Al-driven deep and handcrafted features selection approach for Covid-19 and chest related diseases identification

Saleh Albahli1 · Talha Meraj2 · Chinmay Chakraborty3 · Hafiz Tayyab Rauf4

Received: 1 April 2021 / Revised: 29 September 2021 / Accepted: 13 July 2022
Published online: 3 August 2022
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Abstract
To identify various pneumonia types, a gap of 15% value is being created every five years. To fill this gap, accurate detection of chest disease is required in the healthcare department to avoid any serious issues in the future. Testing the affected lungs to detect a Coronavirus 2019 (COVID-19) using the same imaging modalities may detect some other chest diseases. This wrong diagnosis strongly needs a multidisciplinary approach to the right diagnosis of chest-related diseases. Only a few works till now are targeting pathological x-ray images. Many studies target only a single chest disease that is not enough to automate chest disease detection. Only a few studies regarding the observation of the COVID-19, but more cases are those where it can be misclassified as detecting techniques not providing any generic solution for all types of chest diseases. However, the existing studies can only detect if the person has COVID-19 or not. The proposed work significantly contributes to detecting COVID-19 and other chest diseases by providing useful analysis of chest-related diseases. One of our testing approaches
achieves 90.22% accuracy for 15 types of chest disease with 100% correct classification of COVID-19. Though it analyzes the perfect detection as the accuracy level is high enough, but it would be an excellent decision to consider the proposed study until doctors can visually inspect the input images used by models that lead to its detection.

**Keywords**  AlexNet · COVID-19 · DenseNet201 · Inception-V3 · ResNet101 · ResNetInception-V2

1 Introduction

There are many deadly diseases in the world. Chest-related diseases are also a significant type of those deadly diseases. Due to these diseases, a 15% death ratio is preserved in the world’s total death rate. More than 450 million people in one year are affected by pneumonia-related diseases. Covid-19 is also a chest infection. WHO declared COVID-19 as a pandemic. It starts at the last of 2019 in Wuhan, China. It is similar to Pneumonia but also shows other illnesses in the other parts of the body [39]. To test this COVID-19 and distinguish it from other pneumonia types, medical health care centers needed an accurate tool. Usually, to diagnose the abnormalities in the body, doctors prefer to diagnose using radiographs.

To diagnose abnormalities, standard diagnostic tools are used. These radiographs images diagnosed by its specialist, called Radiologists. Using these radiographs, analyses for an ordinary person or doctor is complicated. Similarly, COVID-19 in some countries is diagnosed using the same radiographic tool. However, this pandemic decreases the number of specialists in this domain. The demand for such specialists increases all over the world [29, 33]. Lung diseases overlap in symptoms which confuses the radiologist to detect the disease accurately. Lung cancer shows several symptoms like shortness of breathing, chest pain, cough, weight loss, headache, and many more. These symptoms are reported by many experts using different screening procedures. These symptoms based on lung disease detection can also overlap with other lung diseases as many other lung diseases have the same symptoms.

Similarly, Pneumonia is much similar to Covid-19 in its symptoms. Pneumonia is an infection that comes mostly in a specific season of the year; its abnormality can be life-threatening. Pneumonia diagnostic modalities vary from country to country, but most diagnostic centers use X-ray, CT, and MRI scans. Using these imaging modalities, most radiologists diagnose manually. These diagnoses can be subjected to overlapping with other lung diseases. [4] There is a need to diagnose lung diseases using computer aid. However, many countries are not too stable economically; it is challenging to have enough experts in each hospital [11], Italy as an example. Moreover, with the panic caused by COVID-19, it is clear that there is a need for intelligent systems that can detect chest diseases effectively and efficiently.

CT scan imaging diagnostics can lead us to diagnose lung diseases. To detect the suspected population to decide for lung disease detection needs the appropriate solution. A non-contrast CT scan of chests is used in which Reverse Transcription Polymerase Chain Reaction (RT-PCR) is applied to detect the viral nucleic acid. Viral nucleic acid detection is the current standard to detect the COVID-19. Patient history is also evaluated in terms of fever, respiratory symptoms. RT-PCR testing is repeated once COVID-19 is confirmed in any patient. This RT-PCR testing lacks sensitivity and is reported many times by researchers. This False rate leads to severe concerns regarding other lung diseases. Other types of lung diseases like Pneumonia
are also reported as COVID-19, which is a false diagnostic result [8]. American Thoracic Society and European Respiratory Society give us the uniform criteria and guidelines to diagnose idiopathic interstitial cases of Pneumonia.

However, these guidelines have been updated by the new concerns of Fleischner Society. These updated guidelines are associated with radiologic patterns and idiopathic pulmonary fibrosis (IPF) diagnosis. A board of pulmonologists and histologists looks into the High-Resolution CT scans (HRCT) in this diagnostic method. In this method, this team looks into the specific patterns to detect the actual lungs disease. Under the decision of this team, further proceedings of treatment [7]. Diffuse Interstitial Lungs Disease (DILD) is a disease in which chronic abnormal changes occur in Lung Parenchyma. HRCT and volumetric scans are used to diagnose this disease. This diagnosis also needs to compute using computer aid rather than manual diagnosis [27].

This method sensitivity is far-right, but manual diagnosis lacks the perfectness. It leads researchers and medical industry professionals to develop efficient Radiographic image tools that can identify the maximum chest type diseases with great confidence.

