axis dimension with lymphnode size of ≥ 10 mm); and

Consolidation defined the opacification with margin obscuration of airway walls and vessels, while ground-glass opacification defined as enhanced hazy lung attenuation with preservation of vascular as well as bronchial margins [60].

- **CT Visual Quantitative Evaluation**

Most of the assessments include the independent review of images by radiologists subjected to provide the clinical information. Radiologists record the involvement percentage of overall lungs along with every lobe and termed as "total severity score (TSS)". Such process assess the percentage of lobar involvement of each of the five lung lobescategorized in the group of severe (76–100%), moderate (51–75%),mild (26–50%), minimal (1–25%) ornone (0%), with their respectivescore as 4, 3, 2, 1 or 0. Afterwards, the summing of overall values (five lobe scores) indicates the TSS(range from 0 to 20) [61] and the overall score decides the further procedure.

- **Clinical Classifications**

There are four major groups for all kind of cases; critical, severe, common and minimal, based on the shock, respiratory failure, pneumonia severity, clinical symptoms, other organ failure, etc. According to the standards of National Health Commission (7th ed.) (China) as the Treatment Plan and Diagnosis of COVID-19, the common categories are:

- Critical type: Mechanical ventilation for respiratory failure, ICU treatment and monitoring for other organ failure and shock;
- Severe type: ; In resting state, oxygen saturation ≤ 93%; PaO2/FiO2 ≤ 300MMHG; respiratory distress, respiratory rate ≥ 30 times/min;
- Common type: Respiratory tract, fever and other signs with pneumonia in imaging;
- Mild type: Minor clinical signs excluding the pneumoniain imaging.
- **Statistical Analysis**

Most of the statistical assessment can be conducted by utilizing the analysis tools such as IBM SPSS Statistics for Windows. It delivers the mean and standard deviation for the normal distribution of continuous data. The consistency of TSS scores can be tested by using intra group correlation coefficient (ICC). The standard values are >0.75, 0.4~0.75, and < 0.4 indicate good repeatability, moderate and poor, respectively. The numbers of included lobes with several clinical types as well as distribution balance of included lobes were compared by Fisher exact test or chi-squared test during the small sample sizes and variance tests assessment. Another test for TSS comparison with different clinical type is Wilcoxon-rank test as the TSS never follow the normal distribution. The severe critical type group and common type group carries the ROC for differential diagnosis assessment to check the potential ofTSS.

Feature Extraction Techniques

Generally, feature extraction techniques can categorize the coronavirus into two stages. The first stage consists the implementation of classification method including four different subsets excluding the feature extraction. SVM classifies the vectors coming from transformed subsets. Second stage consists five different feature extraction processes such as Discrete Wavelet Transform (DWT) (62), Grey Level Size Zone Matrix (GLSZM) (63), Grey Level Run Length Matrix (GLRLM) (64), Local Directional Patterns (LDP) (65) and Grey Level Co-occurrence Matrix (GLCM) (66) for feature extraction. Furthermore, SVM classifies the features. The classification process involves the using of cross-validation methodologies for 10-fold, 5-fold and 2-fold. It is significant to attain the mean classification findings after cross-validations.

Coronavirus classification can be conducted by using the feature sets developed from DWT, GLSZM, GLRLM, LDP and GLCM. Feature extraction can be performed by SVM for image classification as it has an impactful binary classifier. Therefore, the key feature extraction methodologies utilized by several research activities are as follows:

- Discrete Wavelet Transform
- Grey Level Size Zone Matrix
- Grey Level Run Length Matrix
- Local Directional Pattern
- Grey Level Co-occurrence Matrix
- Support Vector Machines
- **Discrete Wavelet Transform**

DWT discriminates the image into the sub-bands of frequency by utilizing a *g* high-pass filter as well as *h* low-pass filter. Diagonal details (HH), vertical details (HL), horizontal details (LH) and approximation coefficients (LL) indicate high frequencies, vertical high frequencies horizontal high frequencies and lowest frequency in both directions, respectively. LL coefficients developed the feature set after DWTthat consists the dimension as the half of input size. Db1 wavelet generates the LL coefficients as well as there is the conversion of coefficient matrix into a feature vector.

