An Automated System for the Classification of COVID-19, Suspected COVID-19 and Healthy Lung CT Images based on Local Binary Pattern and Deep Learning Features

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Abstract

Because of the inadequate capacity and a substantial surge of probable COVID-19 cases, several health systems around worldwide have collapsed. As a result, the requirement for a rapid, effective, and precise way to reduce radiologists' workload in diagnosing suspected instances has arisen. The goal of the present study is to develop a novel system to automatically diagnose and classify lung CT scans into three categories: suspected covid-19, covid-19, and healthy lung scans. Before feature extraction using convolutional neural network (CNN) and Local Binary Pattern (LBP) approaches, the CT scans are first pre-processed through implementing a set of algorithms. Lastly, with the use of the support vector machine (SVM) model, such features are divided into three groups. The maximum accuracy attained in classifying a dataset of 351 CT scans of the lungs was 98.22%. The outcomes of the experiments show that merging the extracted features increases the effectiveness of lung classification CT scans. 436

Key Words: Deep Learning, COVID-19, LBP, CNN, CT Lung Scans, SVM Classifier.

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Introduction

The process and approach of imaging a body interior for medical the interventions and clinical analyses, along with visual representation regarding function of particular tissues or organs [1], is known as medical imaging. The WHO declared the emergence of a new viral disease known as coronavirus (COVID-19) as an international public health concern on Jan. 30th, 2020 [2]. COVID-19 has been a major outbreak that quickly spread throughout China and after that to other nations. Various economic, political, and sporting events were disrupted by the virus, which impacted the lives of many individuals around the world. The novel coronavirus's most notable feature is its capacity to propagate quickly and widely. The infection can induce severe pneumonia, which can be fatal. COVID-19 is also extremely contagious, which is why it should be diagnosed promptly so that the infected person can be isolated and the disease can be contained. Today, The virus is primarily transmitted directly from infected persons to others; however, it can also be spread indirectly via surfaces and air in environment when infected individual come into touch with it [3].

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Thus, appropriately diagnosing the symptoms of those who have this disease and quarantining them have a significant impact on disease prevention. COVID-19 can be identified early on, which allows the patient to be isolated and the disease to be contained [4]. Physicians, on the other hand, are extremely busy fighting the disease, necessitating the development of AI-based decision support technologies that can not only detect, yet also segment infection at lung level in an image [5]. Deep neural networks [6] have been used as a first tool to handle a variety of issues, including speech recognition [7], object detection [8], image classification [9], and drug interaction [10]. CNNs [11] in particular produced incredible breakthroughs in image processing [12]. Several researches have demonstrated the robustness and power of such approaches for image segmentation [13]. For mitigating the over-capacity of a significant amount of patients who have COVID-19, computer-aided detection and diagnoses should be used to assist the radiologists in the process of the diagnosis. COVID-19 is diagnosed using three different approaches: X-rays, blood tests, and computed tomography (CT) scans [14]. CT can be defined as one of the non-invasive medical imaging technologies that was selected because it is thought to be a significant approach for an advanced internal porosity detections and characterizations [15]. CT technology, based on Zonnveld [16], is useful in the image-guided interventions, diagnostic medicine, and evaluation of surgical and therapeutic results. Progression of the Computed Tomography applications and technology has resulted in shorter acquisition times, improved image quality, and a dramatic expansion of modern CT's clinical applications [17]. Furthermore, a diagnosis of the Computed Tomography scan could be more precise when compared to blood test like CRP (C-reactive protein Level) [18]. One of instances was tested twice negative with CRP testing before being identified positive with Computed Tomography scan and 3rd CRP test being reported positive, as indicated in [18], demonstrating that CT imaging could be more accurate compared to blood tests. Even though Computed Tomography is a useful tool for early diagnosis and screening of COVID-19, it might share textural characteristics with the COVID-19 and suspected COVID-19, making differentiation challenging, as illustrated in Figure1 [19].