To diagnose chest-related diseases accurately, including COVID-19, is the need of the day. The proposed framework aiming to provide the following contributions:

- Classify the COVID-19 and other chest diseases.
- Using X-ray images, multiple machine learning models are classifying chest diseases.
- A new resampled and enhanced dataset for chest-related diseases.
- Extracted different in-depth and HOG features.
- COVID-19 useful classification using different in-depth and HOG features.

The rest of the script consists of the following sections: Section 2 as Related Work, Section 3 Materials and methods, Section 4 Results and Discussion, Section 5 Comparison, and Section 6 Conclusion.

2 Related work

At this time, COVID-19 and other chest-related diseases are satisfying using image processing tools because these all seem to have a radical change in them. Many computers vision and image processing researchers apply deep and machine learning algorithms to achieve the best performance [1]. There are many benefits of these computer vision-based approaches to advance the diagnosis of chest-related diseases or some other diseases. These computer vision-based approaches help radiologists and patients as well to understand technically and discuss the cases. Manual diagnosis may face wide fluctuations due to some un-expertise of radiologists or less experience in some chest disease diagnosis. These computers-based classifiers cover these without more training on more data with all types of given classes.

The increasing demand for radiologists needs radiologists as equal to increasing demand. National Health Services (NHS) declare that radiologists’ demand increases by up to 30%, where the actual radiologists increase with a 15% rate. This gap ultimately creates a shortage of radiologists in this COVID-19 pandemic. Due to this increased workload on available radiologists, the rate of false diagnosis also increases. All this situation led us to say that there is a tool based upon research and development is badly needed. Many of the patients with similar symptoms of COVID-19 are diagnosed as COVID-19 where they were not. To
examine the patient correctly, the replacement of currently available diagnosis systems is also becoming another need for intelligent systems. Only a few studies are available to diagnose the chest types of diseases using Computed Tomography (CT) scans. Using a CT scan dataset of only 81 patients, the 324 lung regions are effectively reported with 80% accuracy [42]. In [28], the authors show another study that proposed a framework that can observe view-based radiographic scans to classify chest-related diseases. The authors [5] show a framework that uses projection-based profile features, and to classify the radiographic scans, a deep neural network is used.

In [3], the authors implemented a framework which is a feature mapping technique to detect chest-related problems. Authors [18] proposed the K-nearest-neighbor (KNN) based framework to detect Hernia disease categories. Meanwhile, [11] another study utilizes two features-based frameworks to identify body symmetries with background knowledge to classify radiographic scans. Similarly, [15] proposed a model to provide a new view-invariant chest infection detection.

In [20], the authors implemented Bayes’ decision theory (BDT) to classify Pneumonia. This study uses features in which they use the shape, localization with spatial facts of the medial axis of given scans, also the mean intensity of the lesion area. Study in [19] exploits a deep learning-based model called (COVNet) to classify Pneumonia and non-Pneumonia using 4356 chest scans. This study examines 3,322 patients, with an age range of 49 ± 15, males were more than female patients. This study claims a model with high sensitivity of 90% and a specificity of 96% to detect the COVID-19. However, the COVID-19 in more recent papers that contribute to COVID-19 identification using X-rays and CT scans are [19, 34, 40, 44].

These all-proposed studies deal with the binary classification of whether COVID-19 infects the patient or not. COVID-19 can be misclassified as a patient might have usual Pneumonia or some other chest-related disease. A 3D CMixNet based method is proposed to reduce the false positive to classify the lungs nodules. In this method, 3D customized mixed link structure and Gradient boosting machine-based Recurrent Convolutional Neural Network (R-CNN) are used. This method is mainly associated with physiological symptoms and clinical biomarkers. Wireless body area networks (WBANS) are used for live body diagnosis. Also, this study is tested on the LIDC-IDRI dataset [26].

A 3D analysis and 2D-Slice level Covid-19 analysis is performed in which Segmentation is performed using the U-Net method. Hospitals and doctors collect datasets and ground truth labels. This method achieves high accuracy in terms of Sensitivity and Specificity [8]. A Neural Network-based framework to classify lung cancer and Pneumonia is proposed. A modified AlexNet (MAN) is developed, and then a comparison is performed with state-of-the-art algorithms such as VGG16, VGG19, ResNet50, and AlexNet. Results show that the proposed MAN performs more than these pre-trained models in terms of accuracy rate to classify Pneumonia and lung cancer [4]. Noise is removed with the weighted histogram equalization method in Lungs CT scans. After removing noise, scans are enhanced, and then the Improved Profuse Clustering Technique (IPCT) is used to segment the lesion areas. Various Spectral features are used, and a deep convolutional neural network (D-CNN) is used to classify lung cancer. This model achieves 98.42% accuracy [33].

Abnormal Lungs 2D slices are classified using fine grain localization, and then an unsupervised-based clustering technique is used to separate the lesion area. This study used COVID-19 as a significant positive class where all other cases are considered antagonistic classes [9]. Robust U-Net-based lung segmentation on HRCT and Volumetric CT scans is
performed. The segmentation model shows accurate segmentation results, evaluation matrices used are Dice Similarity coefficient (DSC), Jaccard similarity coefficient, and other coefficients. This study claims that they proposed an accurate lung lesion segmentation method for both HRCT and Volumetric CT scans [27].