- **Grey Level Co-occurrence Matrix**

GLCM attains the statistical features of second-degree on the datasets. GLCM contains the correlation of various angles between image pixels. The representation of co-occurrence matrix attained from an *I* image is *P=[p(i, j | d, Ɵ)]*. Such phase the ith pixel frequency features with respect to jth features of neighbor [pixel frequency as the co-occurrence matrix by considering the d length and *Ɵ* direction. Most of the researches have the assumption as *I=d*. Therefore, *Ɵ* = 0° for such studies. GLCM process performs the extraction of several parameters as inverse difference features, maximum probability, cluster prominence, cluster shades, dissimilarity, autocorrelation, information measures of correlation 1/correlation 2, difference variance, difference entropy, entropy, sum entropy, sum variance, sum average, inverse difference moment, variance, sum of squares, correlation, contrast andangular secondary moment from all subsets.

- **Local Directional Pattern**

LDP method integrates the directional components by utilizing the Kirsch compass kernels. Let assume thati_c as image density on the coordinates of (x_c, y_c) as well as $i_n$is the pixel density of center pixel $i_c$is outside of 3 × 3 neighborhood of (x_c, y_c). The mathematical expressions will be:

$$YYS(x_c, y_c) = \sum_{n=0}^{7} s(i_n - i_c).2^n$$

$$S(x) = 1 \text{ when } x \geq 0 \text{ and } 0 \text{ for others}$$

LDP process generates the output matrix equivalent to the size of input image. SVM converts such matrix into a vector for classifier input.

- **Grey Level Run Length Matrix**

GLRLM generates the high level of texture feature extraction. Let *P* is pixel number in the image, *R* is the longest run and *L* be grey-levels number. A GLRLM matrix is $L \times R$, and each $p(i,j \mid \theta)$ component provides the occurrences number in the direction ofθ direction with *j* run length and *i*grey level. GLRLM conducts the type of feature extraction as high/low grey-level run emphasis, run percentage, run-length non-uniformity, grey-level non-uniformity and, long/short rum emphasis from all subsets. GLRLM process generates the feature vector of 1×7 for classifier input.

- **Grey Level Size Zone Matrix**

GLSZM is an advanced version of GLRLM algorithm that performs feature extraction process. GLSZM conducts numerous feature extraction tasks as size zone variance, grey-level variance, large zone high/low grey-level emphasis, small zone high/low grey-level emphasis, high/low grey-level zone emphasis, zone percentage, size zone non-uniformity, grey-level non-uniformity, long zone emphasis and small zone emphasis from all subsets. GLSZM process generally generates the feature vector of 1×13 for classifier input.

- **Support Vector Machines (SVMs)**

Several applications consists the high classification accuracy provided by SVM. An SVM depends on two ideas. First idea consists the mapping of feature vectors into a high dimensional space including a nonlinear process with the utilization of linear classifiers. The second idea discriminates the information with a high margin hyperplane. This plane can differentiate the information and is the best plane. The SVM algorithm takes the cost parameter (C)as 1 that is a default value for all classification methods when using SVM algorithm.

Segmentation

Literature exhibits several methodologies for lung segmentation focused to solve different issues [67-68]. For example, U-Netis a general methodology used for COVID applications that conduct the segmentation on both lung lesions as well as regions [69]. Ronneberger [51] proposed the fully convolutional network process as U-Net as it has the U-shape structure along with symmetric encoding/decoding of signal paths. Shortcut connections link the two paths of having the same level layers. Such case involves the network with detailed contextures and superior visual semantics learning that is appropriate for medical image segmentation.

Researchers have developed several U-Net and its constraints attaining appropriate segmentation outcomes for COVID-19applications. Çiçek*et al.* [70] suggest utilizes the inter-slice data as 3D U-Net by changing the layers of traditional U-Net by 3D version. Milletari*et al.* [71]suggest V-Net model that uses basic convolutional block as residual block and maximize the performance of network via Diceloss. Shan *et al.* [72] utilize a VB-Net for highly effective segmentation by equipping the bottleneck blocks as the convolutional blocks. Zhou *et al.* [73] suggest another process as UNet++ that is the advance and complex version of U-Net. It has the process that features nested convolutional architecture inserted network between the paths of encoder and decoder. Such network type can enhance the segmentation performance. Although, it becomes hard to train. This process also helps in positioning the lesionsin the diagnosis of COVID-19.

