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Efficient Generative Transfer Learning Framework for the Detection of COVID-19

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Abstract. Deep learning plays a major role in detecting the presence of Coronavirus 2019 (COVID-19) and demands huge data. Availability of annotated data is a hurdle in using Deep learning technique. To enhance the accuracy of detection Deep Convolutional Generative Adversarial Network (DCGAN) is used to generate synthetic data. Densenet-201 is identified as the deep learning framework to detect COVID-19 from X-ray images. In this research, to validate the effectiveness of the Densenet-201, we explored conventional machine learning approaches such as SVM, Random Forest and Convolutional Neural Network (CNN). The feature map for training the machine learning approaches are extracted using Densenet-201 as feature extractor. The results show that Densenet-201 as feature representation with SVM is performing well in detecting COVID-19 with high accuracy. Moreover we experimented the proposed methodology without using DCGAN as well. DenseNet-201 based approach is capable of detecting the presence of COVID-19 with high accuracy. Experiments demonstrated that the proposed transfer learning approach based on DenseNet-201 along with DCGAN based augmentation outperforms the State of the art approaches like ResNet50, CNN, and VGG-16.

Keywords: COVID-19, Densenet-201, DCGAN, Disease Classification, Data Augmentation, Deep learning.

1. Introduction

The first case of novel Coronavirus disease (COVID-19) was reported in Wuhan, China at the end of December 2019. COVID-19 became an epidemic all over the World [11]. This is a respiratory disease caused by a severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). The common symptoms of COVID-19 are fever, cough, short breathing, sore throat, headache, and diarrhea [27]. Vanishing of taste, tiredness, aches, loss of smell, and nasal blockade are the additional symptoms that also have been observed in patients.

Initially, Real-Time Reverse Transcription Polymerase Chain Reaction (RT-PCR) is the only technique to detect the COVID-19 from respiratory samplings [33]. RT-PCR is an effective method for the diagnosis of SARS-CoV-2. The main drawbacks of RT-PCR are time-consuming and error-prone results [24]. This method needs a laboratory kit, the provision of which is difficult or even impossible for many countries during crises and epidemics. Like all diagnostic and laboratory methods in healthcare systems, this method isn't error-free and is biased. It requires an expert laboratory technician to sample the nasal and throat mucosa which may be a painful method, and this is often why many of us refuse to undergo nasal swab sampling. Due to RT-PCR's limited availability and drawbacks, it has posed challenges to prevent the dissemination of coronavirus infection.

In contrast to this, radiological imaging techniques are used for the diagnosis of SARS-CoV-2 by coalescing with the infected person's clinical symptoms, travel history, and laboratory findings. Radiological imaging such as chest X-rays and chest CT scans can be helpful to isolate the infected persons timely and control this epidemic situation. The first choice of radiologists is chest X-ray as most of the hospitals are equipped with X-ray machines [6].

Deep learning (DL) techniques are widely utilized in the automated analysis of radiological images. These algorithms can enhance the accuracy of classifying different types of knowledge [10]. One of the most common uses of DL in radiology was the detection of tissue-skeletal anomalies and, as a result, disease classification. The convolutional neural network has proven to be one of the foremost important DL algorithms and therefore the best technique in detecting abnormalities and pathologies in chest radiographs [18]. DL techniques can train the weights of networks on large datasets as well as fine-tuning the weights of pre-trained networks on small datasets. Hence, the main aim of this project is to use the pre-trained deep learning architectures as an automated tool to detect and diagnose COVID-19 in chest x-ray images.
Our contributions towards COVID-19 detection are :

1. Proposed an automated system that detects COVID-19 from chest X-ray images.
2. The accuracy of detecting COVID 19 is enhanced by using Deep learning generative model, DCGAN.
3. By simulation study identified a best computational model to detect COVID -19 with an F1 score of 96.99%.
4. The statistical significance of the model is evaluated using paired t-test.

Review of literature is presented in section 2, followed by the proposed methodology in section 3. Experiments covering the implementation details of the various deep learning models, discussion on their performance and comparison of the best performing model with existing techniques are given in section 4. Section 5 concludes the work with future directions.

2. Literature survey

Image classification refers to the task of classifying images into various categories. Image classification can be done by applying both machine learning [4] and deep learning algorithms. With the invention of deep learning, image classification has become more widespread. The deep learning model has a powerful learning ability [7],[21] [5], [15] which integrates the feature extraction and classification process. A pre-trained model is a deep learning model that was trained on a benchmark dataset to solve a problem similar to the one that we want to solve and one can re-use the pretrained model in many ways. Transfer learning based pre-trained models are used for image classification in variety of domains [13]. Authors have substantiated the importance of transfer learning and how the pretrained models can be customized for the custom image classification [8].

A large number of research work has been done to detect the COVID-19 from radiological imaging. Due to the ample availability of X-ray machines, disease diagnosis using

X-ray images are widely used by healthcare experts. In case of any suspect of COVID-19, instead of using test kits, an alternate way to detect pneumonia from the X-ray images is required, so that further investigation can be narrowed down for COVID-19 identification. And with the deep learning techniques, we can identify the COVID-19 patient effectively.

