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Enhanced SVM Based Covid 19 Detection System Using Efficient Transfer Learning Algorithms

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Abstract

Diagnosing of the novel coronavirus disease (COVID-19) has recently become a critical task in medical domain. Deep Learning has proved to be a very powerful tool of machine learning because of its ability to handle large amounts of data. One of the most popular deep neural networks is Convolutional Neural Networks (CNN) which is widely used for a variety of applications such as image/object recognition and classification. Since it has been proved that transfer learning (TL) is effective for the medical classification tasks, in this study; COVID -19 diagnosis algorithms are implemented as quick alternative, accurate and reliable diagnosis options to detect COVID-19 disease. In our work, x-rays images of known data set with three pre-trained CNN models (ResNet50, VGG19, AlexNet) have been proposed for diagnosing COVID19 patients. Based on the obtained performance results, the pre-trained models (ResNet50, VGG19 and AlexNet) with support vector machine (SVM) provide the best classification performance compared to the use of each model individually.

Key Words: COVID-19, Support Vector Machine (SVM), VGG19, AlexNet, ResNet50.

1 Introduction

The lives of people and the world's healthcare systems that are a set of organizations that should provide health care to protect and improve the health of the population by health promotion, disease prevention, diagnostic and therapeutic services are in danger because of COVID-19. The year 2019 saw the discovery of a brand-new virus that humanity had never seen before. The first case of COVID-19 positivity was found in Wuhan, China, in December 2019, and it swiftly spread to many other Chinese cities as well as to other countries worldwide **[1]**. Every day, more people are dying from the COVID-19**[2]**. According to the most recent data, there have been more than 6.27 million deaths and more than 523,663,000 positive cases of COVID-19. The most used method for detecting COVID-19 is Real-Time Polymerase Chain Reaction (RT-PCR). Despite having a sensitivity range of 70% to 90%, it has a high rate of false-negative findings and can take up to two days to get results **[3]**. Additionally, radiologists must search for radiological indicators on a Chest X-Ray (CXR) images that point to COVID-19 symptoms. COVID-19 is spreading rapidly throughout the world. Early detection and isolation of patients has proven critical in slowing the spread of the disease. Deep learning strategies are one of the best options for reliably and easily detecting COVID-19. The goal of this study is to automate CXR analysis in order to save time and effort.

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The main contributions of our study are as follows:

• Implementing a computer-aided diagnosis (CAD) system based on chest X-ray images for COVID-19 detection using CNN pre-trained models.

• Applying transfer learning architectures to overcome the problems caused by the limited number of dataset images.

• Proposing the CNN + support vector machine (SVM) on X-ray images to improve the performance of the pre-trained models and identify accurately COVID-19.

Our experimental results show the effectiveness of the proposed algorithms in classification and their potential for COVID-19 classification, prevention, and control in real time.

This paper is organized in 6 sections. In section 2, some related works concerning COVID 19 detection will be discussed as the state of the art. In section 3, the proposed COVID 19 detection system is described. In section 4, a comparative experimental evaluation reveals the advantageous performances of the proposed algorithms in comparison to other methods applied on common data sets. In section 5, conclusions and future perspectives are presented.

2 Related Works

To assist doctors and experts in correctly diagnosing COVID-19 and know if patients are infected with corona virus or not, a number of medical imaging systems based on Deep Learning (DL) methods have been developed **[4]**. Several researchers have obtained excellent reliability values using pre-trained models by utilizing transfer-learning, and numerous studies have attempted to identify COVID-19 infections in CXR images using various DL approaches.

For the purpose of coronavirus pneumonia identification utilizing CXR radiographs, five pre-trained convolutional neural network-based models (ResNet50, ResNet101, ResNet152, InceptionV3 and Inception-ResNetV2) were proposed in **[5]**. The pre-trained ResNet-50 method provides the highest efficiency. Authors in **[6]** proposed using CXR images to automatically establish a new deep architecture called COVID-Net to detect COVID-19 cases, this model had a classification accuracy of 93.3 %. A novel pre-trained model called COVIDXNet was introduced in **[7]** as a deep learning framework for detecting COVID-19 infections in CXR images and the study demonstrated the useful application of the proposed DL architecture to classify COVID-19 using X-ray images. In **[8]**; authors proposed DL architecture composed of three parts; a backbone network, a classification head, and an anomaly detection head. The backbone network was used to extract high-level characteristics from an input chest X-ray image, which were then input into the classification head and anomaly detection head, respectively. In order to train a DeTraCResNet18-based binary model for identifying COVID 19, authors in **[9]** used 196 images (105 for COVID-19, 80 for normal, and 11 for SARS). The model was 95.12% accurate, 97.91% sensitive, 91.87% specific, and 93.36% accurate. Authors in **[10]** used a total of 455 chest X-rays (135 of COVID-19 and 320 of viral and bacterial pneumonia) to pre-train ResNet-50 and they achieved 89.2 % of accuracy.

