
# Improving Convolutional Neural Networks' Accuracy in Covid-19 Detection Using Support Vector Machine

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ABSTRACT

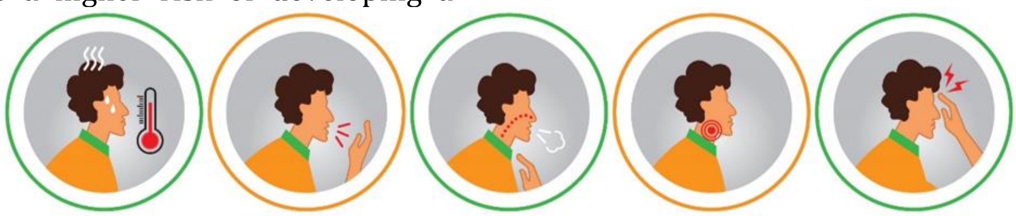
Since December 2019, the coronavirus (COVID-19) pandemic spread in all countries and put health systems under tremendous pressure. Massive efforts have been conducted to find ways to determine the infected patients quickly. Therefore, intelligent systems empowered with Machine Learning and Deep Learning have been utilized in detecting several diseases (especially COVID-19). The systems examine chest x-rays of the suspected patient to decide whether it is a COVID-19 case. This paper evaluates three DL models of Convolutional Neural Networks (CCN): GoogleNet, AlexNet, and VGG16 on COVID-19. The evaluation is based on and without using a Support Vector Machine (SVM) (ML algorithm). To study the robustness of the proposal, we evaluate the following metrics: Accuracy, Precision, Specificity, Sensitivity, and F-measure. The findings demonstrate models empowered SVM superiority in classifying COVID-19 patients perfectly.

**Keywords:** COVID-19, Deep learning, SVM, GoggleNet, AlexNet, VGG16, X-rays.

## 1 Introduction

The coronavirus (COVID-19), caused by the SARS-CoV-2 virus, was discovered in Wuhan, China, in December 2019 and quickly spread worldwide, affecting billions of people and causing lockdowns in all countries [1]. During the Covid-19 era, several health systems have faced challenges, but they could have been somewhat mitigated if individual cases and virus mutations were detected in the early stages [2]. Patients who have cardiac diabetes, chronic lung disease or melanoma have been found to have a higher risk of developing a severe illness [3]. As a result of COVID-19, people of all ages worldwide have become seriously ill or have died [4].

Figure 1 illustrates the common symptoms of COVID-19 [1]. Therefore, to stop the separation of COVID-19, The main recommendations of the WHO are as follows [5]: 1) Cover the nose and mouth when coughing and sneezing; 2) Keep away from the suspected cases (those who have a respiratory infection); 3) Clean hands; and 4) Cook eggs and meat properly.



Fever Cough Shortness of breath Sore throat Headache

Figure 1: Symptoms of COVID-19 [1].

To identify COVID-19, the health system takes one of the following tests: 1) The polymerase chain reaction (PCR), 2) a Blood test, and 3) Imaging [1]. Because of high reliability, chest x-rays are considered the first choice to identify COVID-19 [6]. It is available in most medical treatment locations since it takes a short time to provide a clear view of the suspected chest image. Recently, researchers have utilized Artificial intelligence (AI), Machine learning (ML), and deep learning (DL) algorithms to detect COVID-19 from chest x-rays. DL algorithms demonstrate high performance in many fields, such as face recognition, feature recognition, object tracking, and computer vision [7].

This article evaluates some DL models of Convolutional Neural Networks (CCN) for classifying COVID-19 patients according to their chest x-rays. The selected CNN models are GoogleNet, AlexNet, and VGG16. The evaluation is based on and without using a Support Vector Machine (SVM) (ML algorithm). To study the robustness of the proposal, we evaluate the following metrics: Accuracy, Precision, Specificity, Sensitivity, and F-measure.

This article is organized as follows. Section 2 introduces some important information about the selected ML and DL algorithms. Section 3 explains the main performance metrics used in assessing ML and DL classifiers. Section 4 investigates some of the recently proposed models. Section 5 presents the modeling and methodology of the developing CNN-SVM models. Section 6 discusses the obtained results. Finally, Section 7 concludes this paper. Figure 2 depicts the roadmap of this article.