As Covid-19 is a new illness, there are not enough studies on that yet supporting artificial intelligence-based technologies to detect Covid-19 Pneumonia, non- Pneumonia, and other chest diseases patients. However, all the studies up to now classify only one class of chest-related diseases. There are only some of these studies’ conventional techniques and deliver effective results. However, these studies do not provide any perfectness as they can only identify one type of disease and do not include the others. There are only two techniques that targeted the 14 classes of chest-related diseases. One of them provided the largest publicly available chest X-rays dataset [37] and provided a new contribution to the researchers. It also proposed an in-depth and HOG features-based technique to classify the 15 diseases related to the chest [29].

There are some recent works that have uses features fusion in other medical imaging domains [17, 22, 25] that urges the proposed study to use the features fusion in its work. However, the recent workings on deep features also enhancing the other aspect of field such as knee Osteoarthritis [21]. The recent work regarding ML [6] and DL [30] based approaches on COVID-19 detection also motivated to use some different sort of strategy. Similarly, some of the similar, multi-chest pathologies are also used some other kind of AI-driven features [2, 31].

As far as we know, there is no such significant and effective method that can accurately identify these chests related diseases and declare the multiple class problem with reliable results. The proposed study aimed to productively diagnose the chest related diseases in the following classes, Infiltration, Mass, Nodule, Pneumonia, Pneumothorax, Atelectasis, Cardiomegaly, Effusion, Consolidation, Edema, Emphysema, Fibrosis, Pleural, Hernia, and COVID-19.

3 Materials and methods

Nowadays, deep learning-based tasks take advantage of massive data and utilize expensive training techniques to perform conventional machine learning tasks [41]. These tools and methods need to have comprehensive data to utilize the latest advances. If anyone is trying to use traditional tools, data needs to be very solid, as a useful model can be grasped. The overall flow of work is shown in Fig. 1.

It is shown in a framework that the proposed study uses HOG features at first and then uses resonant transfer learning features to classify lung diseases. At last, the concatenation of both types of features is used for the classification.

3.1 Dataset

The proposed study utilized publicly available datasets provided by [13, 14] to utilize useful techniques. In [14], the data set contains 15 types of different chest diseases, including the ‘No finding’ class, but it contains a different number of images for each class which means that data is not in good condition to give it to predictive models. By changing the number of instances for a particular class, predicting accuracy becomes biased for those classes
containing more instances. It is an open-source and new dataset related to COVID-19 [13], which contains many problems in it that are not a standard size, type, etc. There is a need to make both datasets to make their instances equal for each class with the same sizes and make a new dataset that contains both COVID-19 and other chest diseases images. We make a new dataset with 200 images of each class for 15 types of diseases, including the ‘No finding’ class and the COVID-19 class. New Dataset contains images in this structure as shown in Table 1.

Our proposed Dataset contains many unclear and unequal-sized images, so we need to make them explicit by sharpening and resizing images. However, our Dataset is limited as having 3000 images of all chest diseases; it can be increased.

Table 1  Resampled dataset

| Disease         | Number of Images | Dimension         |
|-----------------|------------------|-------------------|
| Atelectasis     | 200              | 1024×1024×3       |
| Cardiomegaly    | 200              | 1024×1024×3       |
| Effusion        | 200              | 1024×1024×3       |
| Infiltration    | 200              | 1024×1024×3       |
| Mass            | 200              | 1024×1024×3       |
| Nodule          | 200              | 1024×1024×3       |
| Pneumonia       | 200              | 1024×1024×3       |
| Pneumothorax    | 200              | 1024×1024×3       |
| Consolidation   | 200              | 1024×1024×3       |
| Edema           | 200              | 1024×1024×3       |
| Emphysema       | 200              | 1024×1024×3       |
| Fibrosis        | 200              | 1024×1024×3       |
| Pleural         | 200              | 1024×1024×3       |
| COVID-19        | 200              | 1024×1024×3       |
| Hernia          | 200              | 1024×1024×3       |
| Total           | 3000             |                   |
3.2 Resizing

We firstly resize the images using the interpolation method. Interpolation calculation is done using the ‘Nearest-neighbor’ method. According to this method, we use MATLAB-lines Execution Time (MET) and Peak Signal to Noise Ratio (PSNR). A prominent Peak to noise ratio determines the excellent quality of the image. This PSNR value is defined as Mean Square Error (MSE) which can be calculated as in Eq. (1), in which K and I are the noisy approximations of others.

\[
MSE = \frac{1}{mn} \sum_{i,j=0}^{m,n} I(i,j)K(i,j)
\]

We can define the PSNR value as

\[
PSNR = 10 \log_{10} \left( \frac{MAX^2}{MSE} \right)
\]

\(MAX\) representing the max image value which is certainly the lossy image compression value.

From left to right and top to bottom, the image is interpolated with the given rows and columns values for the image’s new size [32]. In [14], the dataset images size was 1024 × 1024 × 3, so we resize the covid-19 [13] images to a new size of 1024 × 1024 × 3. The results of before and after resizing are shown in Fig. 2.

We can see that using the ‘Nearest Neighbor’ method, images result after resizing giving much information, and not losing any information as compared to the original image.