From the above stated works, we can conclude that the main goal of the pre-trained DL models is to detect COVID-19 cases with high detection rate. Thus; our main contribution is to create an efficient deep learning-based model that can detect accurately COVID-19 based on chest X-ray images with enough sensitivity to enable quick and accurate screening.

3 The Proposed Algorithms

The lack of available datasets is one of the most challenging issues that researchers struggle with while analyzing medical data. A lot of data is typically needed for DL models. The key benefit of employing the transfer learning approach is that it reduces computation costs and enables data training with fewer datasets. The pre-trained model transfers its knowledge from a huge dataset to the model that has to be trained. The most effective methods in recent years have included advanced designs like VGG-19, ResNet50, and AlexNet. These pre-trained models, however, weren't always able to provide effective outcomes. As a result, in this research, we suggest developing an enhanced COVID 19 detection system based on transfer learning methods and support vector machines (SVM), the latter of which is suggested to increase the performance of the pre-trained models.

3.1 VGG 19 Model

The Visual Geometry Group (VGG) network is a pre-trained CNN model proposed by Simonyan and Zisserman at the University of Oxford in early 2014 **[11].** The input to the VGG-19 model is a 224x224 image with three channels, 16 convolution layers, and 3 fully connected (fc) layers. The kernel size for the convolutional layers is 3x3, while the padding and stride are each 1 pixel. There are 5 max-pooling layers in the network, each with a 2x2 kernel and a 2 pixel stride. Rectified linear Units are used to represent the nonlinear function (ReLUs). A linear classifier with three fully-connected layers and a dropout follows the convolutional section. The first two fc layers contain 4096 features respectively, while the third one only has 1000 features. After the last fc layer, a softmax layer with the same number of outputs follows, providing probabilities of the input corresponding to each of the 1000 classes in the ImageNet dataset. Figure 1 illustrates the main parts of the VGG 19 model:

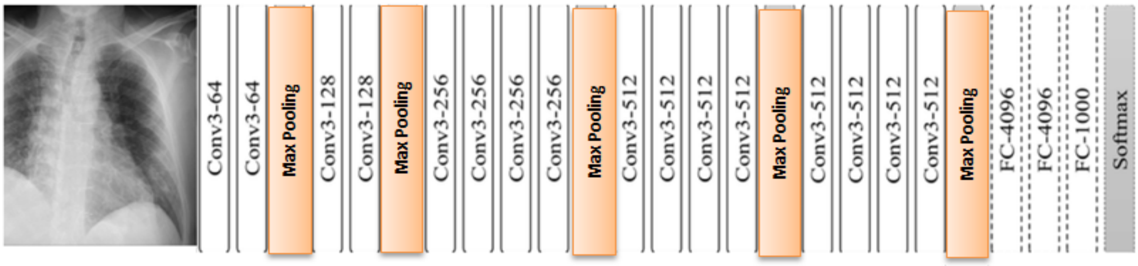

Figure 1: Architecture of VGG-19 model.

3.2 ResNet50 Model

ResNet-50 (residual neural network) is a ResNet architecture variation with 50 deep layers that has been trained on at least one million images from the ImageNet database. Convolutional block sequences with average pooling make up the ResNet-50 architecture. Softmax is used as the final classification layer **[12]**. The five convolutional layers that constitute ResNet-50 are conv1, conv2-x, conv3-x, conv4-x, and conv5-x. The input image is loaded, then processed through a max pooling layer with a stride length of 2 in conv2-x, followed by a convolutional layer with 64 filters and a kernel size of 7X7 (conv1 layer). The layers are arranged in pairs as a result of the way residual networks are connected; there are two levels with kernel sizes of 3 by 3 and 64 and 256 filters, respectively, and a third layer with kernel sizes of 3 by 3 and 64 filters, repeated three times. The procedure was repeated up to the fifth convolutional layer, after which average pooling was used at the fully connected layer, followed by softmax for classification. Figure 2 shows the architecture of ResNet 50 model.