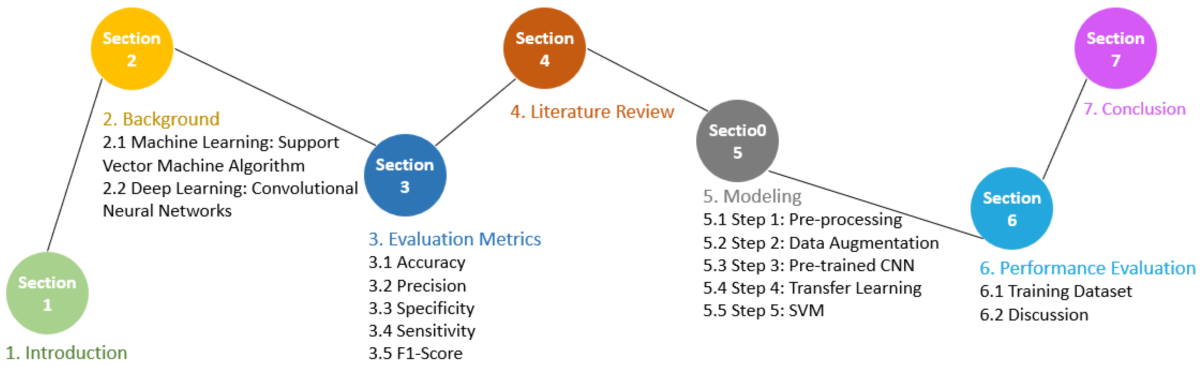



Figure 2: The organization of the article.

## 2 Background

As mentioned earlier, we utilized some CNN models via SVM; therefore, providing critical information about them is vital.

### 2.1 Machine Learning: Support Vector Machine Algorithm

Recently, ML became crucial in diagnosing and prognosis different systems since it demonstrated the robustness to perform complex tasks [1]. As a supervised statistical learning theorem, SVM was developed by Vapnik. It is a well-known algorithm based on the structural risk reduction principle. Between negative and positive samples, determining an optimum hyperplane is the main concept of the SVM algorithm [8]. The following formula represents the samples' linear separation.

$$f(x) = w^T x + b = 0 \tag{1}$$

where b denotes the bias that finds the hyperplane position, and w refers to the weight vector. Finally, to send the input data from one hyperplane to another. a kernel trick is implemented.

## 2.2 Deep Learning: Convolutional Neural Networks

### 2.2.1 CNN Structure

As a branch of ML, deep learning (DL) allows computational models composed of multiple processing layers. CNN (DL branch) is inspired by living organisms' natural visual perception mechanisms [1]. As shown in Figure 3, CNN comprises three major layers [8]:

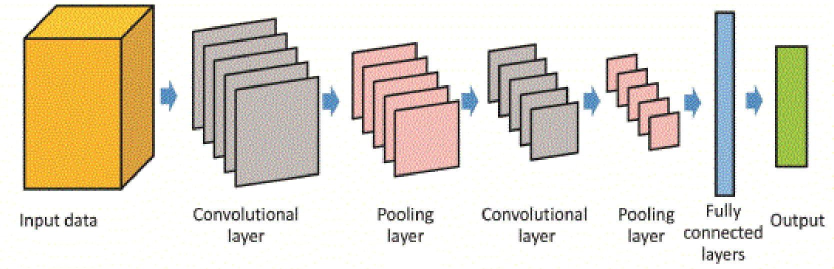



Figure 3: The structure of CNN layers.

- **Input layers:** As the input parameters, this layer is the first layer that specifies the input image according to its height, width, and depth.
- **Convolutional layers:** These layers consist of several activation and padding as the parameters, stride, filters, and filter window size. By calculating the weighted sum, in these layers, we can extract the input location's meaningful feature maps. Then, through an activation function, each feature map is passed. Next, from the output, bias is inserted. As an activation function, CNN uses a rectilinear unit (ReLU). It is important to mention that the model raises in size with a rise in the number of filters. Eventually, it is complex for PCs to accommodate. Therefore, this challenge needs to pooling layers to reduce the complexity.
- **Pooling layers:** These layers reduce the output size of the convolutional layers. To make the computers able to handle the models' size, these layers are inserted to suppress noise and decrease the dimensions for easy computation. These layers are categorized as global average pooling, average pooling, spatial pooling, and max pooling. Usually, max pooling is the most used [9].
- **Fully connected layers:** Fully connected layers: The output of the pooling layers is flattened to form a single-array feature vector. Then, it is fed to these layers, also called the classification layer. Activation functions such as tanh, softmax, and sigmoid are used in this later. Aggregated into class scores, extracted features with the number of specified classes.

To reduce the training time and standardize the learning process, layers, such as Batch normalization, are implemented after activation or input layers. Furthermore, during validation and training, the prediction error is summarized by the loss function. After each epoch, to the CNN model, the loss is backpropagated to enhance the learning process [10].

