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## Research Article

**Keywords:** COVID-19 ; Lung CT scan data ; transfer learning ; ensemble SVM ; VGG16

**Posted Date:** June 3rd, 2020

**DOI:** <https://doi.org/10.21203/rs.3.rs-32493/v1>

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**Version of Record:** A version of this preprint was published on March 18th, 2021. See the published version at <https://doi.org/10.1007/s11517-020-02299-2>.

# Transfer learning based ensemble support vector machine model for automated COVID-19 detection using lung computerized tomography scan data

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Received: date / Accepted: date

**Abstract** The novel discovered disease coronavirus popularly known as COVID-19 is a lung infection disease that causes adverse effects on the human respiratory system. It is caused due to Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) and declared a pandemic by the World Health Organization (WHO). For COVID-19 detection, chest radiography, i.e., computerized tomography(CT) scan, X-rays, etc. are widely investigated. In the proposed work, a deep learning model, i.e., truncated VGG16(Visual Geometry Group from Oxford) is implemented to screen COVID-19 CT scans. The VGG16 architecture is fine-tuned and used to extract features from CT Scan images. Further Principal Component Analysis (PCA) is used for feature selection. The final classification is performed using four different classifiers, namely deep convolutional neural network(CNN) , Extreme Learning Machine (ELM), Online sequential ELM, and Bagging Ensemble with support vector machine (SVM) . The best performing classifier Bagging Ensemble with SVM within 385 ms achieved an accuracy of 95.7%, precision of 95.8%, Area Under Curve (AUC) of 0.958, and an F1 score of 95.3% on 208 test images. The results obtained on diverse datasets prove the superiority and robustness of the proposed work in comparison to the techniques available in the literature.

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**Keywords** COVID-19 · CT scan data · transfer learning · ensemble SVM · VGG16

## 1 Introduction

The chest infection is a kind of infection that affects the proper functioning of the lungs (both larger and smaller airways) [1]. The severity of a lung infection depends on several factors like causes of lung infection (virus or bacteria), and the overall health of the infected person. The most common lung infections are pneumonia, Chronic Obstructive Pulmonary Disease (COPD), asthma, bronchitis, and lung cancer. Coronavirus disease popularly known as COVID-19 is a kind of lung infection disease. It is caused due to the novel discovered virus know as severe acute respiratory syndrome coronavirus 2 (SARS- CoV-2) [2]. Coronaviruses are a family of viruses that are known to cause diseases like a common cold, severe acute respiratory syndrome (SARS), and Middle East Respiratory Syndrome (MERS)[3]. The coronavirus disease is first discovered in Wuhan, China in December 2019. The unprecedented rise in COVID-19 cases is impacting the worldwide economy and declared a pandemic by the World Health Organization [4], [5].

On 22 May, 2020, total 5,207,918 patients are infected with COVID-19, and 334,848 deaths are reported across 215 countries [5]. To control the spread of the COVID-19 virus, its accurate detection and treatment are required. Reverse Transcriptase Polymerase Chain Reaction (RT- PCR) is the standard diagnostic test for COVID-19 [6]. The high popularity of PCR is due to its high selectivity and sensitivity, i.e., over 90%. The limitations of the COVID-19 testing with PCR technique are a) very time consuming, b) expensive, and c) shortage of kits due to long production time [7], [8]. Considering the alarming rates of spread of COVID-19, a faster and cheaper testing mechanism is required to tackle this outbreak. Researchers have found that radiological analysis like X-Rays and Chest CT (Computed Tomography) scans have high accuracy in COVID-19 diagnosis and can be an effective tool for large scale screening. A high correlation between RT-PCR and radiological results for COVID-19 diagnosis is established in [9]. Also, COVID-19 infection is identified through ground-glass opacity patches (GGO) in radiographic scans of patients. This encouraged the development of a faster and cheaper COVID-19 screening mechanism using a radiological approach [10]. Also, deep learning is playing a critical role in medical image analysis which motivates its use in screening of COVID-19. The details of the techniques available in the literature for COVID-19 diagnosis is put forth in Table 1.

Table 1: Summary of techniques available in literature for COVID19 screening.

References	Technique	Key findings
[11]	ResNet-18 (CNN model)	The type of infection and total confidence score of CT case are obtained with following performance parameters: a) AUC - 0.996, b) sensitivity - 98.2%, and c) specificity -92.2%.

References	Technique	Key findings
[12]	Resnet50 and VGG16 (Deep learning)	COVID-19 positive cases and pneumonia cases of X-ray modalities are classified with an accuracy of 89.2%.
[13]	infection Size Aware Random Forest method (iSARF)	The sensitivity of 90.7%, a specificity of 83.3%, and an accuracy of 87.9% are achieved on chest CT scan (1658 COVID-19 positive cases and 1027 patients of CAP).
[14]	EfficientNet	The model is trained on 13569 X-ray images (COVID19 positive cases-152, pneumonia-5421, and normal cases - 7966), and tested on 231 X-ray images (COVID19 positive cases-31, pneumonia-100, and normal cases - 100). An accuracy of 93.9%, a sensitivity of 96.8% and positivity prediction of 100% is obtained.
[15]	Pre-trained CheXNet and DenseNet	The model is trained on 5323 chest X-ray images (COVID19 positive cases-115, pneumonia-3867, and normal cases - 1341), and tested on 654 X-ray images (COVID19 positive cases-30, pneumonia-390, and normal cases - 234). An accuracy of 90.5%, a sensitivity of 100% is achieved.
[16]	Domain Extension Transfer Learning (DETL) with Gradient Class Activation Map (Grad-CAM)	The Data A-Binary classes normal and disease (13 lung, heart and chest-related diseases). Data B- Four classes (normal, other diseases, pneumonia, and Covid19). The accuracy of 95.3% is obtained on the proposed X-ray dataset.

References	Technique	Key findings
[17]	ResNet, Inception, and GoogleNet	The binary classification of COVID-19 positive cases and normal patients based on X-ray modality is done. The deep learning-based approach achieved 98% of accuracy with VGG19, ResNet50- 95% of accuracy, and InceptionV3 - 96%.
[18]	ResNet18, ResNet50, SqueezeNet, and DenseNet-121	The model is trained on 5000 chest x-rays dataset and the model achieved a specificity of 90 and sensitivity of 97.5% on testing data of 3000 chest X-rays (COVID and Non-COVID patients).
[19]	Joint Classification and Segmentation (JCS)	JCS system is implemented on COVID-19 dataset 400 COVID-19 patients (144,167 images) and 350 Non-COVID patients. On the test data, classification is done with a specificity of 93% and a sensitivity of 95% and a dice score of 78.3% is obtained for the segmentation task.
[20]	AlexNet, VGG16, VGG19, GoogleNet, and ResNet50	The CNN based pre-trained models are trained on 742 chest CT scans into two binary classes, i.e, COVID and Non-COVID. The highest accuracy of 82.91% is achieved with the ResNet50 pre-trained CNN model.
[21]	Detail-Oriented Capsule Networks (DECAPS) +Peekaboo (patch crop and drop strategy)	An accuracy of 87.6%, recall of 91.5%, precision of 84.3%, and AUC of 96.1 is achieved for binary classification (COVID-19 and Non-COVID) of chest CT scan.

References	Technique	Key findings
[22]	3-Dimensional deep learning	For binary classification of chest CT scan of COVID and Non-COVID dataset, the 3-D CNN model achieved a sensitivity of 98.2%, the specificity of 92.2%, and AUC of 0.996. Further, the 3D volume and corona scores are obtained for COVID-19 positive cases.
[23]	Multi-Objective Differential Evolution (MODE) deep learning	In comparison to authentic CNN models, the performance parameters of MODE outperforms by 2.09% of F-measure, 1.82% of sensitivity, 1.68% of specificity, and 1.927% of Kappa statistics.

From the detailed analysis of state-of-the-art-of COVID19 diagnosis field, it can be inferred that chest radiography (X-rays and CT scan) is the best alternative for COVID-19 detection in comparison to the RT-PCR test kits [24], [25]. However CT scan modality seems to be most efficient in comparison to chest X-ray due to following reasons: a) CT scan gives a detailed 3-Dimensional view of the diagnosed organ whereas X-rays give a 2-D view, b) the CT scan does not overlap the organ, whereas in X-rays ribs overlap the lungs and heart. Due to the high precision of a CT-scan based screening system, a deep learning-based 3 step model is proposed which consists of a transfer-learning based feature extractor, a feature selector and a feature classifier. To increase the model's generalization, the training set includes images of non-COVID pneumonia and Tuberculosis patients along with healthy patients. In the proposed work, a truncated VGG16 architecture is proposed for extracting features. The architecture is based on a representation learning model using ImageNet weights. The last two blocks of the truncated architecture are fine-tuned with differential learning rates for more accurate extraction. The model thus gives a reduced representation of raw data with accurate features to be used for the classification. For the classification task, four different classifier models are trained on the features selected by the PCA, and their performance is compared.