The most discriminant section of network features can be learnt from the recent advanced trending mechanisms. Oktay*et al.* [74] suggest an appropriate model for lung nodules and lesions segmentation by capturing the fine structures via U-Net in medical images ofCOVID-19 applications. Sufficient labeled data required to train a robust segmentation network. The definite training data for segmentation operations in COVID-19 image segmentation is generally unavailable as manual delineation for lesions is time consuming as well as labor-intensive. Human knowledge with a straightforward method can address this computation. For instance, Shan *et al.* [72]combine the methodologies of human-in-the-loop into VB-net training depending on segmentation network that includes the interconnection with radiologists into network training. Qi *et al.* [69] define the lung lesions utilizing U-Net with preliminary seeds delivered by a radiologist. Attention mechanism can identify the infected regions with the help of numerous diagnostic knowledge.

Result

All model has one aim to diagnose the COVID-19 efficiently, mostly by using the heat map of subjects. Such models exhibit the lacking of effectiveness in cases of ARDS as well as pneumonia. The X-ray images of heat map displays higher concentrated zone in confirmed cases of COVID-19with respect to the zones where disease is not visible. Such model can compute the efficiency of clinical procedure depending on heat map as shown in Fig. 2.

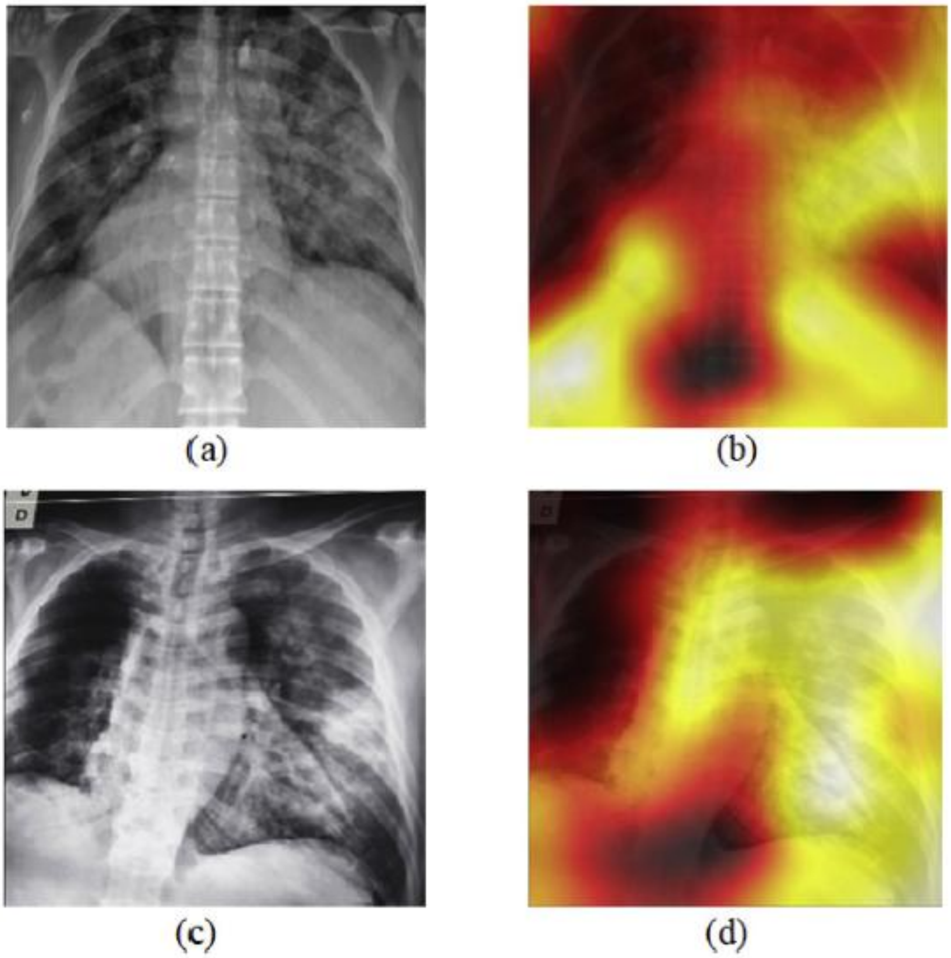

Fig. 2 Representation of heat map via images of X-ray images: (a) first X-ray image, (b) heat map of (a), (c) second X-ray image, and (d) heat map of (c) [75].

Furthermore, it helps to clinical experts in isolation, treatment, follow-up and diagnosis of patients. The difference between pneumonia with COVID-19 patients as shown in Fig. 3. The initial findings monitored by radiologists by chest X-rays of COVID-19 patients are as follows;

- Traction bronchiectasis.
- Bronchovascular thickening (in the lesion).
- Air space consolidation.
- Anirrational paving exterior (intra/interlobular septal thickening and GGOs).
- Ground-glass opacities (GGO) (basal, medial, posterior, peripheral, sub-pleural, multifocal and bilateral).