### 2.2.2 CNN models

Since 1998, several CNN designs have been proposed. Here, we summarize the main CNN models utilized for classification, detection, and localization. We selected the models we implement in this paper, which are as follows.

- **AlexNet:** From Ilya Sutskever, the SuperVision group (Alex Krizhevsky and Geoffrey Hinton) coined Alexnet as a pre-trained CNN model. Different filters with stacked convolutional layers exist in Alexnet, consisting of SGD with momentum for face recognition, dropout, data augmentation, ReLU activations, and convolutions (11x11, 5x5, and 3x3). Due to its performance, Alexnet significantly influences image classification and recognition tasks [11].

- **GoogleNet:** It is significantly deeper in comparison with CNN models. In addition to pooling and convolutional layers, GoogleNet consists of an inception module. Therefore, the layers of GoogleNet are: six convolutional layers, a concatenation layer, a max pooling layer, and four convolutional layers (1x1 size). Many GoogleNet models were proposed in the literature to improve performance with modified inception components, such as Inception V2, V3, V4, and ResNet [12].
- **VGGNET:** VGG stands for Visual Geometry Group, the group that developed VGGNET at Oxford University. Similar to the models mentioned above, it has a top-5 error rate of 7.3%. The structure of VGGNet is very simple and consists of 16 or 19 convolutional layers and small 3x3 convolution filters. Finally, the parameters of VGGNet are three times that of AlexNet [13].

## 3 Evaluation Metrics

In the DL field, the models are evaluated in several parameters. In this article, we calculated five items: accuracy, precision, specificity, sensitivity and F-measure (see Figure 4). They are determined from the model's findings, which are divided into the following [13]:

1. True positive ($T_P$): It means the model classified the case as COVID-19 correctly.
2. True negative ($T_N$): It means the model classified the case as non-COVID-19 correctly.
3. False positive ($F$): It means the model classified the case as COVID-19 incorrectly.
4. False negative ($F_N$): It means the model classified the case as non-COVID-19 incorrectly.

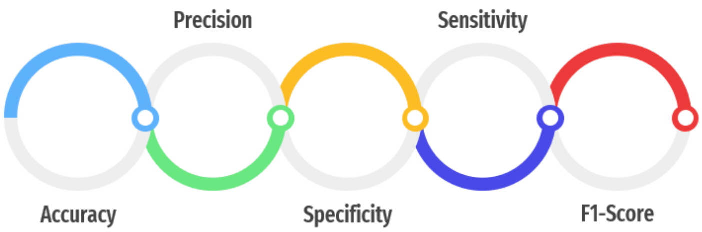



Figure 4: Evaluation metrics.

### 3.1 Accuracy

It determines the model's capability to correctly identify all pixels or classes (positive or negative). It answers the following question: How many patients did we correctly label out of all COVID-19?

$$Accuracy = \frac{T_N + T_P}{T_P + F_P + T_N + F_N} \tag{2}$$

### 3.2 Precision

It determines the proportion of $T_P$ (positives) among all the cases ($T_P + F_P$) decided to be positive (incorrectly and correctly). It answers the following: How many of those who we labeled as COVID-19 really are COVID-19?

$$Precision = \frac{T_P}{F_P + T_P} \tag{3}$$

### 3.3 Specificity

It determines how many ($T_N$) are correctly judged from all negatives ($T_N + F_P$) cases. It answers the following question: How many of those did we correctly predict as non-COVID-19 of all the non-COVID-19 people?

$$Specificity = \frac{T_N}{F_P + T_N} \tag{4}$$

### 3.4 Sensitivity

It determines how many ($T_P$) are correctly judged from all positives ($F_P + T_N$) cases. It answers the following question: How many of those do we correctly classify are actually COVID-19 patients?

$$Sensitivity = \frac{T_P}{T_P + F_N} \quad (5)$$

### 3.5 F1-Score

The F-score is harmonically the mean of accuracy and recall. The perfect precision and recall score means the highest F-score (i.e., equals one).

$$F1 - measure = 2 * \frac{Precison * Sensitivity}{Precison + Sensitivity} \quad (6)$$