The rest of the paper is organized as follows: section 2 illustrates the proposed methodology; section 3 put-forth the details of different classifiers. section 4 gives the details of results and discussion. Then section 5 concludes the proposed work.

## 2 Proposed methodology

The chest CT Scans of COVID-19 patients contain patches of Ground Glass Opacity (GGO), thus a multi-dimensional feature extractor is required for screening [10], [26]. In the proposed work, the VGG16 architecture is fine-tuned and used to extract features from lung CT Scan images. Since, the size of the COVID-19 dataset is very small, a truncated version of the VGG16 architecture is used. PCA is used to reduce the dimensionality of the features obtained from truncated VGG-16. The final classification is performed using four different classifiers.

The self-explanatory block diagram of the proposed methodology for COVID-19 classification is shown in Figure 1.

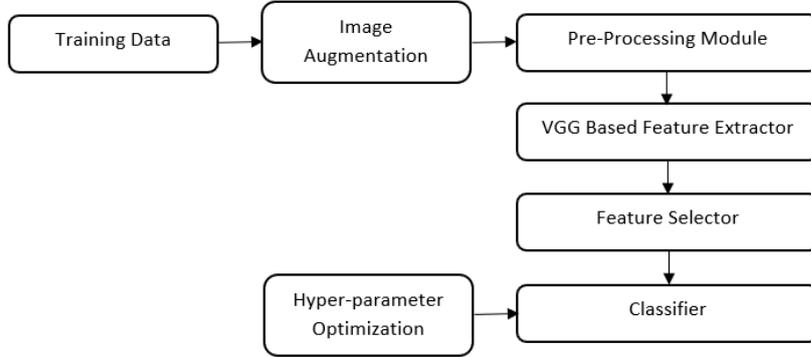


Figure 1: Self-explanatory block diagram of the proposed methodology of COVID-19 screening

### 2.1 Training data

In the proposed work, the dataset is collected from three different sources to ensure the robustness of the model. The brief details of datasets used are: a) Dataset 1 (D1)- A CT Scan Dataset of 718 images (349 COVID and 376 non-COVID) compiled by Zhao et. al, b) Dataset 2 (D2)- COVID-19 image data collection: Joseph Paul Cohen, Paul Morrison and Lan Dao, and c) Dataset 3 (D3)- Italian society of medical and interventional Research [27], [28], [29]. Table 2 puts forth the details of CT scan images available in D1, D2, and D3 along-with the details of training, validation and test set used.

Table 2: The brief details of the dataset for the proposed model.

Dataset	COVID	Non-COVID	Total
D1	233 images (training - 204, and validation - 29)	358 images (training - 228, validation - 33, and test - 97)	591
D2	53 images (test - 53)	0 images	53
D3	58 images (test - 58)	0 images	58
Total	344 images	358 images	702

### 2.2 Image augmentation

Data augmentation allows the model to learn a more diverse set of features and also increases the size of the dataset thereby preventing the model from overfitting.

Each training image is augmented by a random affine transformation, random flip and random changes in hue, brightness and saturation of the image. The random affine transformation consists of shearing and rotation. The details of image augmentation parameters include a) rotation – within range of 0 to 30 degrees, b) shearing – 0.2, c) zooming – 0.2, and d) changing the brightness level – within range of 0.75 to 1.5. The training data after augmentation is a) 612 of COVID19 images and b) 684 of Non-COVID19 images.

### 2.3 Pre-processing module

The Pre-processing module allows the proposed model to extract the most important information from the images. As the input images are of different sizes, thus all the input images are resized to  $112 \times 112 \times 3$  to maintain the uniformity. Further, the Region of Interest (ROI) selection module and artifact removal module ensures that features across the data are homogeneous and the data is artifact-free. This helps the model to extract accurate features and the classifier to have high precision.

CT scans have artifacts like beam hardening, noise, scatter, etc. These artifacts if not handled, reduce the accuracy of the model. To overcome this, an artifact removal module is designed which uses filtering and morphological transformations to remove such artifacts. For filtering, a bilateral filter, with a kernel of  $(5 \times 5)$ , is used because of its edge-preserving property. Morphological transformations namely erosion and closing are applied to reduce background holes and amplify the productive features in the image.

In the proposed work, an adaptive ROI selector is designed, that crops, centers and resizes the CT scan images based on pixel values. Many images in the data-set have labeling and markings around the corners which could affect the performance of the model. To overcome this and to get a more accurate ROI selection, elliptical masks are applied to the CT Scan images. To ensure that masking does not remove any relevant information, pixel value differences are used to cross-check the selected mask. As COVID-19 diagnosis through CT Scans is based only on features of a patient’s lungs, the ROI selector removes the non-lung parts. Figure 2 shows the pictorial representation of the various pre-processing module used in the proposed work.

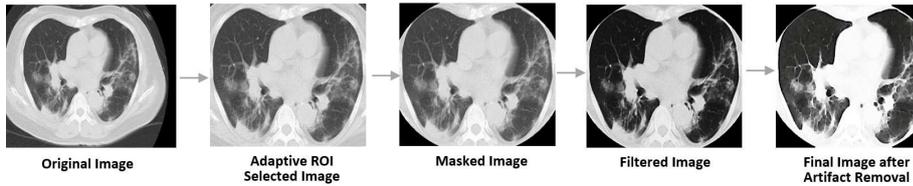


Figure 2: Pictorial representation of various stages of the pre-processing module.

### 2.4 VGG based feature extractor

Initially, the VGG model is trained on ImageNet database with over 14 million images [30], [31]. The more discriminate nature of the VGG16 module comes from

its architecture. Instead of using large receptive fields, VGG16 uses very small receptive fields (3x3 with a stride of 1). VGG16 incorporates 1x1 convolution layers to make the decision function more non-linear without changing the receptive fields. The combined output of the VGG16 module provides rich feature maps of varying perspectives. Owing to the large size of the ImageNet database, the VGG16 architecture has been built to extract complex features with high dimensionality from images. Since the COVID-19 dataset is much smaller with only 591 training images (before augmentation), the high complexity of the feature set will cause the model to overfit the data. To prevent this, a truncated VGG16 architecture is proposed which controls the complexity of the features. The first four convolution blocks of the VGG16 architecture are used for the proposed truncated architecture as shown in Figure 3. The reduced complexity of the architecture (resized the 3-dimensional output to a single vector per image) allows the model to generalize well to the small dataset. The truncation layer is determined by evaluating performance on the validation set with different points of truncation as detailed out in Table 3.

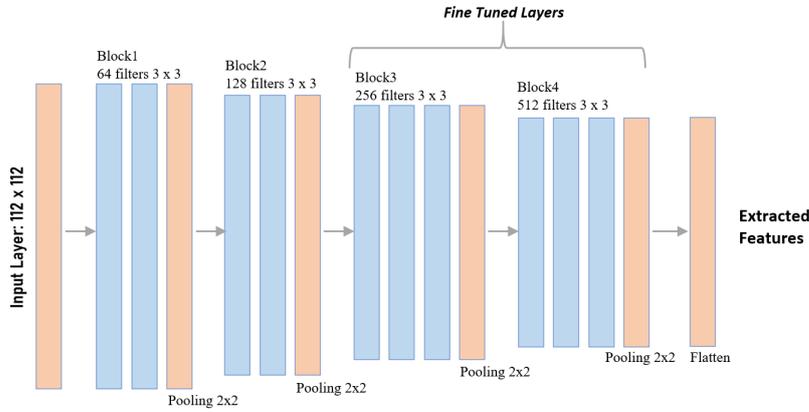


Figure 3: Architecture of truncated VGG16 model.

Table 3: Summary of various VGG16 truncation point accuracy evaluated on the validation set with SVM as classifier.

Sr. No.	Truncation point	Accuracy on test set
1	3 Blocks	73.6%
2	4 Blocks	84.2%
3	Un-truncated	79.1%

### 2.4.1 Transfer learning

Training a Neural Network from scratch requires huge amounts of data. As the COVID-19 dataset available is significantly smaller, transfer learning is applied to extract an accurate and concise feature set from the training data. With transfer learning, a solid machine learning model can be built with a comparatively smaller training dataset, because the model is already pre-trained. In the proposed methodology, a representation learning-based approach is used. A pre-trained VGG-16 model is fine-tuned and its intermediate outputs act as a representation of raw data. This representation serves as features for the classifier module. The first four blocks of the VGG16 architecture pre-trained on ImageNet weights are used for this purpose. Since the Image net set is non-overlapping to the problem, the last 8 layers, i.e., the third and fourth convolution blocks are fine-tuned on the augmented CT scan training data. This ensures that the representation extracted from the data is relevant to the classification. Through transfer learning, an accurate set of reduced feature representations of the data has been extracted. The extracted features are displayed as a color map as shown in Figure 4. The third and fourth convolution blocks of the truncated architecture are fine-tuned. While training these, it is desired that the fourth block adapts more to the data compared to the third block. The third block carries relatively fewer complex features, that do not need to change much. Hence, a higher learning rate has been used for the fourth convolutional block compared to the third convolutional block while fine-tuning. Figure 5 shows the confusion matrices of the proposed model with and without fine-tuning of the VGG16 based feature extractor. The feature

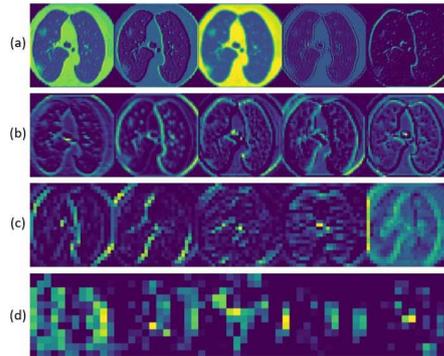


Figure 4: Intermediate color-mapped outputs (a) layer 1, (b) layer 4, (c) layer 8, (d) layer 14.

extractor module, reduces the dimension of the data to 25,000 features per image for an image size of 112 x 112 x 3 pixels. However, with only 591 training examples (before augmentation), the model would still overfit the features. To prevent this, feature selection and dimensionality reduction of data are performed.