3.3 Sharpening

After resizing the images of the COVID-19 class, we made the Contrast stretching on our new dataset to make all regions of the chest clearer. We applied the Contrast stretching technique in which we used the adjust function of MATLAB. In this function, we pass ‘Low_in and

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**Fig. 2** Image resizing, before (Left) and after (Right)
High_in’ values for contrast adjustment. We found 0.2 as Low_in value and 0.7 as High_in value appropriate for image contrast adjustment [23]. Image results can be shown in Fig. 3.

We further check the effect of image enhancement using histogram analysis in which we found that grey levels are much normalized after the enhancement of original images. We can see that in Fig. 4.

Histograms for the image showed that the image was containing a higher frequency of certain gray levels, but when we enhanced it, grey levels reached the normalized form.

3.4 Features extraction

Transferred Learning-based features are also used for the Classification of Covid-19 and other single lung diseases. We firstly extracted Histogram of Oriented Gradients (HOG) features, and then we classified our 15 types of chest disease with a new Enhanced and Normalized dataset.

3.4.1 HOG features

HOG features return us a vector array of features that contain encoded local shape information of a given image. These features help us track the objects in the image; they also help us classify the images containing specific information. These features can also be used to visualize due to tracking or localization quality [24]. We can see the extracted HOG features in Fig. 5.

HOG features containing information for various objects of chest scan, as shown in the above pictures. These features are essential to get the localization of lesions and typical areas. It would be significantly different for 15 types of diseases, which will lead us to classify them. However, there working depends upon these steps, as in preprocessing, the image is resized in such a way that its aspect ratio becomes equal to 1:2. After getting this aspect ratio, the image patches could be of size 8 × 8 and 16 × 16 to extract where in proposed study the patch size is set to 8 × 8. For each patch, the orientation and magnitude are calculated over from its gradient. It is used as to calculate the histogram. The orientation of gradient is calculated as:

![Image enhancement, before (Left) and after (Right)](image-url)
The $g_y$ and $g_x$ are basically the horizontal and vertical gradients that are multiplying the ratio with inverse of tangent. Similarly, to calculate the magnitude of gradients, the following equation is used.

$$\theta = \tan^{-1}\left(\frac{g_y}{g_x}\right)$$

(3)

Basically, it is the Pythagoras theorem that takes the horizontal and vertical inputs with their squares and used to calculate the overall magnitude that is also used in HOG features extraction.

$$g_{\text{total}} = \sqrt{g_x^2 + g_y^2}$$

(4)
3.4.2 Transfer learning features

ImageNet is a well-known state-of-the-art algorithm that has many custom variations with different names published globally.

Similarly, AlexNet is an ImageNet model variation trained on 1.2 million data with 1000 types of classes. It contains 25 layers in which the 6th last layer is of ‘fc7’ fully connected layer with 4096 values returned as a feature map [16]. Image Input layer size is $227 \times 227 \times 3$ in this network, so firstly, we augmented our dataset according to this input size. After that, we use the ‘fc7’ layer and perform activation on our data which returns us to the $3000 \times 4096$ values matrix where the row is considered a feature vector of the individual image.

ResNet101 or Residual Network is another variation of ImageNet which Microsoft provides. It has many versions till now ResNet19, ResNet50, ResNet101. ResNet101 has a 101-layer deep network. It also trained on more than 1 million data to classify the 1000 types of classes. The image Input layer size is $224 \times 224 \times 3$, so we also augmented the data to resize our dataset [10]. In ResNet101, there are many fully connected layers, but ‘fc1000’ is the most recent layer for activation, which we used to activate our features. It returns us a $3000 \times 1000$ size matrix in which the row is represented by a feature vector of a single image.

InceptionV3 is the third version of Inception Mode, also the derivative of ImageNet. It contains 48 layers. It also trained on more than 1 million images with 1000 classes in it. The image Input layer size is $299 \times 299 \times 3$. To make our dataset image size equal to this data, we perform augmentation to make our image size $299 \times 299 \times 3$. In this model, the densest layer with full classification is named ‘prediction’ [35]. We used this layer to activate features on our dataset, which returns us the $3000 \times 1000$ in which each row represents an individual image features vector array.

DenseNet201 is also a variation of ImageNet, which contains 201 deep layers in its structure. The image Input layer size is $224 \times 224 \times 3$ for this variation of ImageNet. To make our data input size equal to it, we again perform data augmentation on our dataset. The Deepest fully connected layer of this model is called ‘fc1000’ [12]. We perform activation on our dataset using this ‘fc1000’ layer which returns us the features matrix of size $3000 \times 1000$. We also get this matrix by row-wise concatenation of image instances.

InceptionResNetv2 is the 2nd version of InceptionResNet variation of ImageNet. It contains 146 layers in its architect, which are the mix-up of Residual and Inception Network. Its deepest, fully connected layer is called ‘predictions’ [36]. We activate this layer on our dataset by augmentation as its image input layer size is $299 \times 299 \times 3$. This returning matrix is also indicated as a row-wise concatenation of the images.

3.4.3 Serial fusion

We see above that we have six types of features. After getting these features. we concatenate them one by one to make new five types of features by making:

- HOG-AlexNet Features.
- HOG-ResNet101 Features.
- HOG-InceptionV3 Features.
- HOG-DenseNet201 Features.
- HOG-InceptionResNetV2.
These variants of new features are tested on our dataset to check the performance effect. The rest section of the article will explain the performance evaluation and the results of these features.