## 4 Literature Review

For COVID-19 and other pneumonia patients, a DL method was used to identify chest x-rays in three and two-class experiments [14]. GoogLeNet architecture was utilized to extract features supplied to different classifiers using the suggested method. Kernel SVM was the most accurate among various classifiers compared to the Bayesian Optimization technique. The model demonstrated overall accuracy of 98.31% for two-class classification between Covid-19 and non-Covid lung chest x-ray pictures and 98.60% for three-class classification between Covid-19, healthy, and viral pneumonia x-ray. In [15], the authors suggested a deep learning approach combining Modified-CNN) and Bidirectional LSTM with Multiple-SVM classifier to detect normal breast, Lung-Opacity, viral pneumonia, and COVID-19. The system demonstrated its superiority over its counterparts (98.67%. accuracy). The evaluation was based on the COVID-19_Radiography_Dataset. The authors in [16] proposed a system for analyzing and classifying anticipation from COVID-19 symptoms. Via Adaptive Neuro-Fuzzy Inference System (ANFIS), the suggested system can determine features that help detect the infection. To model and control ill-defined and uncertain systems, ANFIS utilized risk factor anticipation. Based on a comparative analysis, the accuracy of the classifiers was calculated. Among all classifiers, SVM achieved 100% accuracy. 80% risk estimate for COVID-19 has been achieved by implementing ANFIS in the dataset.

The authors in [17] utilized ML algorithms to detect normal and viral pneumonia and COVID using chest x-rays. The utilized algorithms are stacking model, artificial neural network (ANN), logistic regression (LR), and SVM. From 3 classes, 3486 images have been used in the training and testing. The evaluation showed that SVM, ANN, LR and stacking models achieved a classification accuracy of 90.2%, 96.2%, 96.7% and 96.9%, respectively.

The authors in [18] utilized different CNN models to classify COVID-19 based on x-rays in 19_Radiography_dataset. The models are GoogleNet, MobileNetv2, Inceptionresnetv2, Densenet201, Inceptionv3, ResNet50, ResNet18, and AlexNet. Using ANN and the raw image, the authors performed Lung segmentation. The following ML algorithms used for feature selections: Decision Tree, Naive Bayes, k-Nearest Neighbors, and SVM. The authors used Bayesian optimization to improve the accuracy by determining the hyperparameters of each ML algorithm. The SVM algorithm and DenseNet201 model achieved the highest accuracy, 96.29%. The rest metrics reached the following: Sensitivity (0.9642), Precision (0.9642), Specificity (0.9812), MCC (0.9641), and F1-Score (0.9453). The authors in [9] utilized DeepLabV3+ architecture to classify COVID-19 using chest x-rays. Based on the utilized dataset (COVID-19_Radiography_dataset), the model has been trained using masks of image segments. To enhance the output images, image preprocessing steps were implemented. Modified AlexNet (mAlexNet) and SVM were used for extracting features and classification, respectively. The classification accuracy reached 99.8%.

## 5 Modeling

As illustrated in Figure 5, modeling our proposed models are classified into five steps. Here, we describe the objectives of the adopted steps.

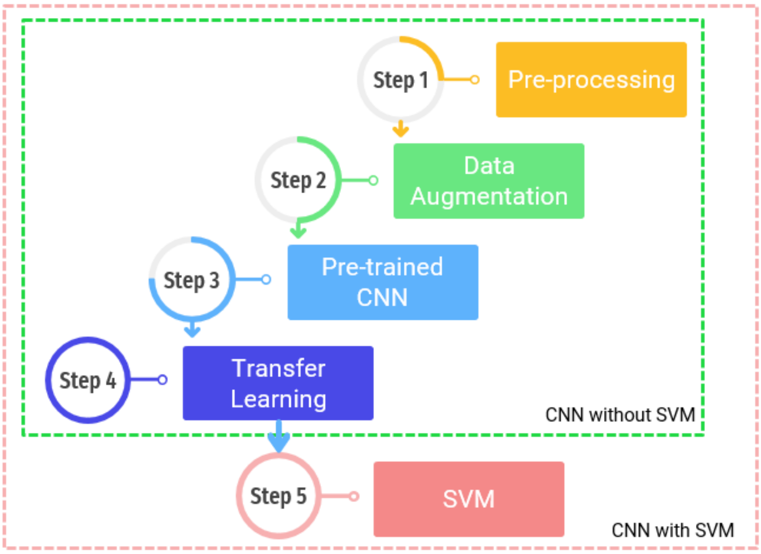



Figure 5: Steps of modeling our CNN models.

### 5.1 Step 1: Pre-processing

All images of the dataset are colored and of different sizes. Previously, to size (227 x 227), the images were resized for the AlexNet model's convenience. Instead of resizing them, we extracted image patches of size (227 x 227) from the original images. For the convenience of the reader, we recommend visiting [19] for more information about pre-processing in the COVID-19 field.