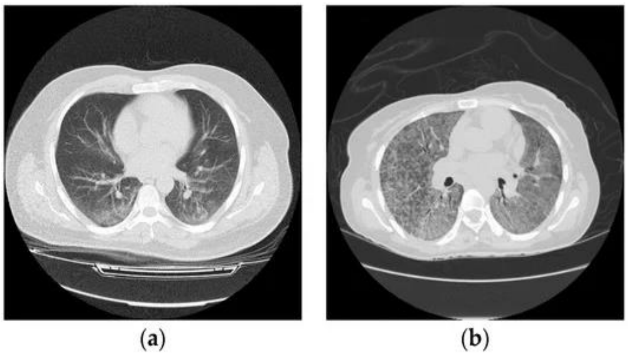

Figure 1. Lung CT slices in the axial view: (a) lung that is infected with COVID19, (b) lung that is infected by suspected COVID-19

The efficiency regarding the suggested LBP and CNN are used to distinguish between suspected COVID-19, COVID-19 coronavirus, and normal CT lung scans in the present work. The SVM is a classifier that is taken into account as an extension type of ML. The remainder of this study has been organized as: Section2 examines a few of the latest related works. In Section3, we offer a comprehensive description of suggested model. In Section 4, detailed experimental results are studied and addressed, and in Section 5, the research's results are presented.

Related Work

Because of the difficulty of detecting inflammatory and infectious lung illnesses in visual inspection, developing automated system CT images' classification of a lung is still a challenge. Even though a visual examination is a good starting point, it's prone to the errors due to a large number of the patients who must be diagnosed. Kang and Wang [20] provided an automated technique for identifying the distinctive COVID-19 features and providing clinical diagnoses regarding pathogenic tests depending on use of a CNN. The data-set, which consisted of 217 cases, had an accuracy of 82.9%. Kaya and Narin [21] developed a deep CNN for the automatic detection of COVID-19 on the X-ray images. To this purpose, they have employed transfer learning-based technique with an extremely deep architecture like InceptionV3, ResNet-50 and Inception-ResNet-V2. In the cross-validation, algorithms have been trained using 100 images (50 non-COVID-19 versus 50 COVID-19). The authors stated that InceptionV3 had a 97% accuracy rate and Inception-ResNetV2 had an 8796. Yet, because of small data-set and deep models, the over-fitting might occur and cannot be ruled out, necessitating the necessity for confirming the results in bigger data-base. Hemdan et al. built many DL models for classifying X-ray images to non-COVID versus COVID classes in Ref. [22], with VGG-16 providing optimal results with a 90% accuracy. With just 50 cases in data-base, this data-base has been severely limited once again (25 non-COVID versus 25 COVID). Research conducted by wang and wang [8] used the ImageNET database [10] for training a CNN, which was after that fine-tuned using X-ray images in order to categorize cases to 1 of 4 categories: bacterial, normal, COVID19 viral infection, and non-COVID19 viral, with a general efficiency of 83.50%. J. Zhao *et al*. [23] used 275 CT COVID-19 to develop a container for CT scans, on which they have also applied transfer learning technique utilizing chest-x-ray 14 [24] and 169-layer Dense-Net [25]. The model's efficiency has been found to be 84.70%, with 82.4% area under ROC curve. The database now has 397 images for non-COVID patients and 347 CT scans for COVID-19 patients. For detecting COVID19 and distinguish it from non-pneumonia and pneumonia illnesses, Qin and Li [19] suggested a fully automated approach based upon employing CNN as feature extractor. The total precision of data-set of 400 Computed Tomography scans in detecting COVID-19 cases was 96%. Jiang and Xu [5] suggested an automated screening approach depending on DL approaches to distinguish COVID19 or influenza-A viral pneumonia cases from these for patients with the healthy lungs. The overall attained accuracy of the classification of data-set composed of 618 Computed Tomography images of the lung has been 86.70%, according to the test results. Zheng and Song [26] created an automated system of DL diagnosis to enable clinicians in detecting and recognizing patients infected by COVID19. Healthy, COVID-19, and cases of bacterial pneumonia were represented by 86, 88, and 100 CT scans, respectively. The suggested model has a 95% accuracy in the classification of bacterial pneumonia and COVID-19 infected cases.

In this paper, we propose a new feature extraction approach depending on handcrafted texture descriptors, LBP, and DL. As a result, combining the handcrafted and DL characteristics would enhance the classification performance between suspected COVID-19, COVID-19, and healthy cases even more. The majority of the employed CNN models have been based upon deep feature extraction, working excellently with specific image types, as shown in the CT scans of lung classification techniques above. To improve the accuracy regarding the diagnosis procedure, LBP derived features are combined with DL characteristics for automated CT scans of lung classification. The following is a summary of our contributions:

(1) We demonstrated that the combined features can efficiently enhance the efficiency of the classification of lungs in CT scans through achieving effective classification results with limited computational resources and smaller number of the parameters on collected 351 chest Computed Tomography scans.