Jianpeng Zhang et al. [34] used the CAAD model which is composed of an anomaly detection network and confidence prediction network. They used the X-VIRAL dataset which consists of 5977 anomaly or positive (viral and non viral pneumonia) and 37,393 negative (healthy) cases. Narinder Singh Punn, Sonali Agarwal [25] used Random Oversampling and weighted approach for data preprocessing and NasNet Large model for classification. They used the dataset of COVID-19 open dataset collection which contains 153 COVID and normal chest X-rays and Radiological Society of North America (RSNA) which contains 923 other pneumonia and normal chest X-rays and National Library of Medicine (NLM) with 138 Other pneumonia and normal chest X-rays. This model performs better in binary classification than multi-class classification. Mizuho Nishio et al. [22] used a combination of data augmentation (conventional and mixup) techniques and VGG-16 (Transfer learning) model for classification. They used the dataset of Github-COVID-19 chest X-rays and RSNA-other pneumonia and normal chest X-rays. In this model, the combination of two types of data augmentation methods was more effective than single type or no data augmentation methods. Marko Arsenovic et al. [28] used traditional data augmentation methods and ResNet (Transfer Learning-pre trained with grayscale images of ImageNet dataset). They used COVID-19 Chest X-ray (publicly available) dataset with 434 COVID-19 chest x-ray images and ChestXray2017 dataset with 2200 normal and other pneumonia chest x-ray images. Though this model is trained in a small dataset, it solved the problem of over fitting due to the dense blocks in ResNet architecture and gave good accuracy.

Terry Gao(2020) [9] used VGG-19 deep learning model for COVID-19 detection. Author have used 1600 publicly available chest x-rays (400 normal,800 other pneumonia, 400 COVID-19). Abbas et al. [2] used DeTraC-Class decomposition,Transfer learning (VGG-19), class composition method for COVID-19detection. They used the dataset of Japanese Society of Radiological Technology (JSRT) with 80 normal chest x-ray images and 105 COVID-19 chest xray images. This model has the ability to cope with data irregularity and the limited number of training images too.

Wang et al. [31] used CNN for COVID-19 detection. They used COVID-19 image data collection and RSNA with normal and other pneumonia chest x-ray images. Halgurd S. Maghdid et al. [20] used CNN for COVID-19 detection and used British Society of Thoracic Imaging (BSTI) and Github dataset with 85 COVID-19 chest x-ray images and Kaggle and Radiopedia dataset with 85 normal chest x-ray images. Sabbir Ahmed et al. [3] used CNN with a multi-level CNN based preprocessor for COVID-19 detection. They used Covidx dataset (Github) dataset and CheXpert (Github) and Kaggle dataset with other pneumonia and normal images. The elegance of the modular network is the preprocessor block that dynamically filters the input images for enhancing signs of COVID-19 infection, thereby making the task easier for the feature extraction and classification block placed in cascade with it. ReCoNet has identified further unwanted structures that were not useful for its learning and/or enhanced the regions that were important for COVID-19 detection. By incorporating different transformations, ReCoNet improved its performance accuracy. Ahmed Sedik et al. [26] used GAN with CNN for COVID-19 detection. They used publicly available dataset. This model solves the problem of inadequate image data by using CGAN (Convolutional Generative Adversarial Network). This enhanced dataset was subsequently used to improve the learnability of the proposed deep learning models. Jaiswal A, Gianchandani N, Singh D, Kumar V, Kaur M. [14] used DenseNet-201 based deep transfer learning for COVID-19 detection, used dataset available in Kaggle. The authors conclude that DenseNet-201 based CNN performs significantly better as compared to some well-known deep transfer learning models.

Similar work is done to detect the COVID-19 images with three optimization algorithms to tune the hyper-parameters [30]. Grey Wolf Optimizer variation (GWO-TL), Differential Evolution variation (DE-TL) and Genetic Algorithm variation (GA-TL) were used to optimize the transfer learning hyper-parameters, among which the DE-TL has outperformed the other model proposed and also passed the Friedman test for statistical significance.

From the literature it is observed that deep learning algorithms are widely used for image classification task. Among the deep learning algorithms, CNN based custom defined networks and pretrained transfer learning networks are extensively applied for the classification. Our proposed system is designed with the novel combination of different algorithms towards the classification of COVID-19 . The class imbalance problem is observed in the dataset, from the literature, it was inferred that Densenet-201 is the one of the best pretrained transfer learning approaches. The class imbalance problem is handled using DCGAN, followed by the feature extractor Densenet-201 and conventional SVM classifier.

Following this context, this work proposes to contribute for early diagnosis of COVID-19 using one of the state-of-the-art deep learning architectures like DenseNet-201 architecture and class imbalance problem is handled using DCGAN.

3. Proposed Methodology

Deep learning plays a major role in disease diagnosis from medical images. Due to the necessity of predicting the presence of COVID-19 from images accurately, we explored various deep learning techniques. The problem of detecting COVID-19 is formulated as a classification problem with three classes COVID-19, Pneumonia, Normal. In this proposed method an efficient learning strategy that combines generative models with deep learning for classification to compensate the lack of annotated data. Thus this proposal supports knowledge sharing by enabling high accuracy in classification.

When the dataset is analysed, it was observed that the samples in each class are not balanced. The class imbalance problem of the dataset has been a contributing factor for not providing a better performance. This motivated to perform data augmentation using a Generative Adversarial Network (GAN) which is Deep Convolutional Generative Adversarial Network (DCGAN) in specific. The augmented images added to the existing dataset and used for the further classification in this proposed work.

The deep learning algorithm chosen for classification is Densenet, which has four different variants such as DenseNet-121, DenseNet-169, DenseNet-201 and DenseNet-264. Among these Densenet-201 is chosen to detect the presence of COVID-19 in this work, since it is found to be the better classifier on medical images [32].