## 2.5 Feature selector

Principal Component Analysis (PCA), autoencoders, and variance-based selectors are the most popular feature selectors for image data [32]. PCA finds the eigenvectors of a covariance matrix with the highest eigenvalues and then uses those to project the data into a new subspace of equal or fewer dimensions. Autoencoders compress the input to a lower dimension. Variance based methods select the features which have the highest variance over the data. PCA, Autoencoder and Variance based Selector have been used to select about 300 features, and then their accuracies on the validation set are compared after classification with an SVM. While using PCA 95% variance is retained which yielded 359 features. The Autoencoder and variance-based selectors were also configured to select 359 features. The results of the analysis are tabulated in Table 4. For the proposed model, PCA gives the highest accuracy because it represents the low-dimensional sample and synchronized variables. Further, the extracted features from the training set are used to train the classification module to screen COVID-19 CT Scans.

Table 4: Performances analysis of feature selection techniques on validation set using SVM as classifier.

Sr. No.	Feature selection technique	Test accuracy
1	PCA	93.4%
2	Autoencoder	89.6%
3	Variance based Selector	87.3 %

## 2.6 Classifier

For the classification task, the required features are extracted using the truncated VGG16 model and selected using PCA. In machine learning no single algorithm is suitable for all problems. Thus, for achieving the highest performance, 4 different classification models are evaluated. Various classification techniques used in the proposed work are as follows: a) Deep CNN, b) Bagging Ensemble with SVM, c) Extreme Learning Machine (ELM), and d) Online Sequential ELM (OS-ELM).

## 3 Classification

### 3.1 Deep CNN

One of the most common approaches to image classification is Deep CNN. The main reasons for such popularity of CNN are their fewer parameters, object position invariance and generalizing capabilities. CNN can successfully capture the Spatial and Temporal dependencies in an image through the application of relevant filters. The architecture performs a better fitting to the image dataset due to the reduction in the number of parameters involved and the re-usability of weights [33]. Since, VGG is itself a CNN architecture, for the Deep CNN model, a fully connected layer of size 1024 is added to the truncated VGG architecture followed by a Softmax layer for classification. This gives us the most direct classification model

where the feature extraction and classification are in the same CNN architecture. The deep CNN utilizes the fine-tuned weights and uses it to directly predict the output.

### 3.2 Extreme Learning Machine (ELM)

ELMs are single-hidden layer feedforward neural networks (SLFNs) that randomly choose hidden nodes and analytically determines the output weights of SLFNs through the generalized inverse operation of the hidden layer output matrices [34]. ELM can produce good generalization performance but it lacks robustness. For classification using ELM, various activation functions like gaussian, multiquadric and polyharmonic RBFs were implemented [35]. The number of hidden layers in the model is 1000 with the best-suited gamma (Width multiplier for RBF distance).

### 3.3 Online Sequential ELM (OS-ELM)

OS-ELM can learn data chunk by chunk with varying chunk size and provides faster sequential learning [36]. It uses the idea of ELMs with a sequential determination of the output weights through the recursive least-squares (RLS) algorithm. OS-ELM consists of two phases, namely an initialization phase and a sequential learning phase. In the initialization phase, a base ELM model is trained using a small chunk of initial training data. For classification using OS-ELM, SLFN is implemented with a sigmoid activation function with 2500 hidden layers.

### 3.4 Bagging Ensemble with SVM

To improve the limited performance of the SVM (accuracy of 93.4%) due to the high complexity of time and space, the SVM ensemble with Bagging is used [37], [38]. A single classifier may have a high test-error, but many small classifiers can produce a low test error and increase robustness because diversity compensates for error. For classification using the Bagging SVM, the data-set is randomly divided into 10 parts. The individual classifiers are trained independently with bootstrap technique and aggregated to make a joint decision by the deterministic averaging process [39]. The proposed classifier model with 'RBF' kernel and tuned hyperparameters is used as the base estimator. Bagging Ensemble with SVM achieves the highest accuracy of 95.7% on the testing data. Due to the high accuracy of the Bagging with SVM model, it is the proposed classification method for COVID-19 screening.

## 4 Results and discussion

The proposed methodology is implemented on python software, run on a CPU. The system requirements are an Intel Core i7 processor with 4 GB graphic card, 64-bit operating system at 1.80 GHz, and 16 GB RAM.

### 4.1 Screening of COVID-19 based on different classifier

Figure 6 shows the convergence graph of training and validation accuracy of the transfer learning-based CNN model for the Bagging ensemble classifier with SVM. fig:8 shows the confusion matrices of the proposed architecture with and without fine-tuning of the VGG16 based feature extractor. The confusion matrices are obtained by evaluating the models on the test set with Bagging SVM as the classifier. The learning curve obtained for the bagging SVM is shown in Figure 7.

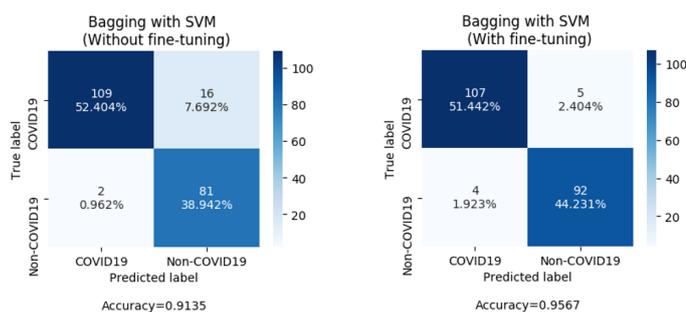


Figure 5: Comparison of confusion matrices before and after fine-tuning of the VGG16 based feature extractor. The confusion matrices are obtained by evaluating the

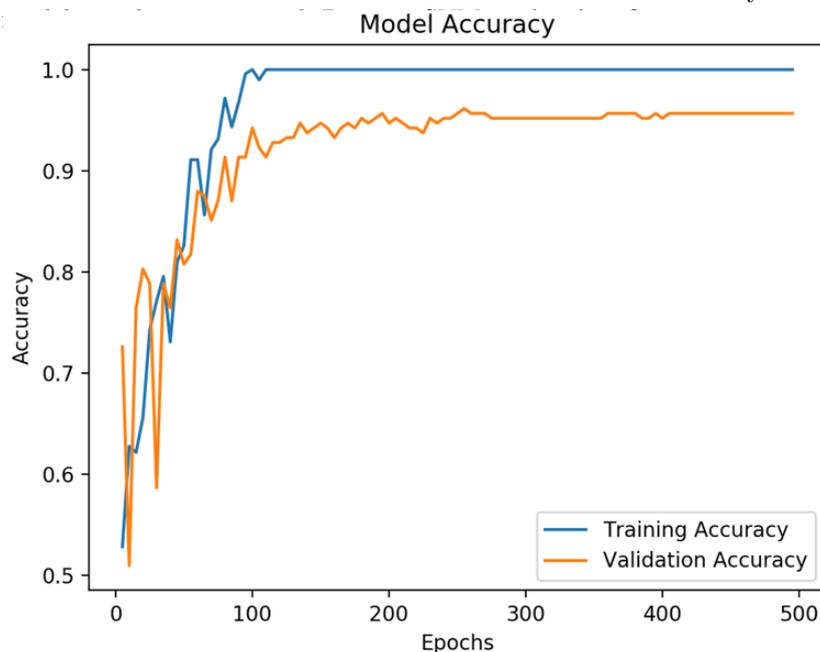


Figure 6: Convergence graph of accuracy vs epoch for proposed methodology (VGG16+PCA+Bagging Ensemble with SVM)

This is a 10-fold cross-validation curve plotted against the number of training examples. It compares the robustness of the model with experience and shows that the proposed model is well generalized. The parameters for the learning curve are: a.) 80:20 split of data for training and validation is used, and b.) average scores of 10 random divisions are plotted.