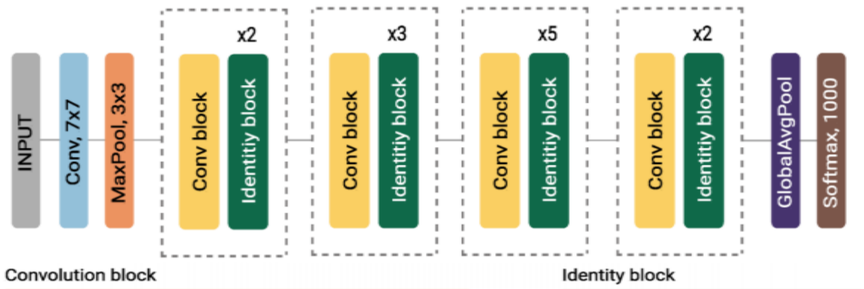

Figure 2: Architecture of Resnet50 model.

3.3 AlexNet Model

AlexNet is a deep neural network created by Alex Krizhevsky **[13]** in 2012. It was developed to classify images for the ImageNet LSFRC-2010 competition and won first place. AlexNet has eight weight layers, five convolutional layers, three fully connected layers, and three max-pooling layers after the first, second, and fifth convolutional layers. The first convolutional layer has 96 filters, each measuring 11x 11, with a stride of 4 pixels and padding of 2 pixels. Other convolutional layers' stride and padding are set to 1 pixel. 256 filters of size 55 are present in the second convolutional layer. The third, fourth, and fifth convolutional layers, respectively, comprise 384, and 256 filters with a size of 3x3. Figure 3 shows the layers of AlexNet model.

Figure 3: Architecture of AlexNet model.

3.4 Transfer learning using Support Vector Machines

Deep learning using neural networks has claimed cutting-edge performance in a variety of tasks. Support vector machine (SVM) is a popular alternative or classification method **[14]**. Using SVMs (especially linear) in combination with convolutional neural network has previously been proposed as part of a multistage process. To learn good invariant hidden latent representations, a deep convolutional net is first trained using supervised/unsupervised objectives. Data samples corresponding hidden variables are then treated as input and fed into linear (or kernel) SVMs. Usually, this technique enhances the performance of transfer learning models **[15].** The foundation of deep feature extraction is the acquisition of features from a pre-trained CNN. In order to train the classifier, the fully connected layer's deep features are retrieved.

SVM classifier uses the deep characteristics that were collected from each CNN network. The classification is then carried out, and the effectiveness of every classification model is evaluated. Support vector machines (SVMs) are a subset of supervised learning techniques used in regression and classification. They belong to the family of generalized linear classifiers. Using machine learning theory, SVM is a classification and regression prediction technique that seeks to enhance predicted accuracy while automatically avoiding overfitting to data. A set of training data is used in the procedure. This permits the best spots to be separated by a hyper-plane. When pixel maps are used as input, SVM gains popularity. It involves creating a hyper-plane that divides two or more groups of points. The initial concept behind SVM is built on employing kernel core functions that provide the best categorization of the plan's points **[16]**. Figure 4 illustrates the SVM concept:

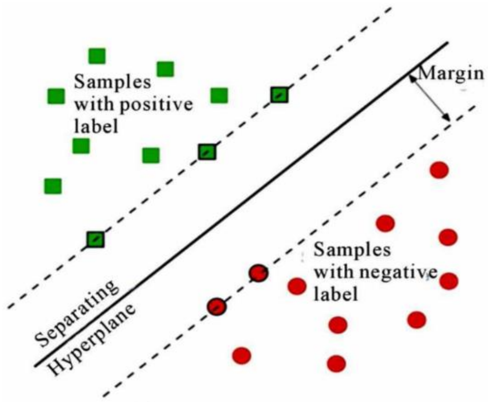

Figure 4: Illustration of SVM technique **[16].**

4 Results And Discussions

This study proposes two different approaches based on three pertained neural network models (ResNet-50,VGG19, and AlexNet) and the same models using SVM Classifier for COVID-19 detection using chest X-ray images. Figure 5 illustrates the schematic methodology for the COVID19 detection system, We have used transfer learning based pre-trained models namely VGG-19, resNet50, and AlexNet for classifying X-ray images into two different classes : Covid-19 and Normal . To extract features The pre-trained models are modified and trained and tested with the data that is already divided to training data and testing data after the pre-processing and the data augmentation phase, The fully connected layer is the in-charge of classifying and making decisions whether it is COVID-19 or the otherwise. In the other case the pre-trained model is modified and fine-tuned by replacing the fully connected layer with the SVM classifier which has the same functionality as the fully connected layer does.