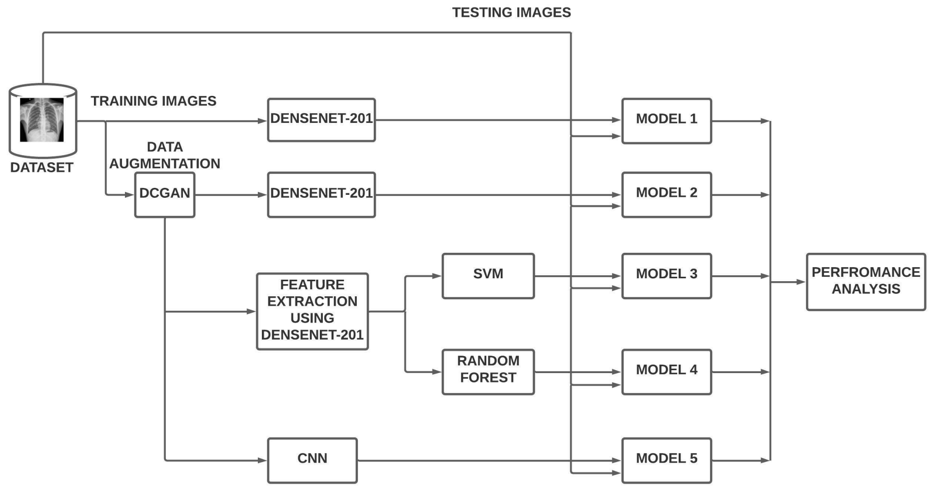


Fig. 1. Proposed architecture

To evaluate the effectiveness of DCGAN, the classifier DenseNet-201 is trained with the dataset without augmentation and termed as Model 1. To address the challenge of feature representation in conventional machine learning, we employed DenseNet-201 for feature extraction. SVM and RF classifiers are trained over the features extracted using DenseNet and the models are represented as Model 3, Model 4. On top of these we trained the pretrained deep learning models DenseNet–201 and CNN with the COVID-19 dataset augmented with DCGAN, whose models are termed as Model 2 and Model 5. The overall system architecture is illustrated in Fig.1.

The effectiveness of all the models are evaluated using the performance metrics and identified Model 3 with DenseNet-201 as feature extractor and SVM as classifier is the best model for detecting the presence of COVID-19 effectively. Following two subsections describes about the two deep learning building blocks used in out proposed work.

3.1. DCGAN

Conventionally, a GAN model consists of two stages: Generator and Discriminator. The generator network generates feature maps from the input images, while the discriminator network discriminates between the real and generated images using a classification layer. The GAN architecture is shown in Fig. 2.

However, GAN will have problems like instability during the training process. Compared with the simple GAN, DCGAN up-samples the images by using transposed convolution layer. Moreover, the leaky ReLU activation function is employed within the discriminator to stop gradient sparseness and no maxpoooling is employed here in both generator and discriminator.

The generator phase of DCGAN consists of 5 convolutional transpose layers (Conv2D Transpose) - ConvTranspose1, ConvTranspose2, ConvTranspose3, ConvTranspose4, each consisting of 128 filters. The input images are first enrolled into a denoising dense layer

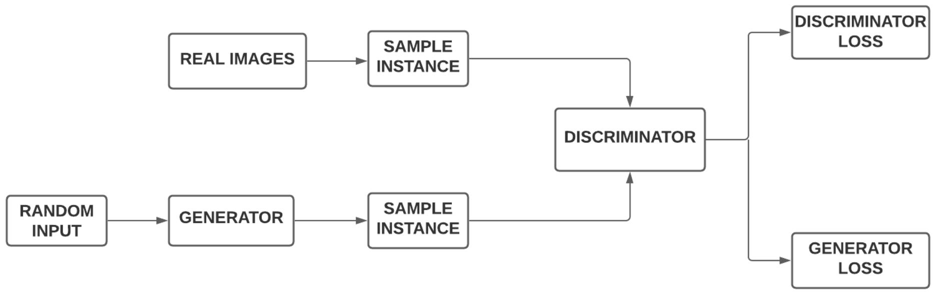


Fig. 2. Working of GAN [1]

that is primed at a size of 128*8*8, following a sequence of Conv2D Transpose layers and Leaky RELU layers and in turn is followed by a Conv2D layer with tanh activation are applied to generate a feature map of the input images.

The discriminator phase of DCGAN consists of five convolutional layers (Conv2D) Conv1, Conv2, Conv3, Conv4, and Conv5 each consisting of 128, 64, 32, 16 and 8 filters respectively, and a sequence of LeakyRELU layers. Finally, the Dense layer in the discriminator is used to classify the real and fake data.

After data augmentation using DCGAN, the augmented dataset contains 4000 images in each class of the training set which solves the problem of imbalanced data.

3.2. DenseNet-201

DenseNet, which is a short form of Dense Convolutional Network, needs fewer number of parameters than a conventional CNN as it does not learn redundant feature maps. The layers in DenseNet are very narrow i.e., 12 filters, which add a lesser set of latest feature maps. A 5 layered dense block representing direct connections between layers is shown in Fig. 3. Each layer in DenseNet has direct access to the original input image and gradients from the loss function. Each layer receives collective knowledge from the previous set of layers. Therefore, the computational cost is significantly reduced, which makes DenseNet a far better choice for image classification.