### 3.4.4 Classification

We tried only one well-known classifier, Support Vector Machine (SVM), on all features one by one, which gives us good results. We made 11 machine learning models by passing the above-explained features one by one. The SVM classifiers which we build using different features are given below:

- HOG Features.
- AlexNet Features.
- ResNet101 Features.
- InceptionV3 Features.
- DenseNet201 Features.
- InceptionResNetV2 Features.
- HOG-Alex Features.
- HOG-ResNet101 Features.
- HOG-InceptionV3 Features.
- HOG-DenseNet201 Features.
- HOG-InceptionResNetV2 Features.

The proposed study sees further increase and decrease in accuracy with each approach of features. Moreover, the results are shown in a later section.

### 4 Results and discussion

For results and comparison, the proposed study check fact of one-to-one features feeding to the Support Vector Machine. The facts and accuracy measures of each class have been shown below. Firstly, start with HOG features and shown its confusion chart with predicted accuracy and error of individual disease are shown in Fig. 6.

From the above image, we can see that Cardiomegaly, Emphysema, Fibrosis, hernia, and Pneumonia achieve 100% accuracy, where overall global accuracy is 87.56% with a specificity of 99.11%. However, after getting HOG features predicting accuracy results on our data, the proposed study further moves to extract resonant transfer learning features. The AlexNet Features predictions on testing data are shown in Fig. 7.

From the above image, the individual accuracy and error are shown where the global accuracy of AlexNet features is 89.56% with a 99.25% specificity value—however, Cardiomegaly prediction downs where Fibrosis, Hernia remains constant as per 100% accurate predictions. Let us move towards the next deep features extraction and prediction results. The ResNet101 is used to extract features where prediction results are shown in the confusion chart in Fig. 8.

As shown in the above image, the COVID-19 gives 100% true negative and optimistic prediction where pneumonia predictions are also shown the same accuracy results. However, if
we see other individuals, some predictions are wrong, but the global accuracy reaches up to 90.22% with a specificity of 99.30%. For this approach, future studies may consider these features as meaningful features for COVID-19 and Pneumonia identification. After getting these results, the InceptionV3 is used to extract the next feature set. The results are shown in Fig. 9.

The above image shows that we again got COVID-19 100% prediction results, but this time we more two classes include 100% identification results. The global accuracy reaches up to 89.11%, with a specificity of 99.22%. After getting these results, we move next to get in-depth features of DenseNet201. The testing data prediction results are shown in Fig. 10.

The above image showed that COVID-19 accurate predictions are still constant where other accuracies are varying. The global accuracy is 89.78% of all classes, where the specificity value is 99.27%. To get more in-depth features and observations, we further extracted InceptionResNetV2 features. The predicting results on testing data are shown in Fig. 11.
The predicted results with InceptionResNetv2 are shown in the above image, which clearly states that COVID-19 is not more than 100% accurately predicted disease, where Cardiomegaly and Hernia predict 100% accuracy. However, global accuracy of 88.67% with a specificity value of 99.19%. After getting these all deep and HOG features, the proposed study further concatenates or fuse the features to check results. The HOG features are concatenated with AlexNet features to perform testing and training upon the Support Vector Machine. The results are shown in Fig. 12.

Above image shown a 100% accurate prediction of COVID-19 with more than four types of chest diseases where both approaches as individuals were not improving the results to this extent. The global predicting accuracy reaches up-to 89.33% with a 99.24% specificity value. However, the results are good, but the proposed study further approaches the HOG features concatenation with other in-depth features. The HOG features concatenation with ResNet101 prediction results are shown in Fig. 13.

![Fig. 8]: ResNet101 Features testing using SVM

![Fig. 9]: InceptionV3 Features testing using SVM

![Table 1](image1.png)
The above image shown 100% results of Individual COVID-19 in ResNet101 are not anymore 100% with HOG features’ concatenation. However, three diseases showed better performance. The global accuracy of this approach is 88.11%, with 99.15% specificity values. The further concatenation is respectively done with InceptionV3. The results are shown in Fig. 14.

The predicting accuracy is further down for COVID-19 as 89.4%, where four diseases predicted 100% true. The global accuracy achieved is 88.22%, with a 99.16% specificity value. The further concatenation of features is being done using DenseNet21. The testing results are shown in Fig. 15.

COVID-19 is no more 100% in these features, but the other four classes have good results. The prediction results globally show 86.67% with 99.05% specificity as the lowest accuracy.
among all proposed study approaches. The further and last approach of the proposed study with features concatenation of InceptionResNetV2 is shown in Fig. 16.

This approach also fails to achieve any better results as COVID-19 accuracy is 93.2%. However, the global accuracy is 87.78%, with a 99.13% specificity value. The proposed study trained and tested features using a 70 − 30 ratio.

We got 900 testing images of all 15 classes of our new dataset according to this split ratio. Moreover, we can see that COVID-19 classified as 100% true using four types of features. The proposed study can be considered a high positive rate of classification of COVID-19 from other lung diseases. Table 2 representing all features selection approaches results as a comparison of the proposed study. The ResNet101 results are bolded that are showing the best results among all of achieved results.