### 5.2 Step 2: Data Augmentation

Independent of data collecting and labeling issues, the simplest way is to gather several training examples with abundant variance. Data augmentation, which entails the addition of sample copies with label preservation, is another strategy for addressing this issue. By applying changes such as flipping and rotation to actual data, data augmentation generates artificially created sample images. Random scaling, jittering, rotations (270, 180, and 90 degrees) and horizontally flipping are common data augmentation types. Because chest x-ray images may exhibit a variety of orientations and sizes, this data enhancement produces suitable training examples. Using flipping around the vertical axis, this model applies the data augmentation technique. For the convenience of the reader, we recommend visiting [20] for more information about data augmentation in the COVID-19 field.

### 5.3 Step 3: Pre-trained CNN

For training and fine-tuning strategies, this part evaluated three specific CNN architectures. From the ImageNet Dataset [25], approximately 1.2 million images were used to train the models (AlexNet, GoogleNet, and VGG16). These models have been adapted to classify histopathological breast images with different magnification factors and compare their performance. As fixed feature extractors, the first layers from all the pre-trained CNNs are saved. Figure The last fully-connected layer connects to 1000 classes, and the rest of the network is considered as a feature extractor. For the convenience of the reader, we recommend reading [21] for more information about pre-trained CNN in the COVID-19 field. Figure 6 illustrates the reuse pre-trained network.

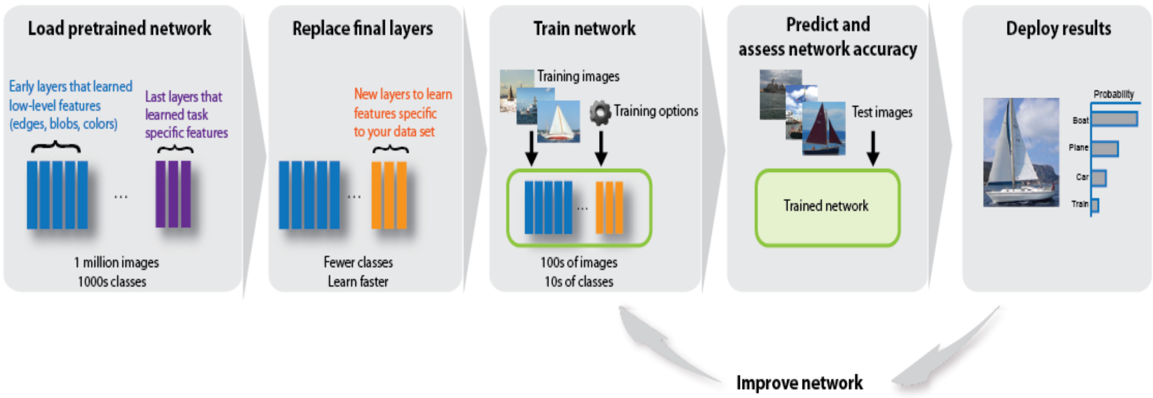



Figure 6: Reuse Pre-trained Network.

## 5.4 Step 4: Transfer Learning

As mentioned earlier, for classifying 1,000 classes, we used the ImageNet dataset (1.2 million raw images) for the pre-trained models. After that, a new layer is used instead of the fully connected layer to classify two classes (normal and COVID-19). While some parameters are set to default values, we modified others, such as primary learning rate ($10^{-4}$), max epoch number (10), weight decay ($4^{-5}$) and momentum(0.9). After fine-tuning the fully connected layer to 2 classes, we set them to retain the models. These setups guarantee that the parameters are optimized for COVID-19 medical diagnosis. The Stochastic Gradient Descent (SGD) (as an optimization algorithm) with a mini-batch size of 10 is used. Since the length of output neurons in the various CNNS is not equal to the number of classes in our job (2), the corresponding softmax layer and classification layer must be revised. Softmax layer and a new classification layer with only two classes were used as a new randomly-initialized fully connected layer with two neurons (Malignant and Benign).

Next, training options were set. Before training, three subtleties were checked:

1. For transfer learning, a small training epoch has been set (training epochs =10).
2. to slow learning down since the early parts of this neural network were pre-trained. the global learning rate was set ($10^{-2}$).
3. SGD has been used in performing the experiments with the following settings: primary learning rate ($10^{-4}$), max epoch number (10), weight decay ($4^{-5}$) and momentum (0.9).

For the convenience of the reader, we recommend visiting [22] for more information about transfer learning techniques in the COVID-19 field.