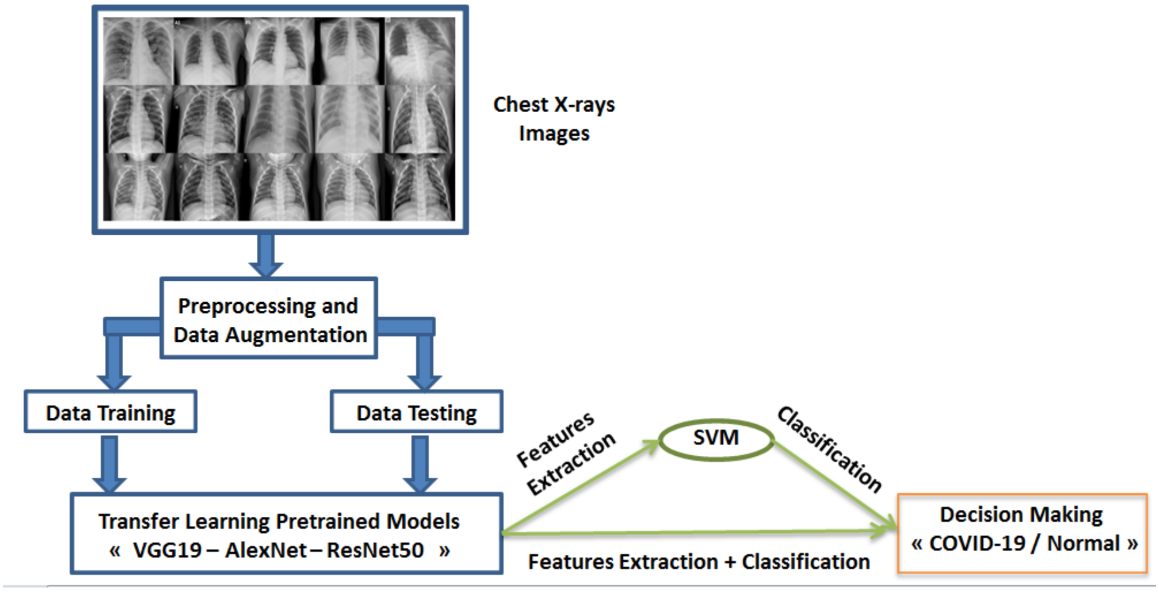

Figure 5: The proposed COVID19 detection system.

4.1 System Requirement

In this work; the hardware used for all experiments were on an 6th generation Intel-i5 laptop PC with a 8GB RAM, and 256GB of SSD with the usual Windows OS. Matlab programming language was used to train the proposed deep transfer learning pre-trained models.

4.2 Data set (COVID-19 chest X-ray Image)

With the global spread of COVID-19, deep learning researchers have worked tremendously to diagnose the novel virus using chest X-ray images. The kaggle COVID-19 chest X-ray dataset **[17]** was used in this work as an important diagnostic test to assess the lung for the damaging effects of COVID-19 .A total of four hundred and fifty (450) images of chest X-ray , these images of Chest X-rays were divided into two groups . Group 1 included one hundred and twenty (120) images of chest X-rays labelled as Normal, Group 2 is comprised of three hundred and thirty (330) images of chest X-rays labelled as COVID-19 patient (table 1).

Type	Number of Image
Normal	120
COVID 19 Patient	330
Total	450

Table 1: Details of the used dataset

After splitting the database %80 for training and %20 for testing; we get values that are shown in table 2:

Type	Number of Training Image	Number of Testing Image
Normal	96	24
COVID 19 Patient	264	66
Total	360	90

Table 2: Details of Training and testing of dataset

4.3 Pre-processing and Tuning Hyper-Parameters

We have applied a number of augmentation techniques to avoid overfitting problem. Such as random reflection, translation, and random scaling. We have randomly translated the images up to thirty pixels horizontally and vertically, each image is reflected vertically with 50% probability and horizontally scaling. All images were resized to (224x224) pixels before being fed to the pre-trained models resNet50 and VGG19. For AlexNet model the images were resized to (227x227) pixels.