For each Dense Block, Pre-Activation Batch Normalisation (BN), and ReLU, then 3×3 Convolutional layers are used. To reduce the model complexity and size, BN-ReLU-1×1 Conv is completed before BN-ReLU-3×3 Conv. 1×1 Conv followed by 2×2 average pooling is used because of the transition layers between two contiguous dense blocks. Feature map sizes are equivalent within the dense block in order that they will be concatenated together easily. At the top of the last dense block, a global average pooling is performed followed by classifier with a softmax activation.

Densenet-201 with and without data augmentation DenseNet-201, is trained with the dataset, the features extracted are given to one or more fully connected layers with a softmax activation in final layer. The extracted features are given to a Average Pooling layer followed by flattening, Dense layer and dropout layer. The softmax activation outputs the probability distribution over each possible class label. Here the Densenet-201 is used as

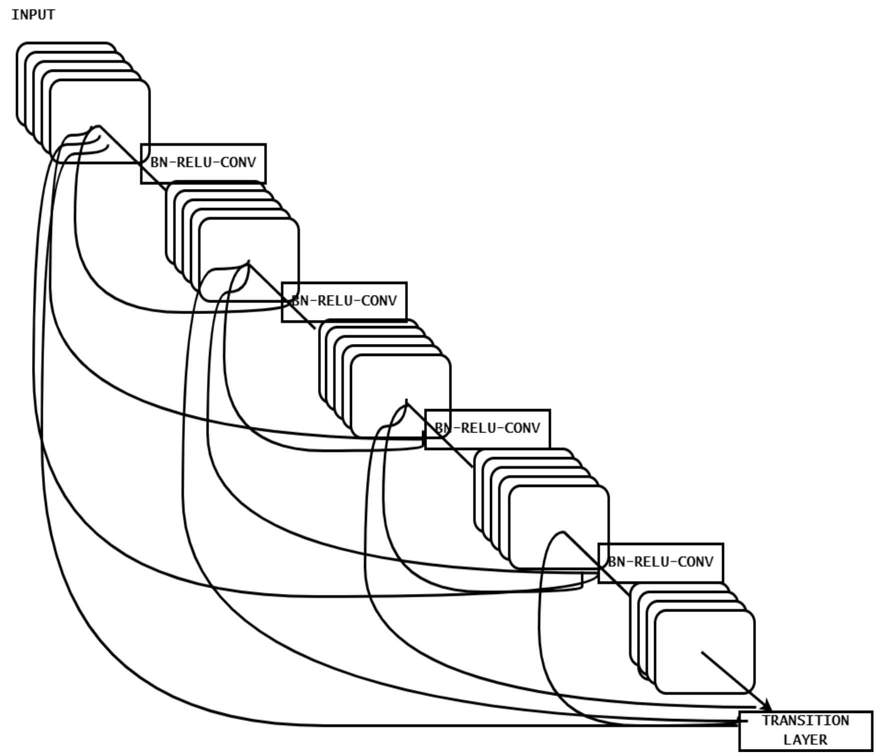
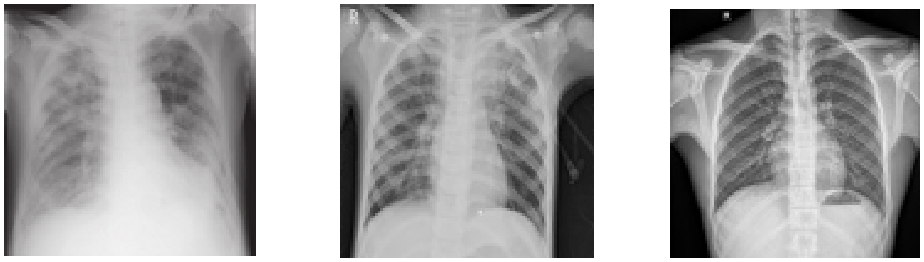


Fig. 3. A 5 layered dense block representing direct connections between layers [12]

the classifier trained with the images with and without augmentation in order to study the class imbalance problem among the classes of images in the dataset.

Support Vector Machine (SVM) SVM is used as a classifier that classifies the feature maps from DenseNet into COVID-19, Pneumonia, and normal. Tang (2013) [29] claims that training an SVM classifier on the features generated by the convolutional base can enhance classification accuracy. SVM has deployed linear kernel.

Random Forest (RF) Random forest is a supervised machine learning algorithm, ensemble by sequence of decision trees. Random forest classifier selects the best feature from the set of features which enhances the accuracy in prediction. Individual decision trees are trained in parallel and aggregates the decisions with good generalization without over fitting issue. Our architecture has used 100 trees with gini as the criteria with default minimum split as 2 and the maximum depth of tree is defined until all leaves are pure or until all leaves contain less than 2. The maximum number of features is taken as the default square root of the n_features and the the there is no limit to the number of leaf nodes. A node in this architecture will split when it triggers a decrease in impurity below the default threshold 0.



(a) Covid 19 image of a patient [23]

(b) Pneumonia Chest image [23]

(c) Normal Chest image of a patient [23]

Fig. 4. Chest X- ray images

3.3. Simple CNN

CNN has been widely used as image classifier with a stack of convolutional layers, the network learns and extracts features used to discriminate images into COVID-19, Pneumonia and normal. In our proposed approach, CNN is applied after the images are augmented. CNN consists of an input Conv layer of 32 filters and 3 blocks of Conv layer with 3x3 kernel size, max pooling layer with 2x2 kernel size, and dropout layer which is followed by a flattening layer. The flattened feature vector is fed to a dense layer with 64 filters and a dropout layer which is connected to a final dense layer with a sigmoid activation function.