(2) The suggested fully convolutional network design has seven layers and is utilized for extracting deep characteristics from CT scans of the lungs.

Materials and Methods

The core-aim of the present study was to build an automated algorithm that informs COVID-19, suspected COVID-19 and healthy lung scans of CT.
This will also increase the quality of diagnosis procedures because clinicians will be able to devote more attention to patients with pathological lungs. In addition, it assists clinicians in ignoring CT lung images of healthy patients. It all starts with the Cancer Imaging Archive data download. The suggested system is divided into four stages: As can be seen in Figure 2, CT images are preprocessed, deep and handcrafted feature extraction is performed, feature selection is made, and then an SVM network is utilized for classifying the chosen features to 3 classes (which are: suspected COVID-19, COVID-19, and healthy).

1. Data Collection

This research included 337 chest CT scans from Radiopaedia and the TCIA (i.e. Cancer Imaging Archive) website [27], comprising 118 Computed Tomography scans of the COVID-19 infected patients, 112 Computed Tomography scans of patients that have been suspected to have COVID19, and 107 Computed Tomography scans of the unaffected individuals with no visible chest infections.

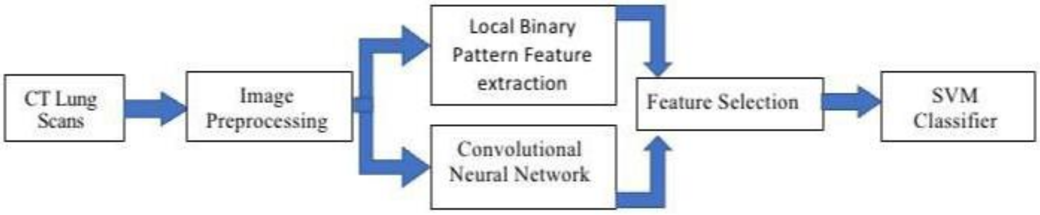

Figure 2. Diagram of suggested model

The former is a free international collaborative radiology educational web source, including open-access data-sets for massive archive of the medical images for the public downloads, whereas the latter comprises open-access data-sets for big archive that includes medical images. The National Cancer Institute's (NCI) Program of Cancer Imaging and Univ. of Chicago are both sponsors of the site. The healthy Computed Tomography scans have been taken from persons with diseases in one of the lungs and a healthy lung in the other.

2. Pre-processing of Lung CT Scan

The collection of a million independent detector measurements is used to determine the various forms of Computed Tomography artifacts that result from the process of image reconstruction. Any errors in such measurements will impact scans and cause intensity variations across consecutive re-constructed Computed Tomography scan slices [28]. The lung CT slices are pre-processed by running an algorithmic set on them for preparing them for the feature extraction stage. This step contains lung CT slice enhancement with a Gaussian filter, as well as CT slice intensity normalization. Furthermore, because an axial image of Computed Tomography scan comprises a large amount of the insignificant pixels, such processes aid in distinguishing the edges of the lung from the surrounding thoracic tissues [29]. Through thresholding the values of the intensity by an average value of every one of the Computed Tomography slice separately, the thresholding of the histogram has been utilized in order to extract the lung CT scan's background. Following that, morphological techniques like hole filling and dilation are used for removing any holes that occur in the segmented image [29, 30]. The segmentation process' flaws are after that addressed by deleting all small connected objects. Therefore, the original CT lung scan is multiplied with binary mask with 0's representing the background 1's representing the lung and to extract just the effective pulmonary areas [5]. A sample of how the lung CT slice has been segmented is shown in Figure 3.

3. LBP Feature Extraction

The feature of the texture is vital in various analyses of the medical images, and it offers a major benefit in medical image classification. LBP can be defined as a second order statistical approach that is used to provide information about the CT lung scan texture patterning. It is based upon signs of the differences between the adjacent pixels and the central ones.