#### 4.2 Adversial Defense

Deep learning models are often fooled with noise perturbations in the image. Such perturbations or attacks lead to miss classification of images. To defend the model against such noise attacks, a defense module has been designed. To remove noise from an image before prediction, three image denoiser have been applied

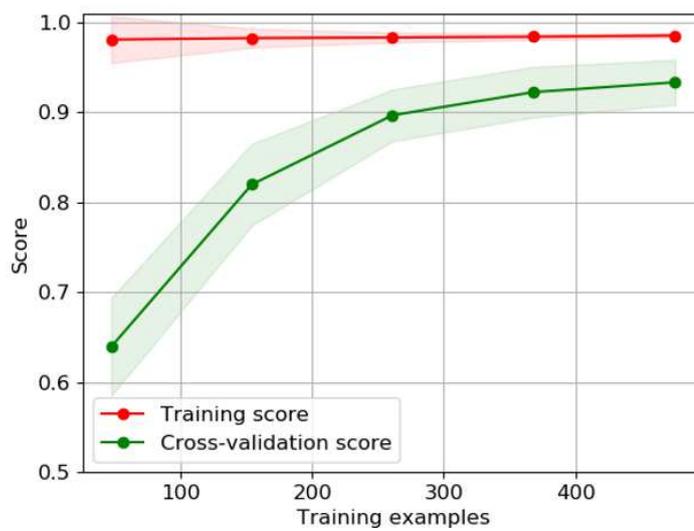


Figure 7: Learning curve for proposed method using 10-fold cross validation

namely total variation, Gaussian filter and wavelet denoising [40]. The prediction of all three denoised images is passed to an ensemble which finally classifies the image. On evaluating this module with the test set after adding random noise, the model gave an accuracy of 82.34%.

### 4.3 Evaluation Metrics

Confusion Matrices for different classifiers are shown in Figure 8. The classifiers are evaluated on the test set with 111 COVID-19 Images and 97 non-COVID images. The features for the model are extracted using the truncated VGG16 model and selected using PCA. The screening performance of the model is assessed using generalized performance parameters derived from the confusion matrix. Table 5 put forth the generalized performance parameters, namely, True Positive (TP), False Positive (FP), True Negative (TN), False Negative (FN), AUC, Accuracy (ACC), Precision (PRE), Sensitivity (S1), Specificity (S2), Negative Predictive Value (NPV) and F1 Score (F1).

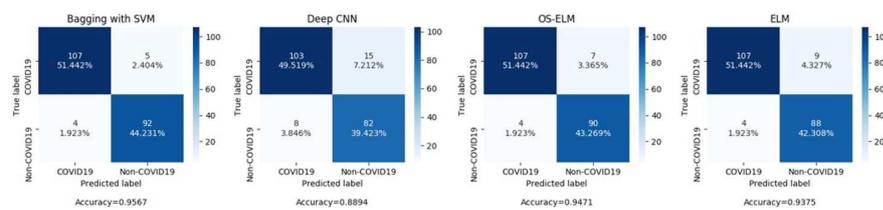


Figure 8: Confusion matrices of the proposed methodology with different classifiers

Table 5: Performance parameters of different classifiers on testing data.

Classifier	TP	TN	FP	FN	AUC	PRE	NPV	S1	S2	F1	ACC
Bagging with SVM	107	92	5	4	95.8	0.955	0.958	0.963	0.948	0.959	0.957
ELM	107	88	9	4	93.8	0.922	0.956	0.963	0.907	0.942	0.937
OS-ELM	107	90	7	4	94.9	0.938	0.957	0.963	0.927	0.951	0.947
Deep CNN	103	82	15	8	89.5	0.872	0.911	0.927	0.845	0.899	0.889

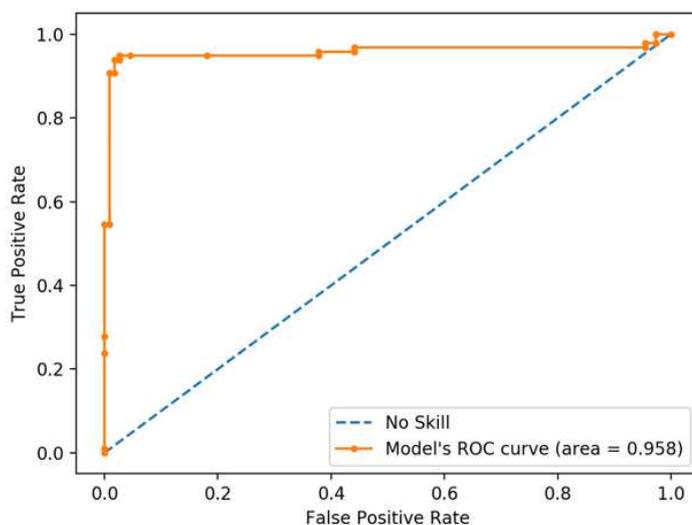


Figure 9: ROC characteristics curve for the proposed methodology (VGG16+PCA+Bagging Ensemble with SVM).

In the proposed work, the best performing model achieves an accuracy of 95.67% along with a precision of 96.83%. The area under the ROC curve (AUC) obtained is 95.8, as shown in Figure 9. The proposed method aims to reduce the false-negative rate as much as possible since false-positive cases can potentially be identified in subsequent tests, but false-negative cases might not have that chance. The proposed model has a false negative rate of 4.33%, which is significantly lower than other COVID-19 CT Scan screening models. The model proposed in this study achieves a very high accuracy of 95.67% on the testing data with a very low prediction time of 358 ms. This proves that deep learning-based approaches could be used to effectively and accurately screen COVID-19 at very large scales. The Table 6 puts forth the comparative analysis of the proposed methodology with other existing techniques.

Table 6: Comparative analysis of COVID-19 detection proposed methodology with techniques available in the literature on the used dataset.

Sr. No.	Techniques	Dataset	Performance evaluation
1.	DECAPS + Peekaboo [21]	Binary classification of total 746 chest CT images COVID-19 and non-COVID-19 [29]	Accuracy - 87.6%, AUC- 0.961, and precision - 84.3%.
2.	Resnet50 and VGG16 [12]	Total 102 X-ray images of COVID-19 positive and pneumonia patients [28], [41], [42], [27]	Overall accuracy achieved is 89.2%.
3.	AI methods (JCS and DenseNet169) [29]	Binary classification of CT scan data into COVID (349 images) and non-COVID (463 CT images) [43]	Accuracy - 0.83, AUC - 0.95, and F1 - 0.85.
4.	Proposed methodology VGG16+PCA+Bagging Ensemble with SVM	Binary classification (COVID19 and Non-COVID19) using 702 CT Scan images (344 COVID-19 images and 358 non-COVID images) [27], [28], and [29].	Prediction time is 385ms, Accuracy - 95.7%, Precision - 95.8%, AUC - 0.958, and F1 score - 95.3%.

## 5 Conclusion

A deep learning-based truncated VGG16 model is proposed in this study to screen COVID-19 patients using chest CT Scans. The VGG16 architecture is fine-tuned and used to extract features from CT Scan images. Due to the high complexity and small size of the data, a feature selector is required to reduce the number of features. In this study, PCA is used to select features since it produces independent and uncorrelated features. The model is evaluated on 208 test images collected from multiple datasets. Further, the classification is performed using four different classifiers and their performances have been analyzed using generalized parameters. The best performing classifier Bagging Ensemble with SVM obtained an accuracy of 95.7%, precision of 95.8%, Area Under Curve (AUC) of 0.958, and an F1 score of 95.3%. The prediction time of 385ms is negligible compared to physical CT Scan screening and tests like PCR. The high robustness of the model along with the lower time complexity proves that deep learning is an effective technique for screening COVID-19 patients using CT Scans. The future work will focus on improving the specificity of the model, marking the infected area of the regions in the lungs, and analyzing the rate of the severity of disease in COVID-19 infected patients.