4. Experiments

4.1. Dataset

Chest X-ray dataset from Kaggle [23] having chest x-ray images of COVID-19, Pneumonia and normal patients is used for evaluating our system. It has 6,432 images in total where 80% is used for training and 20% is used for testing. In the training set, it has 460 COVID-19, 1266 normal and 3418 pneumonia images. In the testing set, it has 116 COVID-19, 317 normal and 855 pneumonia images. The sample images of COVID-19, Pneumonia and normal samples from the actual dataset before augmentation are shown in Fig. 4.

4.2. Implementation

The implementation was done in Python using Nvidia GPU system and the code is available in github. [1]

[1] https://github.com/infantsneha-s/COVID-19-Detection-using-Deep-Learning.git

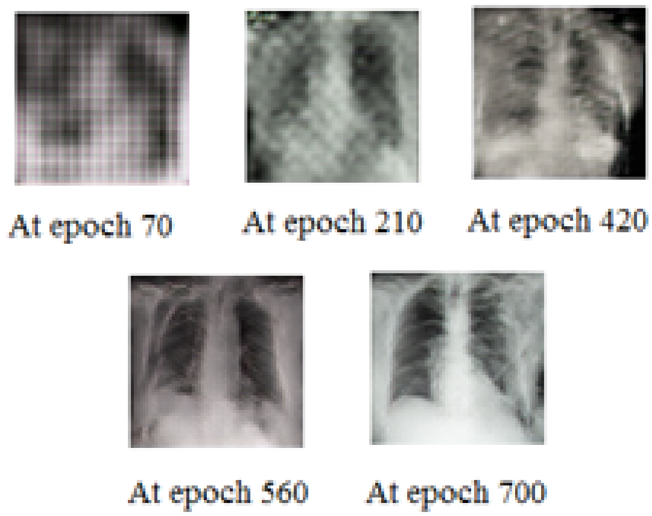


Fig. 5. Generated images of COVID-19 during the training process of DCGAN

Model 1: DenseNet-201 without augmentation Input dataset without augmentation is directly fed into the DenseNet-201 model for training which extracts features from the chest images. The features are then fed into its fully connected layer which classifies the images into COVID-19, pneumonia and normal. Model 1 is trained for 150 epochs and is evaluated. It has achieved a training accuracy of 97.31%.

As the dataset lacks in number of samples, generative models are used to enhance the dataset. DenseNet-201 framework is modified by enhancing the dataset with DCGAN based augmented images for the three classes. The images generated in different epochs is illustrated in Fig. 5, where the quality of the generated images are observed to be enhanced at epoch 700. DCGAN executed for different epochs with goal of reducing the loss, sample shown in Figure 6. In this plot the loss is saturated towards 0 across generations with the loss of real and fake samples of discriminator and generator shown during training. DCGAN is experimented with different hyper parameters and are listed in Table 1.

Now, the trained DCGAN model is used to generate the augmented images for each of the three classes and then added with the original dataset. The augmented dataset has around 4000 images in each class which solved the problem of imbalanced data. A sample set of augmented images are shown in Fig. 8.

Model 2: DenseNet-201 with DCGAN To improve the performance of the model 1, DCGAN is used to overcome the problem of an imbalanced dataset. Input dataset is fed into the DCGAN to augment the dataset. Augmented dataset is then fed into DenseNet-201 model which extracts features from the chest images. **The features are then help to discriminate** the images into COVID-19, other pneumonia and normal. **This model has achieved training accuracy of 99.33% after 150 epochs.** The data augmentation using DCGAN has shown an increase in training performance from 97.31 % to 99.33%

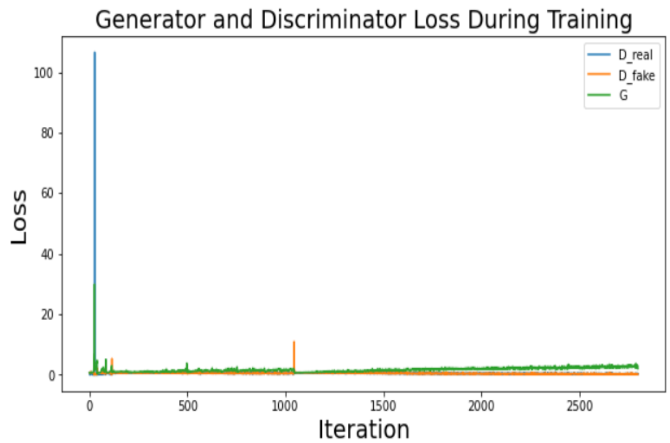


Fig. 6. DCGAN loss across epochs

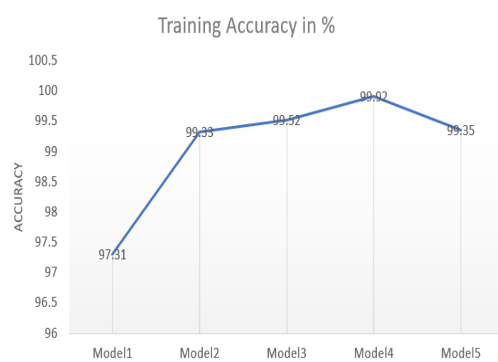


Fig. 7. Accuracy obtained during training

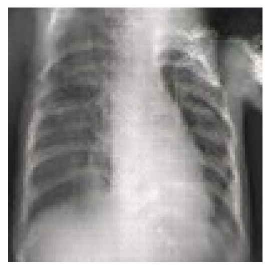
Model 3: SVM Using DenseNet-201 with DCGAN Model 3 uses the DenseNet-201 as feature extractor, that work upon the DCGAN augmented dataset. The features are then fed into the Support Vector Machine (SVM) classifier which classifies the images into COVID-19,other pneumonia and normal. SVM uses linear kernel, l2 penalty, with C set 1 whose stopping criterion tolerance is $1e^{-}3$, and the maximum iterations is not limited. This model has yielded a training accuracy of 99.52%.