## 5.5 Step 5: SVM

In this part, the image patches are classified as either COVID-19 or Normal according to the features. As a supervised learning method, SVM is used because of its robustness in classification issues. The support vectors are considered the data points that the margin pushes up. By separating hyperplanes in a high-dimensional feature space, SVM seeks to provide a computationally efficient learning method. Many hyperplanes could identify two datasets. The optimal hyperplane to select is the one with the most significant margin. Before hitting a data point, the margin is defined as the width by which the boundary could rise. The CNN output is the input image's class decision [8].

# 6 Performance Evaluation

## 6.1 Training Dataset

The experiments are conducted in (MacBook Pro, Intel Core i7, and 32 GB RAM). CNN models for object recognition, a new dataset of COVID-19 images, and Normal pictures are proposed. GitHub [23] and Kaggle [24] are both published. The x-ray chest or CT pictures in GitHub belong to COVID-19 instances. It was developed by combining medical photos from websites and publications accessible to the public. This dataset comprises

120 X-ray images from COVID-19 and 165 non-COVID-19. On the other side, the Normal images were 120 in total. The Dataset is split into 70% for training and 30% for testing for both classes. A comparison of the training model of using AlexNet structure (with/without the SVM classifier) has been shown in Figures 7 and 8, respectively.

From the results obtained in Figures 7-10, it is possible to see the performance of the generated models in the training and test stages. The analysis parameter used was the accuracy per season: the success rate in each season. The Proposed CNN-SVM structures achieved a faster convergence than using CNN alone, both in the training stage and the test. It is worth noting that there was a discrepancy between the curves in the test stage, which shows that the Proposed CNN-SVM achieved better performance.

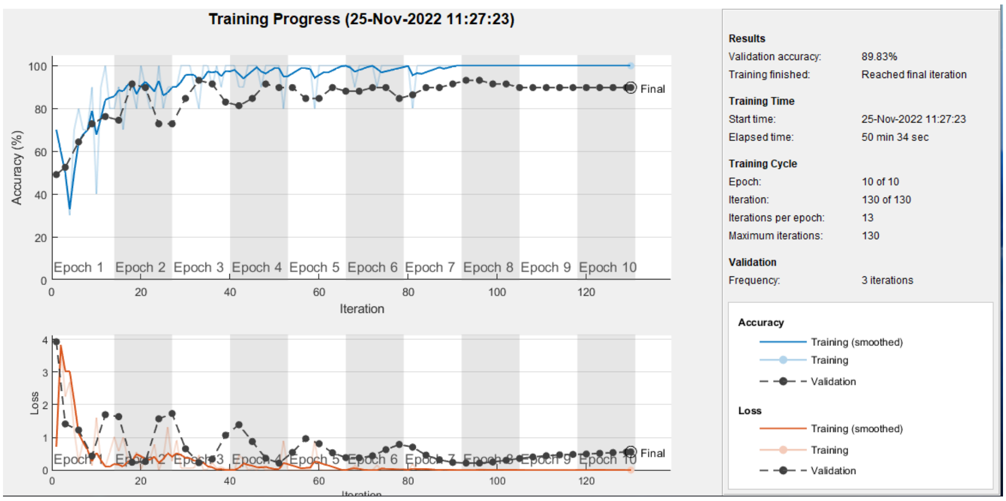



Figure 7: Training accuracy average of 89.83 % for Alexnet without SVM.

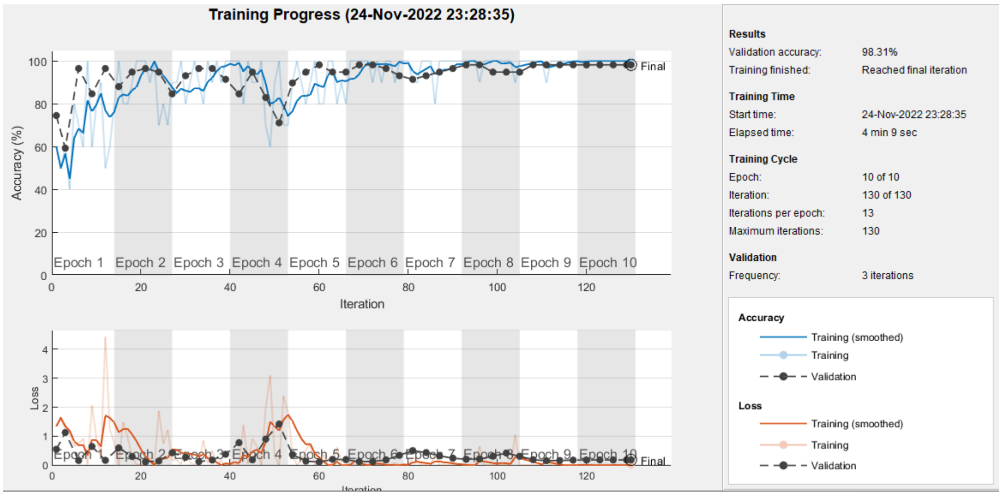



Figure 8: Training accuracy average of 98.31 % for Alexnet with SVM.