Similarly, chest X-ray findings of pneumonia patients are observed as follows;

- Bronchial wall thickening
- Distribution more along the bronchovascular bundle
- Vascular thickening
- Reticular opacity
- Unilateral and central distribution of Ground-glass opacities (GGO)

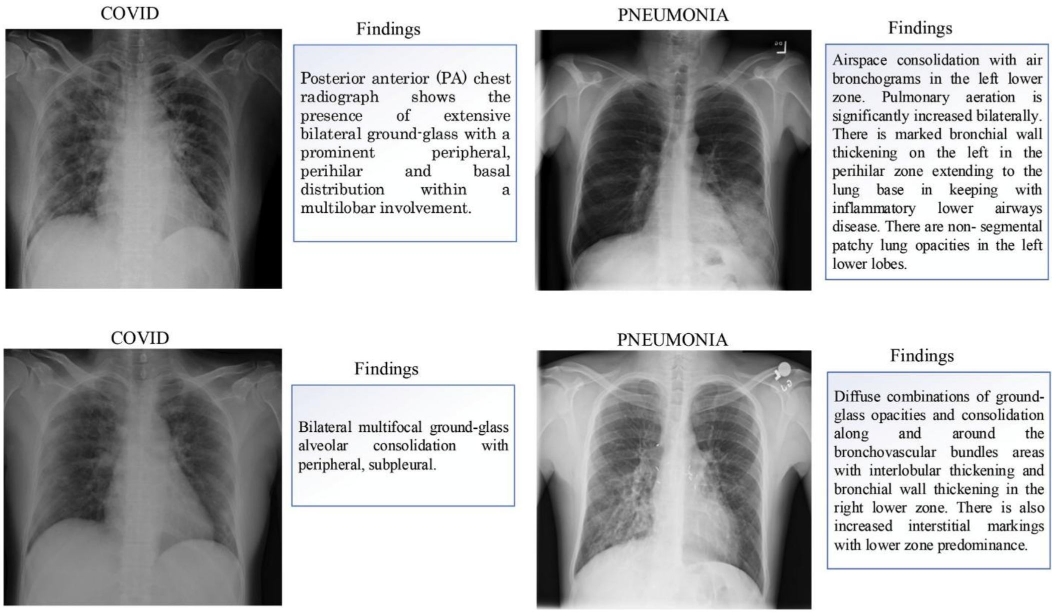

Fig. 3Differences observed by the radiologist between some COVID and pneumonia case images [75].

The COVID-19 cases involve the segmental consolidation or seperated lobar excluding GGO, pleural effusion with hilar lymphadenopathy smoother interlobular septal thickening, cavitation, pneumothorax, tree-in-buds and several tiny pulmonary nodules are rare, while such signs are often observed in pneumonia.

Conclusion

The radiological imaging plays a significant role in such COVID-19 pandemic as the diagnostic examinations conducted for preliminary diagnosis, isolation stages and treatment of the disease. In case of COVID-19, chest radiography can identify some feature findings from the respiratory organs as lungs. Advance image processing techniques can detect the sensitive zones affected by COVID-19 and therefore the accuracy rate of diagnostic is very high. The model evaluation uses the PCR test for the confirmation as positive cases of patients via X-ray images of COVID-19. Such methodologies can easily identify the COVID-19 on X-ray images by the detection of nodular opacities, consolidation zones and GGO that are pathognomic outcomes of patients. The image processing models can identify the lesion localization by monitoring the peripheral, lower lobe and bilateral involvement.

Such systems are specifically significant in detecting the preliminary stages ofCOVID-19 patients. It is important to diagnosis the disease at its early stage in order to deliver the instant treatment and to avoid disease spreading. Such systems can also play an essential role in patients having the insufficient symptoms.Such process also involves the error margin in patients with meaningfully condensed lung ventilation as well as in patients with diffuse late lung parenchyma because of poor X-ray image quality. Radiologists found it difficult to evaluate if the X-rays are not of optimal quality. The later stage patients showing the radiological and clinical images are well recognized and easier to identify the symptoms. Image processing can prominently diagnose and screen the images when the disease is at initial stage. Healthcare centers can readily utilize such models. People do not require to wait for long hours as the completion of basic procedure such as images screening. Therefore, patient relatives as well as healthcare workers can isolate the doubtful cases so that further treatment can initiate. It prevents the further spreading of disease.

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