Because all the models require 3 channels; images dataset of one channel (grayscale) channel were converted to Red-Green-Blue (RGB) image, which is a three-channel image data. In this research, we have performed binary classifications with (COVID-19 and normal). Table 3 shows the tuned parameters during the implementation of the proposed algorithms.

Software	Matlab (2021.b)
Optimisation	SGDM
Mini-Batch	10
Learning Rate	0.0003
Max Epochs	6

Table 3: Tuning Hyper parameters

4.4 Evaluation Metrics

Measuring the model's performance is equally crucial after preparing the data and testing the suggested transfer learning models. It is also crucial to understand how effectively the model generalizes the hidden data and whether it can be used to address various issues. For various machine learning tasks, many assessment metrics may be applied. The focus will be on measures that may assess classification performances because our methods are dependent on categorization. **[18]**.

4.4.1. Confusion Matrix

The confusion Matrix (CM) is N x N matrix required in many machine learning algorithms, especially those used in supervised learning. CM is a table with two rows and two columns that reports the number of false positives, false negatives, true positives, and true negatives. CM allows us to quantify the accuracy of a model by visualizing the type of errors it makes. This helps identifying areas of improvement to get better model performance. CMs are especially important for models that make multiple classification decisions.

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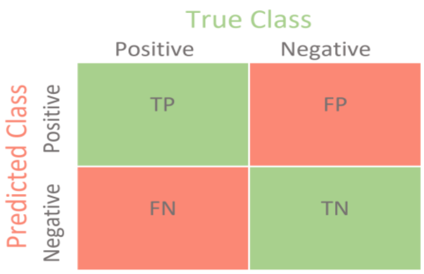

Figure 6: The structure of Confusion Matrix (CM).

Here are the values stated in the confusion matrix:
- True Positive (TP) - A result where the model correctly predicts the positive class.
- True Negative (TN) - A result where the model correctly predicts the negative class.
- False Positive (FP) - A result where the model incorrectly predicts the positive class.
- False Negative (FN) - A result where the model incorrectly predicts the negative class.

4.4.2. Accuracy

A common measure used to evaluate how well machine learning models perform is accuracy. Equation 1 demonstrates that accuracy is the ratio of accurate categories to all other classifications:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{1}$$

An easy-to-use yet powerful assessment criteria is accuracy. It may be employed, for instance, if the data are significantly out of balance and the model is biased toward categorizing the data as the majority class.

4.4.3. Recall

Recall is defined in Equation 2, which emphasizes getting no false negatives while also being correct. False positives are not considered a concern since recall does not take them into consideration. This is preferable when categorizing for a rare disease, for instance, as misclassifying someone as healthy when they are unwell might have catastrophic implications.

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

4.4.4. Precision

Equation 3 illustrates how accuracy is defined differently and with a higher emphasis on lowering false positives. This could be desired if false positives are demonstrably worse than false negatives. The categorization of email as spam is one example of this; wrongly classifying a genuine email as spam may prevent a user from obtaining important information. **[19]**.

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

4.4.5. F1-score

If recall and accuracy are necessary, and the data must be divided uniformly throughout the classes, the F1-score is the best choice. Accuracy and F1-score are quite close **[19]** if the distribution across classes is more equal. Equation 4 gives the definition of F1 score :

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

4.5 Experimental Results

To evaluate the efficacy of the proposed models, for the purpose of diagnosing the COVID-19 cases from CXR images, we have conducted both transfer learning pre-trained models evaluation with SVM as well as without SVM. This section presents the results from two different experiments. the tables 4, 5, and 6 show the accuracy, specificity, F1 score, sensitivity and precision for the following transfer learning pre-trained models with and without SVM classifier.

4.5.1. Results of VGG 19 with SVM

The results of the VGG-19 experiment for COVID-19 detection are summarized in Table 4.

Model	VGG 19	VGG 19 with SVM
Accuracy	96 %	**98.9 %**
Recall	100 %	**98.48 %**
F1 Score	97.8 %	**97.9 %**
Specificity	87.5 %	**100 %**
Precision	100 %	**96 %**

Table 4: Result for VGG19 model + SVM.

Figure 7 shows the confusion matrix for VGG19, in which we observe 3 images of COVID-19 and 0 NORMAL images are not correctly classified. And for VGG19 + SVM; figure 8 depicts that out of these 66 COVID19 images only one image is misclassified.