Model 4: Random Forest Using DenseNet-201 with DCGAN Similarly, Densenet-201 is used as feature extractor from DCGAN augmented images and given to random forest classifier that classifies the features into COVID-19, other pneumonia and normal with a training accuracy of 99.92%. Random forest takes the default parameters namely the estimators are set to 100 with gini impurity, minimum number of samples at the leaf node set to 1 and the maximum number of feature will be taken as the square-root of the number of features with unlimited number of leaf nodes.

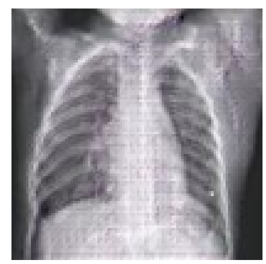
Table 1. DCGAN hyper parameters

Parameter	value
number of epochs	700
batch size	128
Size of z latent vector	100
Image size	128, 128
Number of channels	3
Learning rate for optimizers	0.0002
Activation Function	LeakyReLU (for all layers except last) and Sigmoid
Loss	binary crossentropy
Optimizer	Adam

(a) Augmented COVID-19 Chest X-ray image.



(b) Augmented PNEUMONIA Chest X-ray image.



(c) Augmented NORMAL Chest X-ray image.

Fig. 8. Augmented Chest X- ray images

Model 5: DCGAN with CNN To analyse and compare our proposed Densenet-201 model with other models, we used a simple CNN model. After augmentation with DC-GAN, the augmented dataset is then fed into CNN model which extracts features from the chest images and classifies the images into COVID-19, other pneumonia and normal. This CNN model is trained for around 150 epochs and obtained a training accuracy of 99.35%.

The training accuracy of all the five models are shown in Figure 7. From this figure, it can be observed that the model 4 has shown good accuracy followed by Model 3. But when tested the Model 3 out shown the other models, discussed elaborately about its performance in the next section.

4.3. Results and Discussion

The proposed deep learning based system for COVID-19 detection is evaluated with the testing dataset and compared with the state of the art techniques.

Performance Metrics Performance of the model is evaluated using the metrics namely, Accuracy, Sensitivity, Specificity, Precision and F1-Score.

Table 2. Performance analysis of all models; Model 1: DenseNet-201; Model 2: DCGAN + DenseNet-201; Model 3: DCGAN + DenseNet-201 + SVM; Model 4: DCGAN + DenseNet-201 + RF; Model 5: DCGAN + CNN

Model	Accuracy in%	Sensitivity	Specificity	Precision	F1 Score
Model 1	94.87	0.9289	0.9570	0.9367	0.9413
Model 2	95.18	0.9316	0.9621	0.9560	0.9433
Model 3	**95.49**	0.9378	0.9665	0.9561	0.9699
Model 4	95.03	0.9394	0.9670	0.9476	0.9668
Model 5	94.79	0.9255	0.9672	0.9462	0.9653

The primary building blocks of the metrics are True Positive, True Negative, False Positive and False Negative. True Positive (TP) is the actual value was positive and the model predicted a positive value. True Negative (TN) is the actual value was positive and the model predicted a negative value. False Positive (FP) is the actual value was negative but the model predicted a positive value. This measure contributes to the calculation of Type 1 error or False positive rate (FPR). False Negative (FN) is the actual value was negative but the model predicted a negative value. FN helps to compute False Negative Rate which is also known as the Type 2 error.

Accuracy is a metric that generally describes how the model performs across all classes. It is the ratio between the number of correct predictions to the total number of predictions.

Sensitivity is a measure of the proportion of actual positive cases that got predicted as positive (or true positive rate).It can be interpreted as capacity of a classifier to predict the positive samples.

Specificity is defined as the proportion of actual negatives, which got predicted as the negative (or true negative rate). It can be understood as the capacity of a classifier to predict negative samples.

F1-score is the harmonic mean of Precision and Recall and gives a better measure of the incorrectly classified cases than the accuracy metric.

A Confusion matrix is an N x N matrix used for evaluating the performance of a classification model, where N is the number of target classes. The matrix compares the actual target values with those predicted by the trained machine learning model. Cohen's kappa is another metric computed for all the classification models in this work along with the misclassification rate. Kappa coefficient can assess the performance of a classification model by capturing intrinsic nature of the data.

Table 2 depicts the metrics to compare the performance of various deep earning framework. It is inferred that DenseNet-201 as feature representation with SVM classifier outperforms rest of the DenseNet based architecture.

On feeding our dataset directly to the DenseNet-201 model gives an accuracy of 94.87%. To improve the accuracy of the model, DCGAN is used which solved the problem of imbalanced data and gave an accuracy of 95.18%. To further improve the accuracy of the model, DenseNet-201 is added with Support Vector Machine (SVM) which improved the accuracy by 0.31% and gave 95.49% accuracy. This model performs well than simple CNN by an accuracy difference of 0.70%.