## References

1. WebMD, 2020. URL <https://www.webmd.com/lung/lung-diseases-overview#1>. Last accessed date 22nd May 2020.
2. WHO, 2020. URL [https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technical-guidance/naming-the-coronavirus-disease-\(covid-2019\)-and-the-virus-that-causes-it](https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technical-guidance/naming-the-coronavirus-disease-(covid-2019)-and-the-virus-that-causes-it). Last accessed date 22nd May 2020.
3. WHO, 2020. URL <https://www.who.int/emergencies/diseases/novel-coronavirus-2019>. Last accessed date 22nd May 2020.
4. Hamid R.A. Alwan J.k. et al Albahri, A.S. Role of biological data mining and machine learning techniques in detecting and diagnosing the novel coronavirus (covid-19): A systematic review. *J Med Syst*, 44:122, 2020. URL <https://doi.org/10.1007/s10916-020-01582-x>.
5. Worldometer, 2020. URL <https://www.worldometers.info/coronavirus>. Last accessed date 22nd May 2020.
6. Alireza Tahamtana and Abdollah Ardebili. Real-time rt-pcr in covid-19 detection: issues affecting the results. *Expert review of molecular diagnostics*, 20: 453-454, 2020.
7. Tao Ai, Zhenlu Yang, Hongyan Hou, Chenao Zhan, Chong Chen, and et al. Correlation of chest ct and rt-pcr testing in coronavirus disease 2019 (covid-19) in china: A report of 1014 cases. *Radiology*, 2020.
8. Heshui Shi, Xiaoyu Han, Nanchuan Jiang, Yukun Cao, Osamah Alwalid, Jin Gu, Yanqing Fan, and Chuansheng Zheng. Radiological findings from 81 patients with covid-19 pneumonia in wuhan, china: a descriptive study. *The Lancet Infectious Diseases*, 20, 2020.
9. Zheng Ye, Yun Zhang, Yi Wang, Zixiang Huang, and Bin Song. Chest ct manifestations of new coronavirus disease 2019(covid-19): a pictorial review. *European Radiology*, 2020.
10. Jeffrey P Kanne, Brent P Little, Jonathan H Chung, Brett M Elicker, and Loren H Ketai. Essentials for radiologists on covid-19: an update- radiology scientific expert panel. *Radiology*, 2020.
11. Xiaowei Xu, Xiangao Jiang, Chunlian Ma, Peng Du, Xukun Li, Shuangzhi Lv, Liang Yu, Yanfei Chen, Junwei Su, Guanqing Lang, Yongtao Li, Hong Zhao, Kaijin Xu, Lingxiang Ruan, and Wei Wu. Deep learning system to screen coronavirus disease 2019 pneumonia, 2020.
12. Lawrence O. Hall, Rahul Paul, Dmitry B. Goldgof, and Gregory M. Goldgof. Finding covid-19 from chest x-rays using deep learning on a small dataset, 2020.
13. Feng Shi, Liming Xia, Fei Shan, Dijia Wu, Ying Wei, Huan Yuan, Huiting Jiang, Yaozong Gao, He Sui, and Dinggang Shen. Large-scale screening of covid-19 from community acquired pneumonia using infection size-aware classification, 2020.
14. Eduardo Luz, Pedro Lopes Silva, Rodrigo Silva, Ludmila Silva, Gladston Moreira, and David Menotti. Towards an effective and efficient deep learning model for covid-19 patterns detection in x-ray images, 2020.
15. Arpan Mangal, Surya Kalia, Harish Rajgopal, Krithika Rangarajan, Vinay Namboodiri, Subhashis Banerjee, and Chetan Arora. Covidaid: Covid-19 detection using chest x-ray, 2020.

16. Sanhita Basu, Sushmita Mitra, and Nilanjan Saha. Deep learning for screening covid-19 using chest x-ray images, 2020.
17. Muhammad Ilyas, Hina Rehman, and Amine Nait-ali. Detection of covid-19 from chest x-ray images using artificial intelligence: An early review, 2020.
18. Shervin Minaee, Rahele Kafieh, Milan Sonka, Shakib Yazdani, and Ghazaleh Jamalipour Soufi. Deep-covid: Predicting covid-19 from chest x-ray images using deep transfer learning, 2020.
19. Yu-Huan Wu, Shang-Hua Gao, Jie Mei, Jun Xu, Deng-Ping Fan, Chao-Wei Zhao, and Ming-Ming Cheng. Jcs: An explainable covid-19 diagnosis system by joint classification and segmentation, 2020.
20. Mohamed Loey, Florentin Smarandache, and Nour Eldeen M. Khalifa. A deep transfer learning model with classical data augmentation and cgan to detect covid-19 from chest ct radiography digital images. *Preprints*, 2020.
21. Aryan Mobiny, Pietro Antonio Cicalese, Samira Zare, Pengyu Yuan, Mohammad-sajad Abavisani, Carol C. Wu, Jitesh Ahuja, Patricia M. de Groot, and Hien Van Nguyen. Radiologist-level covid-19 detection using ct scans with detail-oriented capsule networks, 2020.
22. Ophir Gozes, Maayan Frid-Adar, Hayit Greenspan, Patrick D. Browning, Huangqi Zhang, and et al. Rapid ai development cycle for the coronavirus (covid-19) pandemic: Initial results for automated detection patient monitoring using deep learning ct image analysis. 2020.
23. Dilbag Singh, Vijay Kumar, Vaishali, , and Manjit Kaur. Classification of covid-19 patients from chest ct images using multi-objective differential evolution-based convolutional neural networks. *European Journal of Clinical Microbiology Infectious Diseases*, 2020.
24. Ophir Gozes, Maayan Frid-Adar, Nimrod Sagie, Huangqi Zhang, Wenbin Ji, and Hayit Greenspan. Coronavirus detection and analysis on chest ct with deep learning, 2020.
25. Rodolfo M. Pereira, Diego Bertolini, Lucas O. Teixeira, Carlos N. Silla, and Yandre M.G. Costa. Covid-19 identification in chest x-ray images on flat and hierarchical classification scenarios. *Computer Methods and Programs in Biomedicine*, 194:105532, Oct 2020. doi: 10.1016/j.cmpb.2020.105532.
26. Weifang Kong and Prachi Agarwal. Chest imaging appearance of covid-19 infection. *Radiology: Cardiothoracic Imaging*, 2(1), 2020. doi: 10.1148/ryct.2020200028.
27. Joseph Paul Cohen, Paul Morrison, and Lan Dao. Covid-19 image data collection, 2020.
28. Italian Society of Medical and Interventional Radiology, 2020. URL <https://www.sirm.org/en/category/articles/covid-19-database/>. Last accessed date 7th May 2020.
29. Jinyu Zhao, Yichen Zhang, Xuehai He, and Pengtao Xie. Covid-ct-dataset: A ct scan dataset about covid-19, 2020.
30. Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition, 2014.
31. Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton. Imagenet classification with deep convolutional neural networks. *Neural Information Processing Systems*, 25, 01 2012. doi: 10.1145/3065386.
32. Pierre Baldi. Autoencoders, unsupervised learning, and deep architectures. In Isabelle Guyon, Gideon Dror, Vincent Lemaire, Graham Taylor, and Daniel

- Silver, editors, *Proceedings of ICML Workshop on Unsupervised and Transfer Learning*, volume 27 of *Proceedings of Machine Learning Research*, pages 37–49. PMLR, 2012.
33. Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition, 2015.
  34. Extreme learning machine: Theory and applications. *Neurocomputing*, 70(1): 489 – 501, 2006. ISSN 0925-2312. doi: <https://doi.org/10.1016/j.neucom.2005.12.126>. Neural Networks.
  35. Melm-grbf: A modified version of the extreme learning machine for generalized radial basis function neural networks. *Neurocomputing*, 74(16): 2502 – 2510, 2011. ISSN 0925-2312. doi: <https://doi.org/10.1016/j.neucom.2010.11.032>. URL <http://www.sciencedirect.com/science/article/pii/S092523121100213X>. Advances in Extreme Learning Machine: Theory and Applications Biological Inspired Systems. Computational and Ambient Intelligence.
  36. N. Liang, G. Huang, P. Saratchandran, and N. Sundararajan. A fast and accurate online sequential learning algorithm for feedforward networks. *IEEE Transactions on Neural Networks*, 17(6):1411–1423, 2006.
  37. D. Opitz and R. Maclin. Popular ensemble methods: An empirical study. *Journal of Artificial Intelligence Research*, 11:169–198, Aug 1999. ISSN 1076-9757. doi: 10.1613/jair.614. URL <http://dx.doi.org/10.1613/jair.614>.
  38. M. A. Hearst, S. T. Dumais, E. Osuna, J. Platt, and B. Scholkopf. Support vector machines. *IEEE Intelligent Systems and their Applications*, 13(4):18–28, 1998.
  39. Leo Breiman. Popular ensemble methods: An empirical study. *Machine Learning*, pages 123–140, 1996.
  40. Pascal Vincent, Hugo Larochelle, Yoshua Bengio, and Pierre-Antoine Manzagol. Extracting and composing robust features with denoising autoencoders. In *Proceedings of the 25th International Conference on Machine Learning*, page 1096–1103. Association for Computing Machinery, 2008. ISBN 9781605582054. doi: 10.1145/1390156.1390294. URL <https://doi.org/10.1145/1390156.1390294>.
  41. Radiopedia, 2020. URL <https://radiopaedia.org/search?utf8=%E2%9C%93&q=covid&scope=all&lang=us>. Last accessed date 7th May 2020.
  42. NIH, 2020. URL <https://www.kaggle.com/nih-chest-xrays/data>. Last accessed date 7th May 2020.
  43. Xuehai He, Xingyi Yang, Shanghang Zhang, Jinyu Zhao, Yichen Zhang, Eric Xing, and Pengtao Xie. Sample-efficient deep learning for covid-19 diagnosis based on ct scans. *medrxiv*, 2020.