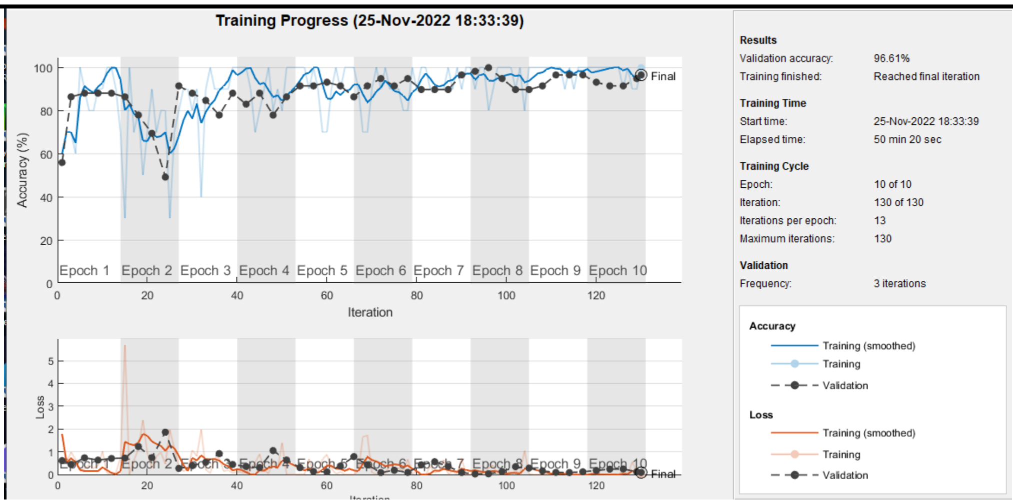


Figure 9: Training accuracy average of 96.61 % for VGG16 without SVM.

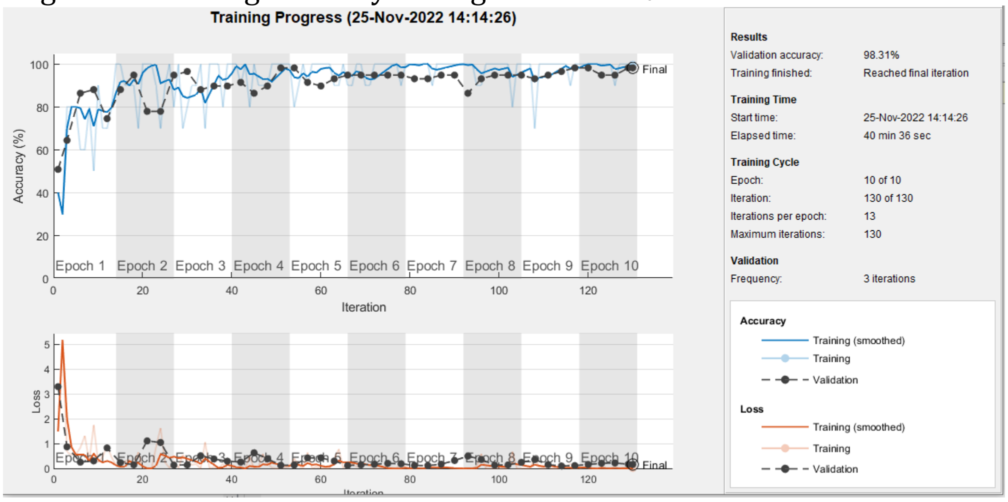


Figure 10: Training accuracy average of 98.31 % for VGG16 with SVM.

## 6.2 Discussion

The experiments were repeated five times, and the performance was measured using the five measurements' average accuracies. The proposed approach was compared with existing CNN approaches with/without using an SVM. SGD has been used in performing the experiments with the following settings: primary learning rate ($10^{-4}$), max epoch number (10), weight decay ($4^{-5}$) and momentum (0.9).