The total 11 types of designed features vectors have been shown with global accuracy, error rate, sensitivity, specificity, F1-score and statistical measure of kappa. The HOG, AlexNet, and then both HOG-AlexNet fused feature is used to get multi-features approach. It is being analyzed that the AlexNet features as individual performs better than the fusion of HOG features with it. However, with multi-type of features approaches, the HOG-Alex accuracy
also achieves 89.33%. The next, ResNet-101 and its fusion with HOG features is being shown. In this case, the ResNet-101 have much accurate results as compared to ResNet101-HOG features. The COVID-19 shown 96.7% accurate results of prediction among other chest diseases. It may be due to more strong features of ResNet-101 as individual. Similarly, in inceptionV3 of extended version of GoogleNet, the accuracy results for individual use of features are good as compared to fused feature vector with HOG. Also, the DenseNet features as individual shown more accuracy than the concatenation. The inception-resnetV2 also shown more accuracy than the fusion of HOG features.

From all above results, its being analyzed that the features activation of individual network, not with fusion of HOG features are improved results. Therefore, the individual use of these architectures with scratch training, may can lead to more confident results of chest diseases detection.

![Fig. 14](image1.png)

**Fig. 14**  HOG-Inceptionv3 Features testing using SVM

![Fig. 15](image2.png)

**Fig. 15**  HOG-DenseNet201 Features testing using SVM
4.1 Evaluation measures

There is different sort of evaluation measures are being used by proposed study that includes mainly accuracy measure, sensitivity, specificity, F1-score and Kappa index. These all can be calculated as described in Eqs. 5, 6, 7, 8 and 9.

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}
\]

The accuracy measure is a global measure of performance for any kind of prediction tasks that is calculated as the ratio of sum of true positive and negatives over the summation of all true and false negatives and positives as shown in Eq. 5.

| SVM Models          | Global Accuracy (%) | Covid-19 Accuracy (%) | Error | Sensitivity | Specificity | F1-score | Kappa  |
|---------------------|---------------------|-----------------------|-------|-------------|-------------|----------|--------|
| HOG Features        | 87.56               | 100                   | 0.124 | 0.8756      | 0.9911      | 0.877    | 0.089  |
| AlexNet Features    | 89.56               | 96.7                  | 0.104 | 0.8956      | 0.9925      | 0.895    | 0.160  |
| HOG-AlexNet Features| 89.33               | 93.3                  | 0.106 | 0.8933      | 0.9924      | 0.893    | 0.142  |
| ResNet101 Features  | **90.22**           | **96.7**              | **0.097** | **0.9022** | **0.9930** | **0.900** | **0.214** |
| HOG-ResNet101       | 88.11               | 90.0                  | 0.118 | 0.8811      | 0.9915      | 0.882    | 0.044  |
| InceptionV3 Features| 89.11               | 86.7                  | 0.108 | 0.8911      | 0.9922      | 0.890    | 0.125  |
| HOG-InceptionV3     | 88.22               | 98.3                  | 0.117 | 0.8822      | 0.9916      | 0.882    | 0.053  |
| DenseNet201 Features| 89.78               | 96.7                  | 0.102 | 0.8978      | 0.9927      | 0.895    | 0.178  |
| HOG-DenseNet201     | 86.67               | 93.3                  | 0.133 | 0.8667      | 0.9905      | 0.869    | 0.066  |
| InceptionResNetV2   | 88.67               | 86.7                  | 0.113 | 0.8867      | 0.9919      | 0.885    | 0.089  |
| HOG-InceptionResNetV2| **88.78**           | **91.67**             | **0.122** | **0.8778** | **0.9913** | **0.881** | **0.018** |
\[
\text{Sensitivity} = \frac{TP}{TP + FN} \tag{6}
\]

The Sensitivity is calculated specifically to evaluate the true positives rates that are calculated over the sum of true positives and false negatives. It specified the true positives predictions ratio as show in Eq. 6.

\[
\text{Specificity} = \frac{TN}{FP + TN} \tag{7}
\]

The Specificity is used to get true negatives rate over the sum of false positives and true negatives as shown in Eq. 7. It mainly highlights the predictivity of a model in terms of true negativity.

\[
F1 - \text{Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{8}
\]

The F1-score is the measure of precision and recall product that is taken as nominator with the denominator of sum of these. The 2 co-efficient is multiplied later on to get the actual F1-score. In proposed study, the main F1-score is compared with other studies as it includes both the precision and recall.

\[
Kappa - \text{agreement} = \frac{\left( \frac{cm1 \times rm1}{n} \right) + \left( \frac{cm2 \times rm2}{n} \right)}{n} \tag{9}
\]

The kappa is the statistical measure that is used to give a level of agreement on given data where it gets calculated by given confusion matrix of all categories. As in proposed study, there are 15 categories. Therefore, it will get multiplied 15 times in a sequence of confusion matrix 1,2,3…15 where \(cm\) representing the column margin in confusion matrix and \(rm\) represents to the row margin and \(n\) is the number of observations taken into consideration.

5 Comparison

Covid-19 classification from other lung diseases is in research nowadays. Much Deep Learning and Machine Learning based techniques are developed to diagnose COVID-19 from other lung diseases. CheXNet is developed for fourteen types of chest pneumonia diseases which achieves good results to classify pneumonia. In this model 127 layer, a CNN architect is proposed [29]. It compares it results in terms of F1-Score with [38] and achieved more accurate predictions. Another uses LSTM rather than using the pretrained models. However, it shown the individual class results using 15 classes including No-findings category as well [43]. However, the proposed study feels to add the COVID-19 as another chest disease that may can be added with given NIH-X-rays dataset. If we discuss about the comparison with each given chest pathological category as shown in Table 3.