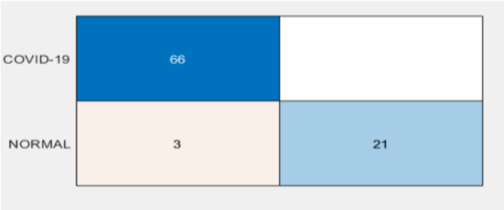

Figure 7: Confusion matrix results of VGG 19.

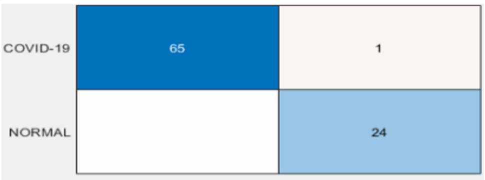

Figure 8: Confusion matrix results of VGG 19 + SVM.

4.5.2. Results of AlexNet with SVM

As shown in table 5; we have obtained the best performance with the AlexNet + SVM, with an accuracy of 100%, a Specificity of 100 %,a recall of 100%, a precision of 100%, and an F1-score of 100%. The lowest performance values were obtained by AlexNet model.

Model	AlexNet	AlexNet with SVM
Accuracy	97.7 %	**100 %**
Recall	100 %	**100 %**
F1 Score	95.6 %	**100 %**
Specificity	91.6 %	**100 %**
Precision	100 %	**100 %**

Table 5: Result for AlexNet model + SVM.

The confusion matrix for the detection of COVID19 obtained from AlexNet model and AlexNet+SVM are given in Figures 9 and 10. Figure 9 shows that there is no misclassified image neither false positive nor false negative. Figure 10 shows there is two false positive, these two are actual non-COVID-19 and the model predicted it as a COVID-19 patients.

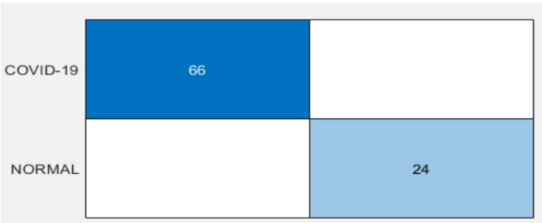

Figure 9: AlexNet confusion matrix results.

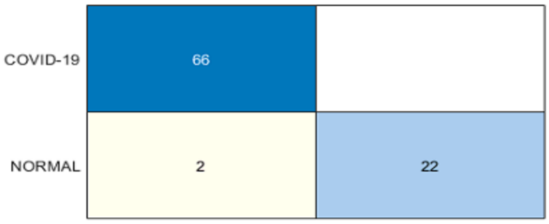

Figure 10: AlexNet + SVM confusion matrix results.

4.5.3. Results of ResNet50 with SVM

The ResNet50 model was also compared with the ResNet50 + SVM method. The comparison is listed in table 6. It can be observed that ResNet50 + SVM method were better with an accuracy, sensitivity, F1 score, precision and specificity equal to 100% compared to the ResNet50 model. Figures 11 and 12 show the confusion matrix for ResNet50 and for ResNet50 + SVM, for ResNet50 we observe 1 image COVID-19 and 0 NORMAL images are not correctly classified. and for ResNet50 + SVM. We see that Out of these 66 COVID19 images none of the images are misclassified.

Model	ResNet50	ResNet50 with SVM
Accuracy	98.9 %	**100 %**
Recall	98.48 %	**100 %**
F1 Score	97.9 %	**100 %**
Specificity	100 %	**100 %**
Precision	96 %	**100 %**

Table 6: Result for ResNet50 model + SVM

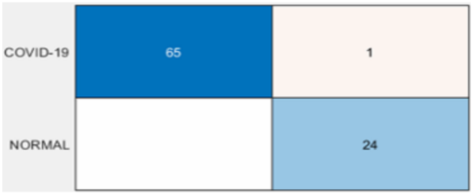

Figure 11: ResNet50 confusion matrix results.

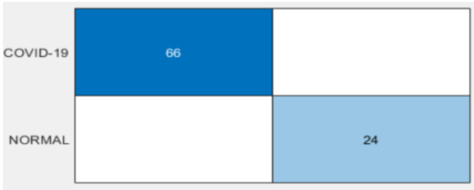

Figure 12: ResNet50 + SVM confusion matrix results.