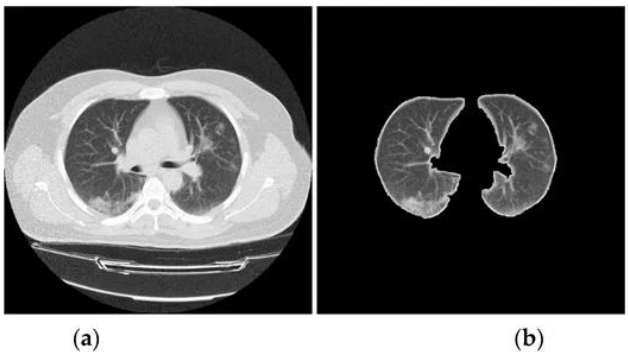

Figure 3. Lung boundary identification example: (a) original CT image, (b) segmented CT image

The adjacent pixel is converted to 1 in the case where the value of the pixel was greater than or equal to the value of the threshold, and it is converted to 0 in the case where that value has been smaller than the threshold. The number of the histogram bins is dependent upon the number of the pixels that are involved in the estimation of the LBP. In the case where the LBP utilizes eight pixels, the number of the histogram bin becomes 10 (i.e. 256) as shown Fig 4.

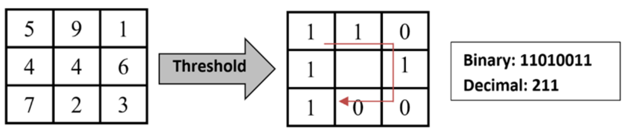

Figure 4. Representation of LBP

LBP divides the image into 3 × 3 sized. The LBP is calculated using Eq.1.

$$LBP\left(gp_x, gp_y\right) = \sum_{p=0}^{p-1} S(gp - gc) \times 2^p \quad (1)$$

gc - the central pixel's intensity value
gp - the neighboring pixel's intensity with the index p

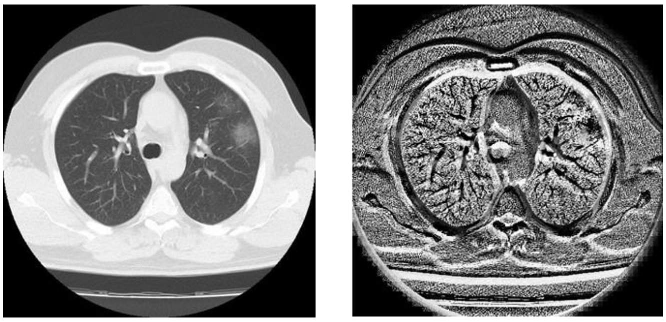

Figure 5. The original image (left) processed by the LBP operator (right) at P=8 and R=1

Function S may be represented in the following form:

$$S(x) = \begin{cases} 1 \; if \; x \geq 0 \\ 0 \; if \; x < 0 \end{cases} \quad (2)$$

Feature vectors that have been obtained through LBP application have been captured into a histogram. The parameter of the radius that has been utilized was set to 1 (pixels) and number of the points that should be considered is set to 8. The resultant histograms will have ten dimensions (i.e. bins) for every one of the CT scan images.

4. Deep Learning for Feature Extraction

In various computer vision systems, the DL approach was shown to be suitable as a feature extractor that may be utilized to improve classification accuracies [18]. The CNN is utilized for learning a feature extraction model which is utilized for extracting deep features so as to extract more effective features. As a result of mixing DL with handcrafted features, accuracy of the classification has been improved.

CNN architecture version includes three layers, which are; pooling layer, convolution layer, and fully-connected layer. Each convolutional layers consists from a set of kernels (i.e. convolution filters). These kernels are accountable for specifying a tensor of the feature maps by convolving with input volume and moving with a certain amount named "stride (s)". While, the dimensionality of feature map is reduced through the pooling layer by using max pooling function. After that, a layer of batch normalization is utilized for the acceleration of the process of training, as well as regulating CNN, through the normalization of feature maps. Ultimately, normalized feature maps have been provided to fully connected (FC) layer, representing the most significant CNN layer. Where high- level traits are extracted for a certain task.

The most significant goal of CNNs is the extraction of high-level characteristics for certain tasks. Which is why, there is a high necessity for knowing how a network has been modeled, the size and the number of the convolution layers, the way those layers have been connected and the way computed tomography slices are provided to network. In the present work, for the purpose of avoiding CNN's computational complexity, CT slice dimensions are re-sized to 128 x 128 pixels. The suggested architecture of the CNN with certain input computed tomography slice of 128 x 128 size is illustrated in Figure 6.