The first diseases, atelectasis achieved more improved F1-score than the compared studies where in cardiomegaly, the 1st compared study have more score than the proposed study where it achieved more F1-score than the other two compared studies. Effusion is better than the [38] reported F1-score where it is less than the other two compared studies. The Infiltration F1-score of proposed study is higher than all compared studies. Similarly, for Nodule, Pneumonia, Consolidation, Edema, Emphysema, Fibrosis, Pleural Thickening, Hernia and COVID-19, the
proposed study achieves higher F1-score. If we look as mean F1-score than the 11 diseases achieve higher results as compared to all compared studies that make it more robust and confident approach.

6 Conclusion

Covid-19 is a chest-related disease that has many symptoms the same as other pneumonia and chest diseases. Many testing and diagnosing tools are developing to classify COVID-19 from other diseases, but most of the Study classifies the COVID-19 from ordinary pneumonia or 2 or 3 other chest-related diseases. The 14 types of chest diseases do not have COVID-19 categories or images in them [14]. The proposed Study makes a new data set by combining two sources, and then by doing resampling, image enhancement, a confined new dataset is prepared. Moreover, the proposed Study applied different types of features with the help of an SVM classifier which shows accurate detection of COVID-19 from 15 types of chest diseases. Also, the global or mean accuracy to classify the 15 types of chest diseases achieved 90.22%. The proposed Study can be used to diagnose the COVID-19 and other chest diseases, which is the need of the present time. It can help out the medical health care department to rightly diagnose COVID-19 from other chest diseases, which ultimately leads to the right treatment of specific diseases.

In the future, researchers can use the proposed Study to include more data and more chest diseases (including COVID-19) which can lead to more promising results. Similarly, big data usage of all chest disease can also make the coming studies more confident. Moreover, different Imaging modality can be used to classify chest diseases.

Declarations

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Conflict of interest The authors declare that they have no conflict of interest.
Informed consent

Informed consent was obtained from all individual participants included in the study.