4.5.4. Results of Training Progress

Figures 13, 14, and 15 show the accuracy scores and loss variation for the six recorded epochs. The AlexNet model had the highest training accuracy, followed by ResNet50 and the VGG19 pre-trained model. The loss value of a model indicates how well or bad it performs after each iteration. Less loss equals better performance. The rate of loss decreased on average as the number of epochs increased. The average loss varied significantly across models.

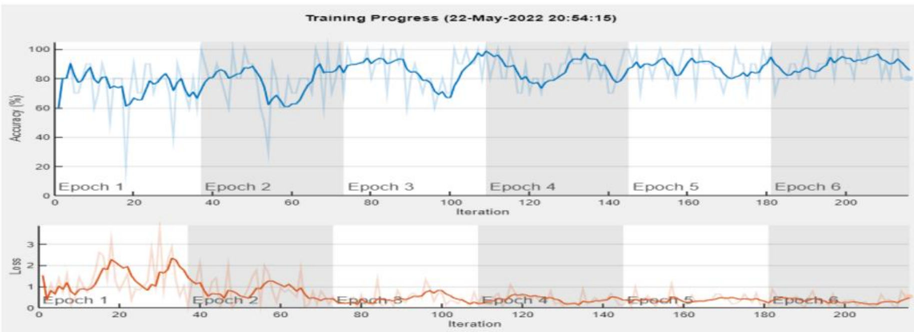

Figure 13: Accuracy / loss training progress for AlexNet.

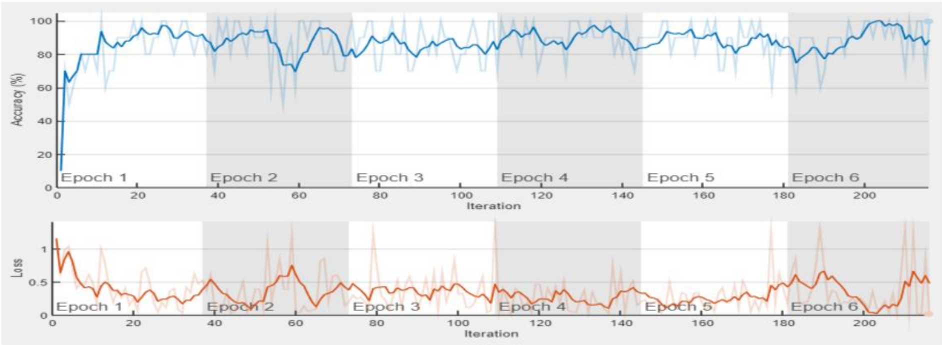

Figure 14: Accuracy/ loss training progress for ResNet50

Figure 15: Accuracy/ loss training progress for VGG19.

4.5.5. Discussion of Obtained Results

This study focused on predicting survival chances for COVID-19 patients. We conducted experiments with an X-ray image dataset. The proposed method can detect COVID-19 patients, allowing preventive measures to be taken to reduce mortality rate.

In medical diagnostic aid in general and decision support for COVID-19 in particular the sensitivity is very important. Indeed, a high sensitivity is equivalent to a very low false negative rate. False negatives are patients who have been diagnosed as Non-COVID by the system but are actually infected patients. Such an error can cause the death of the patient and spread the disease whenever the patient goes, a false positive error does not have the same impact of false negative and it can be quickly corrected with additional tests.

The AlexNet and ResNet50+SVM models have yielded the highest value for accuracy and sensitivity with 100% with 0 false negative case. followed by AlexNet and VGG19 models with a 0 false negative and an accuracy equal to 97.78% and 96.6% respectively. Coming after ResNet50 and VGG19 + SVM with 1 false negative with the same accuracy 98.9%. The ResNet50 and VGG19 pretrained models have achieved better results using SVM, while AlexNet without SVM did much better results.

5 Conclusion

In this paper, we have proposed an efficient methodology of Computer Aided Diagnosis for detecting COVID-19 disease by using the CXR images, and we have evaluated the performances of our algorithms using common evaluation metrics. In this context, we have implemented pre-trained models (AlexNet, VGG19 and ResNet50) of transfer learning technique with and without SVM classifier. The experimental results show that the pre-trained models with SVM have performed better compared to the other models without SVM classifier. Thus, the proposed system can be successfully used for COVID-19 diagnosis and reducing the mortality rate and preventing the world from the spread of corona virus.
As futures perspectives, we recommend adapting our algorithm for diagnosing other types of dangerous chest diseases such as tuberculosis, also we suggest using other types of machine learning classifier.

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