From the confusion matrix of Model 1 (DenseNet-201), it has been observed that the true positives are 110 for COVID-19, 271 as normal, and 841 as pneumonia images. True negatives are 1169 COVID-19, 956 normal, 385 pneumonia images. False positives are 3 COVID-19, 15 normal, 48 pneumonia images. False negatives are 6 COVID-19, 46 normal, 14 pneumonia images. The misclassification error is computed as 5.13% which is the second highest among the models under consideration here. The kappa coefficient is 89% which is the lowest of all the five classification models. This model has classified 13% normal images as Pneumonia and around 1.5% of pneumonia images as normal. Overall observation is more number of images are classified as Pneumonia, the classifier did not extract enough discriminating features to classify the COVID-19, normal and pneumonia samples. This model has got least sensitivity measure among all that is observed as the classifier is not good at detecting the positive samples.

From the confusion matrix of Model 2 (DCGAN + DenseNet-201), it is analysed that the true positives are 107 COVID-19, 284 normal, and 835 pneumonia images. True negatives are 1170 COVID-19, 950 normal,394 pneumonia images. False positives are 2 COVID-19, 21 normal, 39 pneumonia images. False negatives are 9 COVID-19, 33 normal, 20 pneumonia images. This model has shown significant improvement than the classifier without DCGAN in terms of F1 score, but slightly lesser than the Model 3 which has SVM as classifier. It is observed that DenseNet-201's fully connected layers are not discriminating the features generated the convolutional layers of the same as compared with Model 3. This is the second classifier where more number of normal images are predicted as Pneumonia. This behaviour adds to misclassification accuracy, which is 4.82% , but still better than the model without DCGAN, along with the kappa coefficient as well.

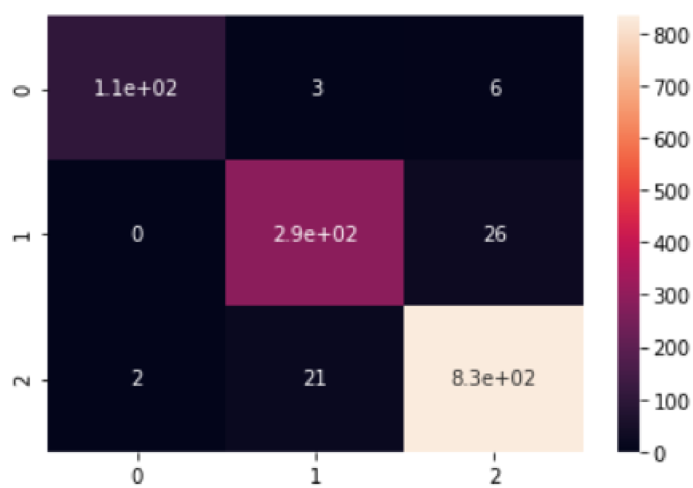


Fig. 9. Confusion matrix for Densenet-201 with SVM

From the confusion matrix (shown in Fig. 9) of Model 3 (DCGAN + DenseNet-201 + SVM), it is analysed that the true positives are 107 COVID-19, 287 normal, and 834 pneumonia images. True negatives are 1170 COVID-19, 949 normal, 397 pneumonia images. False positives are 2 COVID-19, 22 normal, 36 pneumonia images. False negatives are 9 COVID-19, 30 normal, 21 pneumonia images. The misclassification error for this model is 4.5%, the smallest of all the 5 models evaluated, with Kappa coefficient 0.91. These observations have shown that the combination network with DCGAN + DenseNet-201 + SVM has predicted more number of actuals, which was also supported by the F1 score of 96.99%. This infers that, scoring a high F1 score is due to the fact that number of False Positives and False Negatives must be low among all the classifiers. Also adds to the fact that Model 3 has generated more number of True Positives than any other model considered in this work.

Table 4 shows the metrics for each of the three classes for best performing Model 3 (DCGAN + DenseNet201 + SVM). From the results it has been observed that the more images are predicted as Pneumonia. That has also reflected here in the metrics of Table 4 where Pneumonia class of images have higher F1 score of about 96.80 %, followed by the COVID-19 class with 95.11%. This can be interpreted as more number of True positives are predicted by the model. This framework has generated second highest sensitivity among all, which is interpreted as the classifier being good at predicting the positive samples.

The actual training set before applying DCGAN for COVID-19 class has 460 images which were augmented to 4000 by DCGAN. COVID-19 class has the least set of original images among all. The results show that the application of DCGAN for augmentation has performed well and has not degraded the performance of the Model 3 by any means in the prediction.

From the confusion matrix of Model 4 (DCGAN + DenseNet-201 + RF), it is analysed that the true positives are 107 COVID-19, 295 normal, and 824 pneumonia images. True negatives are 1170 COVID-19, 939 normal,405 pneumonia images. False positives are 2 COVID-19, 32 normal, 28 pneumonia images. False negatives are 9 COVID-19, 22 normal, 31 pneumonia images. This classifier has given a second best performance among all with a F1 score of 96.68% with a misclassification rate of about 4.97%. Also this combination has given the highest sensitivity that shows that the classifier is good at predicting the positive samples. With respect to specificity this model has shown a moderate behaviour in detecting the negative samples.