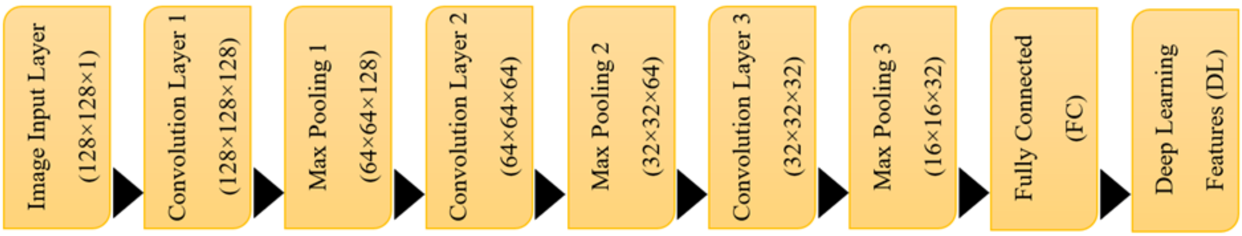

Figure 6. The proposed structure of CNN

The analysis of variance (ANOVA) approach is after that used for combining and refining the handcrafted and DL characteristics. Through specifying the F-statistic value and p-value, ANOVA represents an effective statistical approach for the elimination and ignoring of the redundant and irrelevant features in feature vector.

Experimental Results

Experimentally, ten statistical descriptors were determined by LBP and 3 descriptors are determined by CNN from each CT lung slice. That's mean there are 13 descriptors are determined from each CT lung modalities by LBP and CNN methods respectively. Because of not all features that have been obtained are important and relevant, the number of features is reduced from 13 to 10 significant features by applying ANOVA method. Table 1, demonstrates the selected and ignored features. The ANOVA has been carried out with the use of the IBM SPSS program V.20.

In this investigation, a CT scan in axial viewing was employed since clinicians prefer it for the diagnosis of lung disease since it's very sensitive to COVID19 and suspected COVID-19 infections. The collected data is used to assess the suggested approach, in which 70% of the Computed Tomography scans are utilized throughout training phase, and 30% have been utilized in order to evaluate the final performance. Fig. 7 displays a sample of Computed Tomography lung images from the collected dataset of normal, COVID-19, and probable COVID-19.

The optimal number of the convolution layers, pooling layers, neurons, kernel size and learning rate of the CNN are experimentally determined. The proposed CNN includes 7 layers as summarized in Table 2. The following parameters of suggested CNN are set experimentally: the learning rate is set to 0.001with Adam Optimizer, and the maximal number of the epochs is 40 with minimal batch size of 128. Experiments are implemented on an Intel i7-6700 HQ CPU (2.6GHz) 8GB RAM, NVIDIA GTX950 GPU, 64bit Windows 10, MATLAB 2021a.

Table 1. Comparison between the selected features which is highlighted in white and ignored features which are highlighted in gray.

Features	*F-statistics*	*P-value*
1	515.1	0.003
2	483.74	0.006
3	35.64	0.03
4	7.04	0.09
5	77.62	0.009
6	90.72	0.008
7	243.9	0.007
8	283.12	0.007
9	311.93	0.0065
10	475.92	0.006
11	123.75	0.0078
12	240.15	0.007
13	27.76	0.035

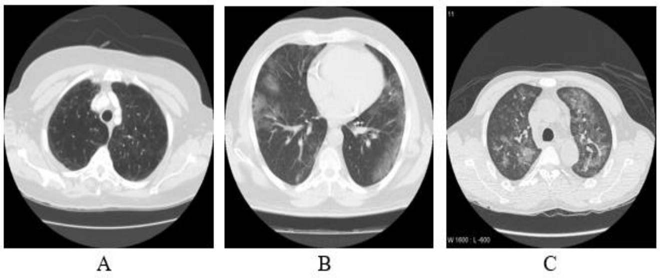

Figure 7. Samples of CT lung from obtained data-set: A) healthy scan, B) COVID-19 scan, C) suspected COVID-19

The training process is depicted in Figure 8 as a function of the number of the iterations. This indicates that CNN's suggested architecture is effective at extracting deep features (DF) from CT scans regarding the lungs. In Table 2, sensitivity, accuracy, and specificity metrics are calculated and put to comparison with the performance of each approach alone to see how effective the combined characteristics are. The lowest classification accuracy, obtained with LBP features, was 93.17%. The DL features, as shown in Table 2, attained a classification accuracy of 95.84%. The combination of LBP and DL features, on the other hand, enhanced classification accuracy to up to 98.22%. As seen in the experiment results, combining features resulted in classification accuracy that was somewhat greater than when the features were used individually.