### **Ethics declarations**

#### Conflict of interest

The authors declare no conflict of interest.

#### Ethical approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

#### Informed consent

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

# Figures

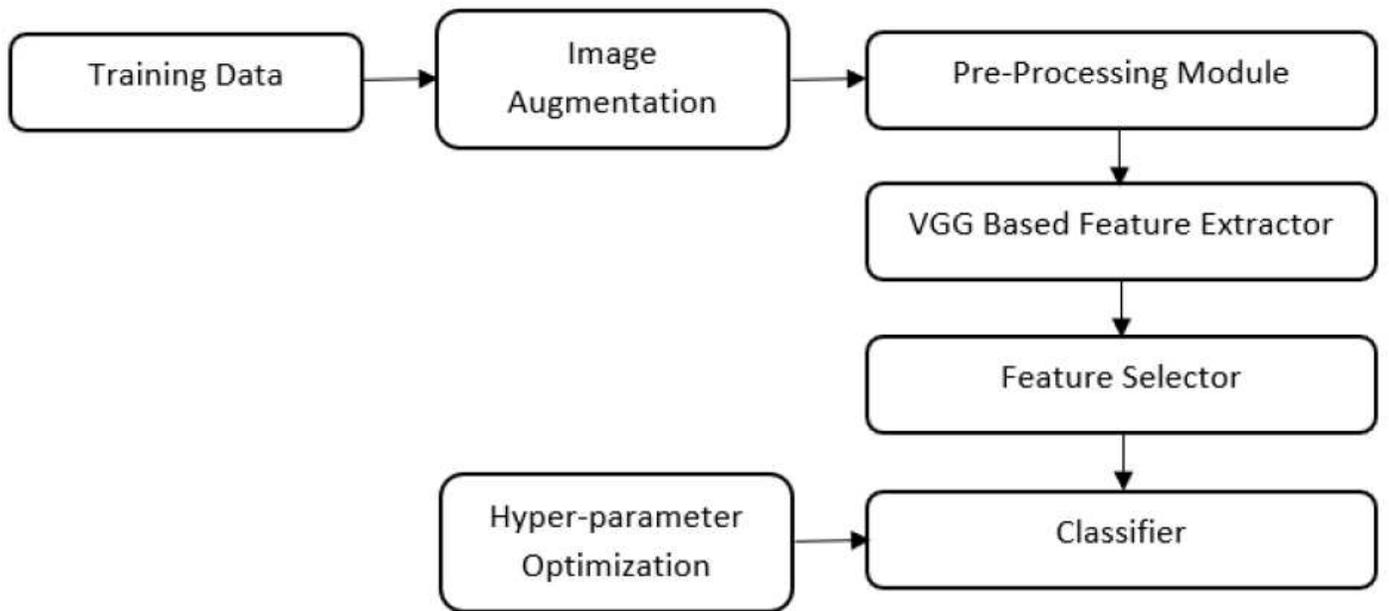


Figure 1

Self-explanatory block diagram of the proposed methodology of COVID-19 screening

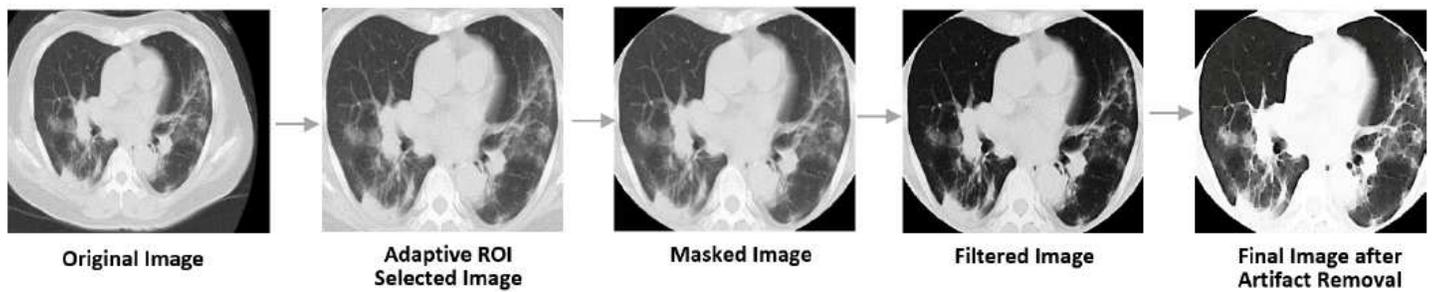
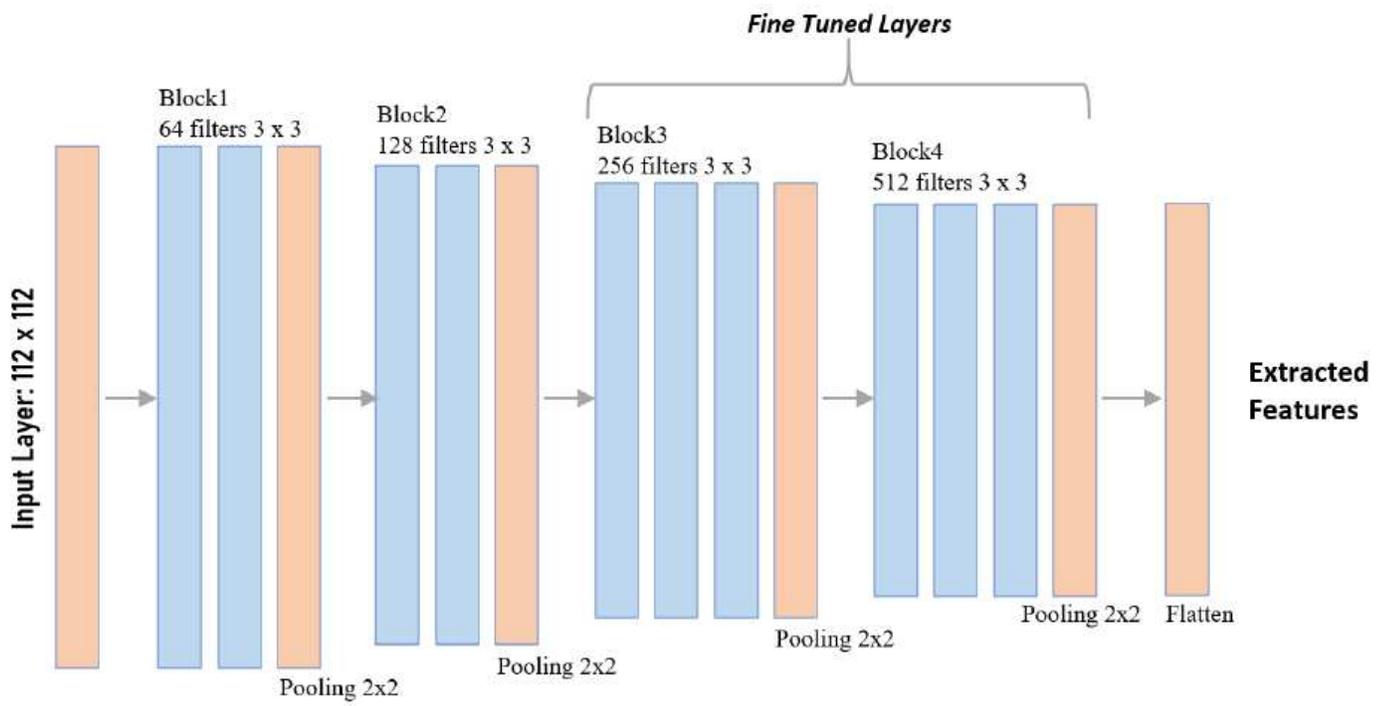