From the confusion matrix of Model 5 (DCGAN + CNN), it is analysed that the true positives are 100 covid, 304 normal, and 817 pneumonia images. True negatives are 1171 COVID-19, 928 normal,410 pneumonia images. False positives are 1 COVID-19, 43 normal, 23 pneumonia images. False negatives are 16 COVID-19, 13 normal, 38 pneumonia images. This model with image augmentation and CNN to generate features and classify is better than model without augmentation in terms of F1 score but significantly lesser than models with DenseNet-201 as feature extractor. This shows that the dense blocks with strengthened feature propagation in the DenseNet-201 have outperform the simple convolutional layers of CNN. The other characteristic exhibited by this framework is having highest specificity that is this classifier is good at detecting negative samples.

To show the proposed approach (DCGAN+DenseNet-201+ SVM) is statistically significant than the other four approaches, Paired t-test with equal variance was applied between the proposed model and the other four models on training accuracy across the dif-

Table 3. Misclassification error and Kappa Coefficient

Model	Misclassification Rate	Kappa Coefficient
Model 1	5.13	0.893
Model 2	4.82	0.90
Model 3	4.51	0.91
Model 4	4.97	0.899
Model 5	5.21	0.895

Table 4. Class-wise metrics for Model 3 (DCGAN + DenseNet201 + SVM)

Class	Per Class Precision	Per class Recall	Per class F1
COVID-19	92.24	98.17	95.11
Normal	91.80	93.38	92.58
Pneumonia	97.31	96.3	96.80

ferent epochs. With 95% confidence interval , the two tailed p value has shown significant difference between the proposed and the four other approaches to detect the COVID-19.

Analysis

1. DenseNet-201 is observed to be a better network as feature extractor than simple sequential CNN layers.
2. Models with traditional machine learning classifiers namely SVM, Random Forest have out performed than the neural network based classifiers. Thus from the research performed, the DenseNet-201 model with SVM outperformed any of the other combinations of models constructed and passed the statistical t-test.
3. From the results shown in Tables 2, 3 and 4 it can be inferred that data augmentation is helping the system to learn better.
4. Most of the Normal samples are misclassified as Pneumonia, since the feature pattern of Pneumonia appear to be similar to Normal samples. Neither the CNN nor the DenseNet-201 has the ability to identify this to reduce the number of False positives.

4.4. Comparison with existing works

The literature [17], [16], [19] show that the effectiveness of deep learning on COVID-19 detection. As reported in [19] simple CNN has obtained an accuracy of 89.75%. It is inferred that CNN is nor performing well because of the data imbalance problem and hence enough samples are not available for training leads to this performance. DCGAN in the proposed framework has handled that problem and has given improvement in performance and obtained an accuracy of 94.79%. This improvement is significant due to the presence of DCGAN. Comparison of other existing methods with our model that have used the same dataset is shown in Table 5.

VGG-16 is a 16 layer architecture with a pair of convolution layers, a pooling layer and at the end a fully connected layer. It features a plethora of weight parameters, the

Table 5. Comparison of other existing methods with our proposed DCGAN + DenseNet-201 + SVM model

Model	Accuracy in %
VGG-16 [17]	66.3
Simple CNN [19]	89.75
ResNet50 [16]	95.10
Proposed DCGAN + CNN	94.79
Proposed DCGAN + DenseNet-201+ SVM	**95.49**

models are very heavy, which also means a long inference time. It also has a vanishing gradient problem. Due to these, results show the poor performing VGG-16 than any any other model taken up for comparison here.

The results show minor difference between ResNet50 [16] and proposed DCGAN +DenseNet-201+ SVM, but the suitable network for the detection of COVID-19 is proven to be the proposed one. The reasons are as follows: ResNet was proposed to beat the issues of VGG styled CNNs. ResNets need less memory, have a faster inference time, and allow for the training of deeper networks. It also solved the problem of vanishing gradient by skipping the connections. Densenet adds shortcuts among layers and has thinner network and having fewer number of channels is better than the identity mapping feature of ResNet. Also, in contrast to ResNet, a dense layer gets all outputs from preceding layers and concatenates them in the depth dimension. Densenet also uses much fewer parameters than ResNet with fewer redundant layers as well. Fewer redundant layers mean more parameter efficiency and less computation and hence DCGAN +DenseNet-201+ SVM proven to be a better framework for detection of COVID-19.

Analysis

1. Compared to CNN and VGG-16, DenseNet-201 is performing well as shown in the Tables 5 and 2, since the Model 1 which is without augmentation has given an accuracy of 94.87%.
2. The presence of skip connections and the handling the vanishing gradient problem have made both ResNet and DenseNet-201 better than VGG-16 and CNN
3. Between ResNet and DenseNet-201, the proposed work with DenseNet-201 (Model 3) has exhibited a better performance, because of the augmentation of images, less complexity in terms of layers, parameters and hence computational time.

5. Conclusion and Future work

In this paper, a novel deep learning model is designed for COVID-19 disease detection with the help of Deep Convolutional Generative Adversarial Network (DCGAN) and DenseNet-201 with SVM classifier. The proposed model is able to detect COVID -19 in chest images with the accuracy of 95.49% and with F1 score of about 96.99%. Comparative analyses revealed that the DenseNet-201, a transfer learning based deep learning framework with SVM classifier performs significantly better as compared to other approaches. Therefore, the proposed model can act as an lead for further research process.

In future we will explore the approaches for evolving and newer data patterns to provide early alerts in addition to detecting the severity of the infection. Also the limitation observed in this work is, Normal images are more often classified as Pneumonia. The features generated are enough but not sufficient to discriminate them with less false positives.

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