Table 2. Suggested CNN model

Layers	**Size of the Kernel**	**Feature Maps**
Input layer	(128×128)	
Conv1	(3x3)	(128×128×128)
Max. Pooling 1	(2x2)	(64×64×128)
Conv2	(3x3)	(64×64x64)
Max. Pooling 2	(2x2)	(32x32x64)
Conv3	(7 x 7)	(32×32x32)
Max. Pooling 3	(2 x 2)	(16×16×32)
Fc	(1 x 3)	(1×3)

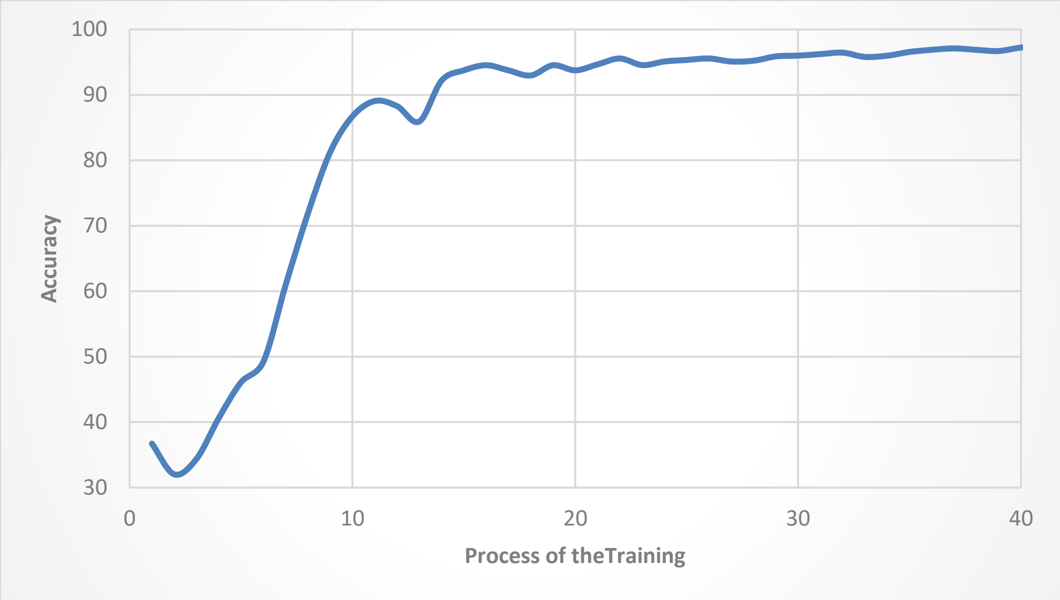

Figure 8. The training procedure of proposed CNN

Table 3. Comparisons of LBP, deep features and combined features respectively using SVM

Method	Accuracy100%	Sensitivity 100%	Specificity 100%
LBP	93.17	84.42	98.14
Deep feature	95.84	89.74	99.10
Combined Features	98.22	96.33	99.12

The performance regarding the SVM classifier is put to comparison with the achieved accuracy of other classifiers like Boosted Trees, Cubic KNN, Linear Discriminant and Nave Bayes in Table 4 to highlight the efficiency of the suggested work. These findings demonstrate SVM's advantage in accurately classifying lung CT scans. The robustness of the SVM network and the combined feature set (DL and LBP) considerably improved the classification efficiency of CT images of the lungs in the presented work.

Table 4. Classification results obtained from Cubic KNN, Boosted Trees, Naïve Bayes, Linear Discriminant and SVM.

Method	Accuracy100 %	Sensitivity 100%	Specificity 100%
Cubic KNN	89.02	76.92	96.61
Boosted Trees	93.17	85	97.69
Naïve Bayes	96.14	91.22	98.65
Linear Discriminant	95.54	89.65	98.64
SVM	98.22	96.33	99.12

Conclusion

To be clear, the visual diagnosis performed using CT images is regarded a personal diagnosis depending on the radiologist's competence, and tissue analysis was explored for creating the diagnostic process using CT images. The current features aid to categorize normal and pathological textures. If a larger number of parameters are extracted for a larger number of patients with lesions. Development of a beneficial model can help specialist physicians for early diagnosis and treatment options in a shorter period. The combined LBP and deep learning features achieve the highest accuracy of 99.22%, with the SVM successfully classifying all CT lung scans except two COVID-19 CT images, two healthy CT images, and two suspected COVID-19 CT images are failed to classify correctly.

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