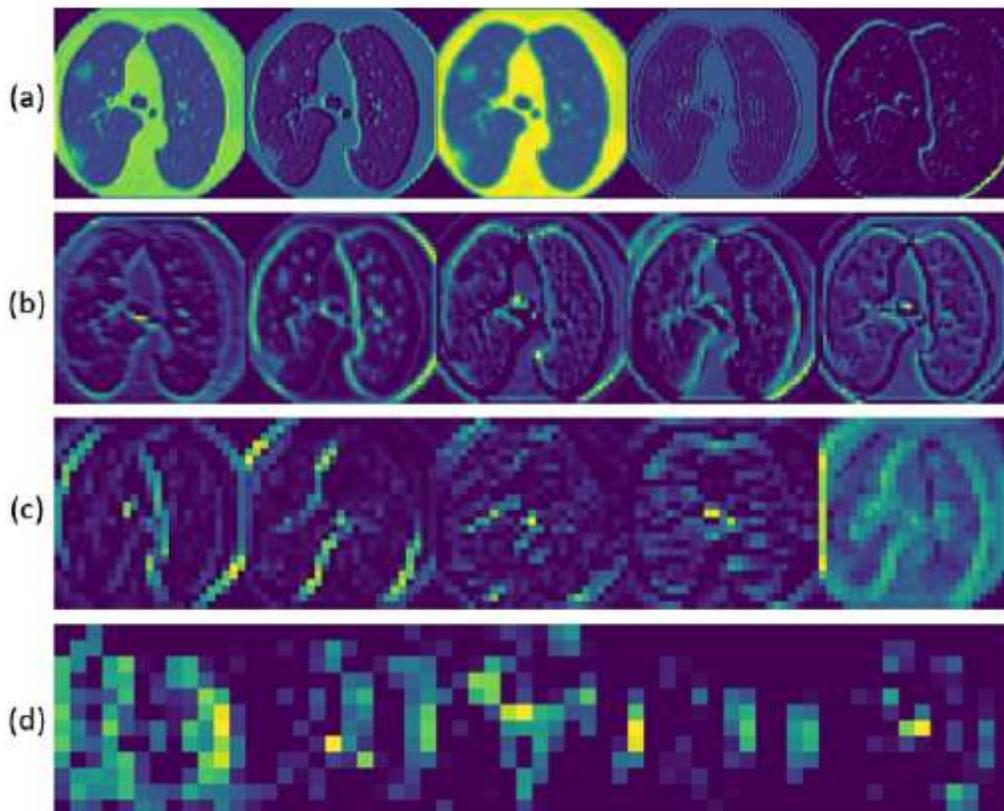
Figure 2

Pictorial representation of various stages of the pre-processing module.



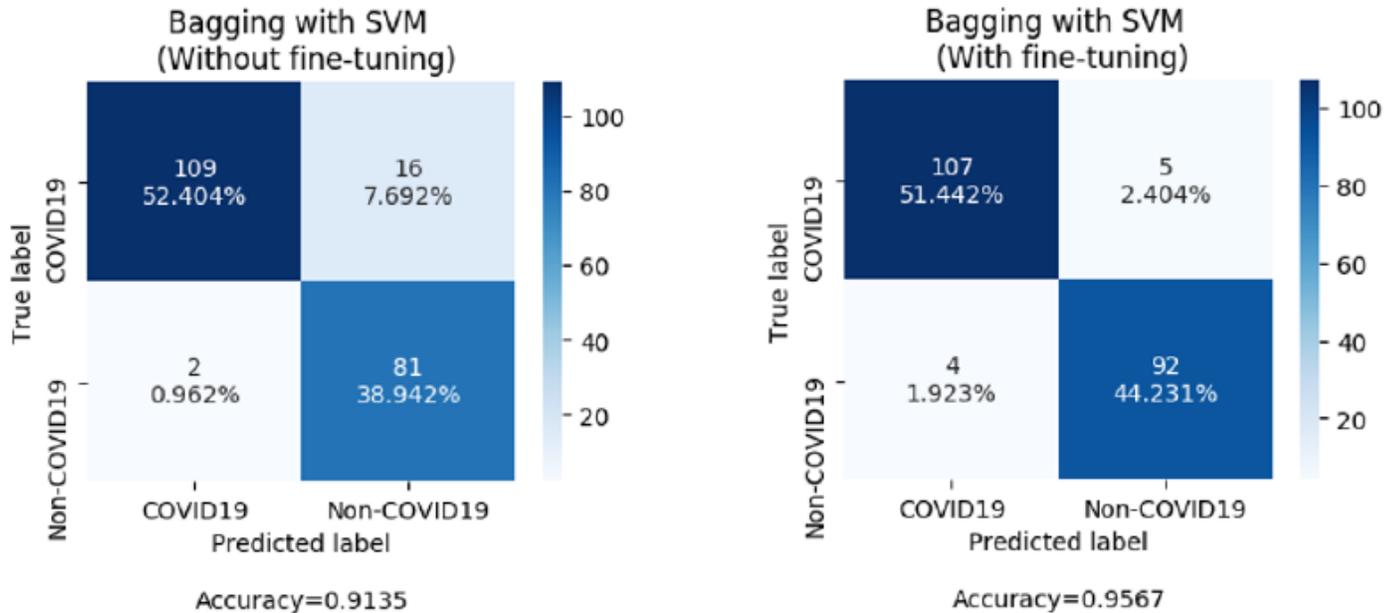
**Figure 3**

Architecture of truncated VGG16 model.



**Figure 4**

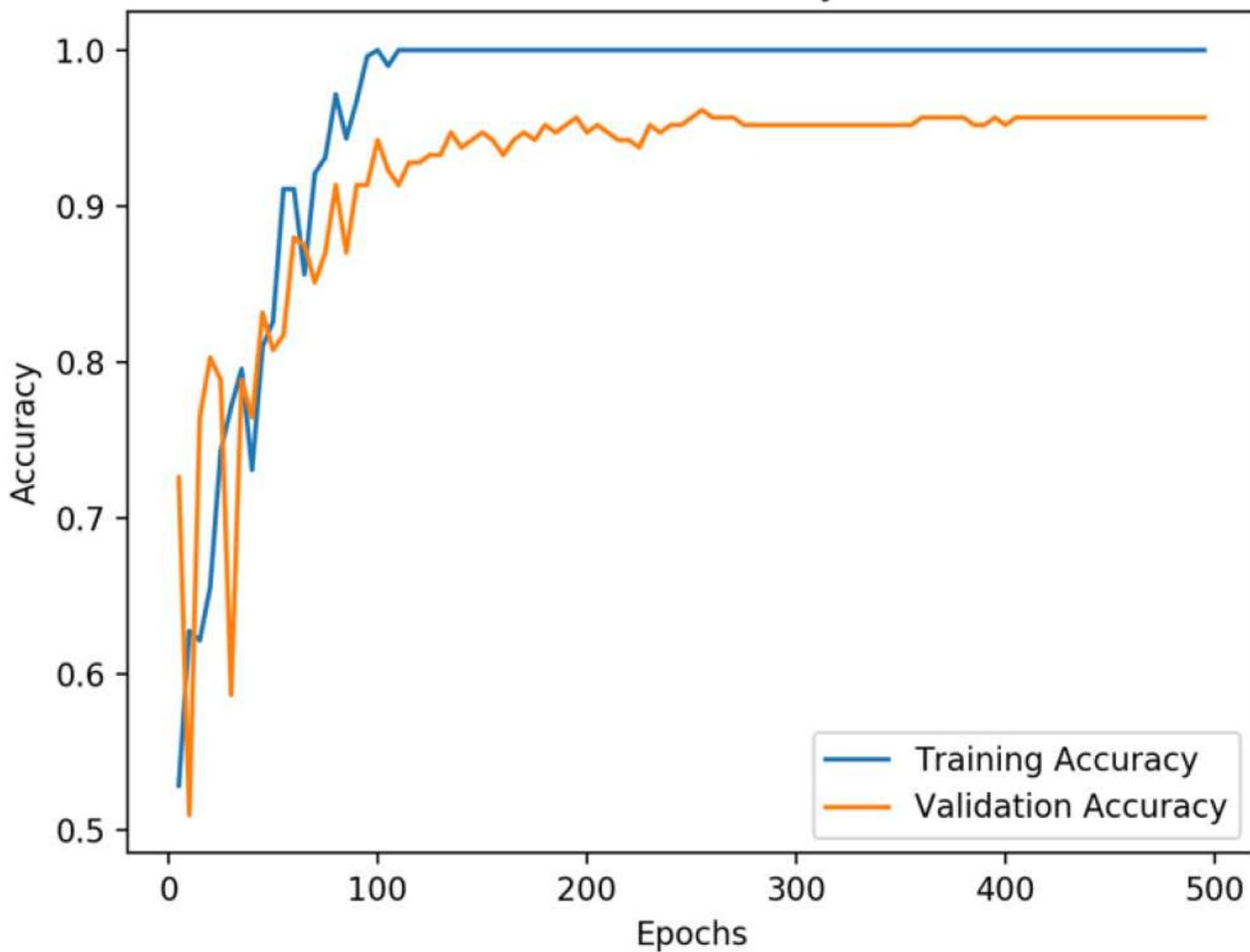
Intermediate color-mapped outputs (a) layer 1, (b) layer 4, (c) layer 8, (d) layer 14.