References

1. Albahli S (2019) A deep ensemble learning method for effort-awarejust-in-time defect prediction. Future Internet 11(12). https://doi.org/10.3390/fi11120246
2. Albahli S, Rauf HT, Algosiba A, Balas VE (2021) AI-driven deep CNN approach for multi-label pathology classification using chest X-Rays. Peer Comput Sci 7:e495
3. Arimura H, Katsuragawa S, Li Q, Ishida T, Doi K (2002) Development of a computerized method for identifying the posteroanterior and lateral views of chest radiographs by use of a template matching technique.. Med Phys 29(7):1556–1561. https://doi.org/10.1118/11487426
4. Bhandary A, Prabhu A, Rajinikanth V, Palani Thanaraj K, Satapathy SC, Robbins DE, Shasky C, Zhang Y-D, Tavares JMRS, Sri Madhava Raja N (2019) Deep-learning framework to detect lung abnormality – A study with chest X-Ray and lung CT scan images. Pattern Recognit Lett 129:271–278
5. Boone JM, Seshagiri S, Steiner RM (1992) Recognition of chest radiograph orientation for picture.. J Digit Imaging 5. https://doi.org/10.1007/BF03167769
6. Chakraborty C, Abougreen A (2018) Intelligent Internet of Things and advanced machine learning techniques for COVID-19. EAI Endorsed Transactions on Pervasive Health and Technology, p 168505
7. Christe A, Peters AA, Drakopoulos D, Neverhagen JT, Geiser T et al (2019) Computer-aided diagnosis of pulmonary fibrosis using deep learning and CT images. Invest Radiol 54(10):627–632. https://doi.org/10.1097/RLI.0000000000000574
8. Gozes O, Frid-Adar M, Greenspan H, Patrick D, Zhang H et al (2020) Rapid AI development cycle for the coronavirus (COVID-19) pandemic initial results for automated detection & patient monitoring using deep learning CT image analysis. Image and Video Processing, vol 3, arXiv:2003.05037
9. Hui K, Zhang X, Ren S, Sun J (2016) Deep residual learning for image recognition. In: IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA
10. Hoyler M, GSR G, Finlayson M, Meara JG (2013) Shortage of doctors, shortage of data: a review of the global. World J Surg 38(2):269–280
11. Huang G, Liu Zhuang MLVD, Kilian Q, Weinberger (2017) IEEE Conference on Computer Vision and Recognition (CVPR), Honolulu, HI, USA
12. Lehmann TM, Guld O, Keyser D, Schubert H, Kohmen M, Wein BB (2003) Determining the view of chest radiographs. J Digit Imaging 16(3):280–291. https://doi.org/10.1007/s10278-003-1655-x
13. Li L, Qin L, Xu Z, Yin Y, Wang X et al (2020) Artificial intelligence distinguishes COVID-19 from community acquired pneumonia on chest CT. Radiology. https://doi.org/10.1148/radiol.2020200905
14. Luo H, Hao W, Foos DH, Cornelius CW (2006) Automatic image hanging protocol for chest radiographs in PACS. IEEE Trans Inf Technol Biomed 10(2):302–311. https://doi.org/10.1109/TITB.2005.859872
15. Mahum R, Rehman SU, Shah JH, Meraj T, Rauf HT, Damaševićius R, Mohammed MA, Abdulkareem KH (2021) Adversarial attack and defence through adversarial training and feature fusion for diabetic retinopathy recognition. Sensors 21(11):3922
16. Manzoor K, Majeed F, Siddique A, Meraj T, Rauf HT, El-Sherbeeney AM, El-Meligy MA (2021) A novel hybrid approach based on deep CNN features to detect knee osteoarthritis. Sensors 21(18):6189
17. Mathworks (2020) imadjust. Mathworks [Online]. Available: http://matlab.izmiran.ru/help/toolbox/images/imadjust.html
24. Mathworks (2020) extractHOGFeatures, Mathworks [Online]. Available: https://www.mathworks.com/help/vision/ref/extracthogfeatures.html
25. Meraj T, Rauf HT, Zahoor S, Hassan A, Lali MI, Ali L, Bukhari SAC, Shaib U (2021) Lung nodules detection using semantic segmentation and classification with optimal features. Neural Comput Appl 33(17):10737–10750
26. Nasrullah N, Sang J, Alam MS, Mateen M, Cai B et al (2019) Automated lung nodule detection and classification using deep learning combined with multiple strategies. Sensors. 19(17). https://doi.org/10.3390/s19173722
27. Park B, Park H, Min LS, Soo JB, Kim N (2019) Lung segmentation on HRCT and volumetric CT for diffuse interstitial lung disease using deep convolutional neural networks. J Digit Imaging 32(6):1019–1026. https://doi.org/10.1007/s10278-019-00254-8
28. Pietka E (1994) Lung segmentation in digital radiographs. J Digit Imaging 7(2):79–84. https://doi.org/10.1007/BF03168427
29. Rajpurkar P, Irvin J, Zhu K, Yang B, Mehta H, Duan T, Ding D, Bagul A, Bal RL, Langlotz C, Shpanskaya K, Lungren MP, Ng AY (2017) CheXnet: Radiologist-level pneumonia detection on chest x-rays with deep learning. arXiv preprint arXiv:1711.05225
30. Ravi V, Narasimhan H, Chakraborty C, Pham TD (2021) Deep learning-based meta-classifier approach for COVID-19 classification using CT scan and chest X-ray images. Multimed Syst 1–5. https://doi.org/10.1007/s00530-021-00826-1
31. Rehman N-U, Zia MS, Meraj T, Rauf HT, Damaševićius R, El-Sherbenny AM, El-Meligy MA (2021) A self-activated CNN approach for multi-class chest-related COVID-19 detection. Appl Sci 11(19):9023
32. Rukundo O, Cao H (2012) Nearest neighbor value interpolation. (IJACSA) Int J Adv Comput Sci Appl 3(4):25–30. https://doi.org/10.14569/IJACSA.2012.030405
33. Shakeel PM, Burhanuddin MA, Desa MI (2019) Lung cancer detection from CT image using improved profuse clustering and deep learning instantaneously trained neural networks. Measurement 145:702–712
34. Shan F, Gao Y, Wang J, Shi W, Shi N et al (2020) Lung infection quantification of COVID-19 in CT images with deep learning. Comput Vis Pattern Recognit 3, arXiv:2003.04655
35. Szegedy C, Vanhoucke V, Ioffe S, Shlens K, Wojna C (2016) Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift. arXiv preprint arXiv:1502.03167
36. Szegedy C, Vanhoucke V, Ioffe S, Alemi AA (2017) Inception-v4, Inception-ResNet and the impact of residual connections on learning. In: Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence, San Francisco, California, USA
37. Wang X, Peng Y, Lu L, Lu Z, Bagheri M et al (2017) ChestX-ray8: Hospital-scale Chest X-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases. Comput Vis Pattern Recognit 5. https://doi.org/10.1109/CVPR.2017.369
38. Wang X, Peng Y, Lu L, Lu Z, Bagheri M, Summers RM (2017) ChestX-Ray8: Hospital-scale chest X-Ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases. IEEE Conference on Computer Vision and Pattern Recognition (CVPR)
39. WHO (2019) Covid-19, WHO [Online]. Available: https://www.who.int/gho/publications/world_health_statistics/2019/en/
40. Xu X, Jiang X, Ma C, Du P, Li X et al (2020) Deep learning system to screen coronavirus disease 2019 pneumonia. Engineering 1. https://doi.org/10.1016/j.eng.2020.04.010
41. Yan L, Zhang Ht., Goncalves J, Xiao Y, Wang M, Guo Y et al (2020) A machine learning-based model for survival prediction in patients with severe COVID-19 infection. COVID-19SARS-CoV-2 preprints from medRxiv and bioRxiv 3. https://doi.org/10.1101/2020.02.27.20028027
42. Yang Jx., Zhang M, Zh L, Ba L, Jx G et al (2009) Detection of lung atelectasis/consolidation by ultrasound in multiple trauma patients with mechanical ventilation,. Crit Ultrasound J 1:13–16. https://doi.org/10.1007/s13089-009-0003-x
43. Yao L, Poblenz E, Dagunts D, Covington B, Bernard D et al (2018) Learning to diagnose from scratch by exploiting dependencies among labels. Comput Vis Pattern Recognit 2, arXiv:1710.10501
44. Ying S, Zheng S, Li L, Zhang X, Zhang X et al (2020) Deep learning enables accurate diagnosis of novel coronavirus (COVID-19) with CT images. Comput Vis Pattern Recognit 1. https://doi.org/10.1101/2020.02.23.20026930

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