**Figure 5**

Comparison of confusion matrices before and after fine-tuning of the VGG16 based feature extractor. The confusion matrices are obtained by evaluating the models on the test set with Bagging SVM as the classifier

### Model Accuracy



**Figure 6**

Convergence graph of accuracy vs epoch for proposed methodology (VGG16+PCA+Bagging Ensemble with SVM)

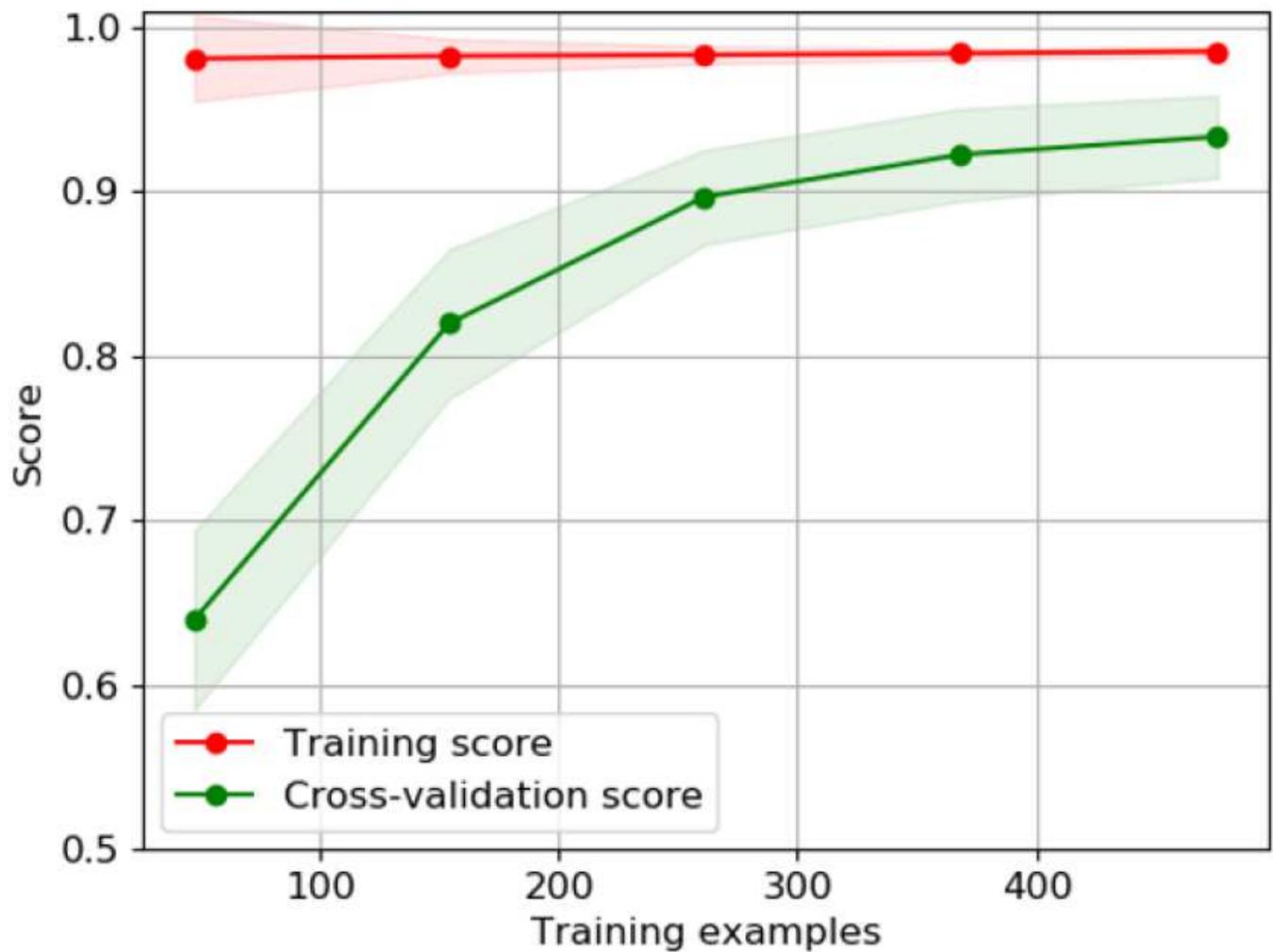


Figure 7

Learning curve for proposed method using 10-fold cross validation

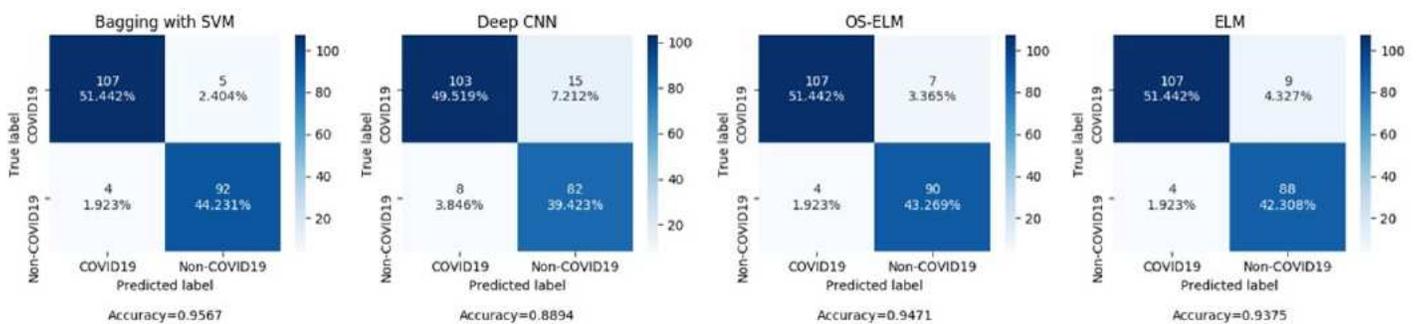


Figure 8

Confusion matrices of the proposed methodology with different classifiers

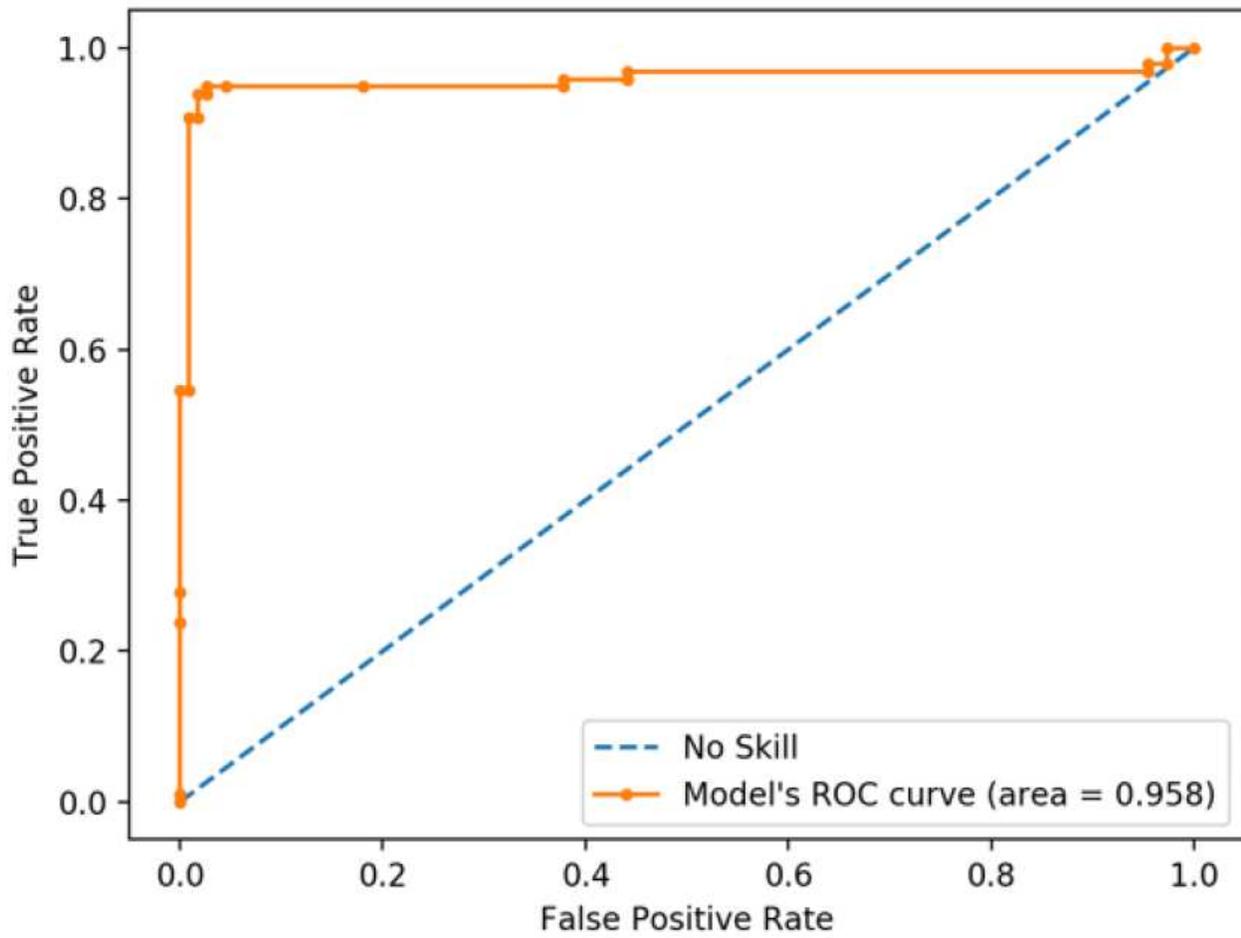


Figure 9

ROC characteristics curve for the proposed methodology (VGG16+PCA+Bagging Ensemble with SVM).