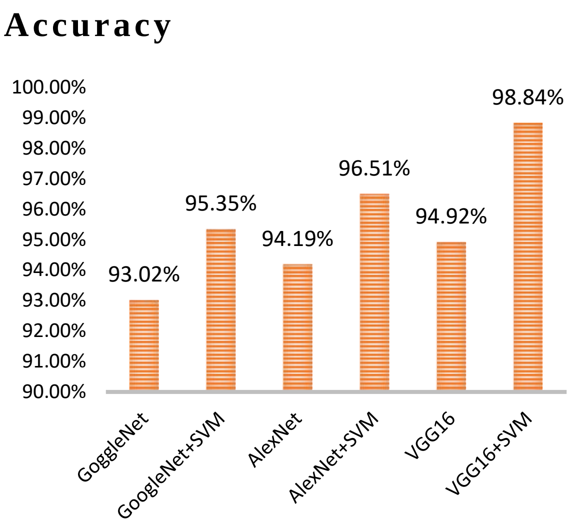
The confusion matrix is generally used in ML, containing information about the accurate and predicted classifications a classifier performs. In a confusion matrix, the lines are real values in each class, while the columns are the predictions made by the model. The values obtained from the confusion matrix are used to generate crucial metrics for evaluating the models, such as Accuracy, Sensitivity, Precision, Specificity, and F1-score. These metrics are commonly used in the evaluation of learning models.

Table 1 and Figure 10 demonstrate that the best result was achieved by the proposed GoogleNet+SVM, Alexnet+SVM, and VGG16+SVM (CNN-SVM). Therefore, the proposed CNN-SVM models cannot confuse the classes (precision) and can find each class's most significant possible number of images (sensitivity). The F1-score is the weighted average of the two metrics.

Table 1: Results for Different CNN Structures ( with and without SVM classifier)

| Algorithm | Accuracy | Sensitivity | Precision | Specificity | F1-Score |
|---|---|---|---|---|---|
| GoggleNet | 93.02 % | 90.39 % | 97.92 % | 97.06 % | 94.00 % |
| GoogleNet+SVM | 95.35 % | 94 % | 97.92 % | 97.22 % | 95.92 % |
| AlexNet | 94.19 % | 100 % | 89.58 % | 88.37 % | 94.51 % |

| | | | | | |
|---|---|---|---|---|---|
| AlexNet+SVM | 96.51 % | 100 % | 93.75 % | 92.68 % | 96.77 % |
| VGG16 | 94.92 % | 93.54 % | 96.66 % | 96.42 % | 95.08 % |
| VGG16+SVM | 98.84 % | 97.96 % | 100 % | 100 % | 98.97 % |

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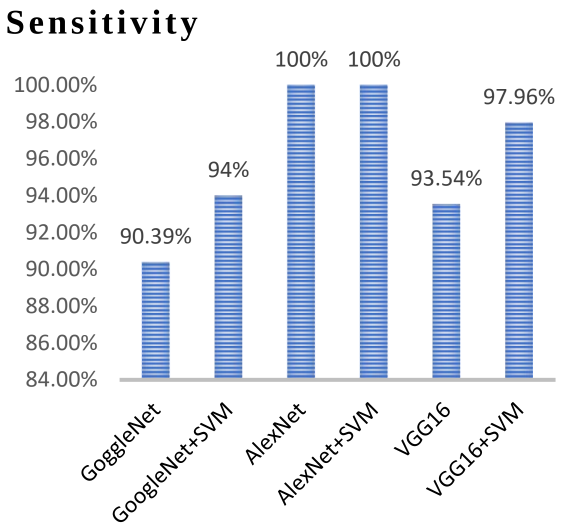


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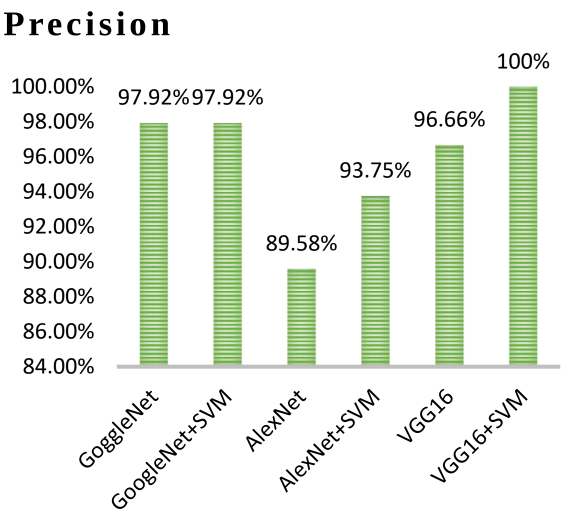


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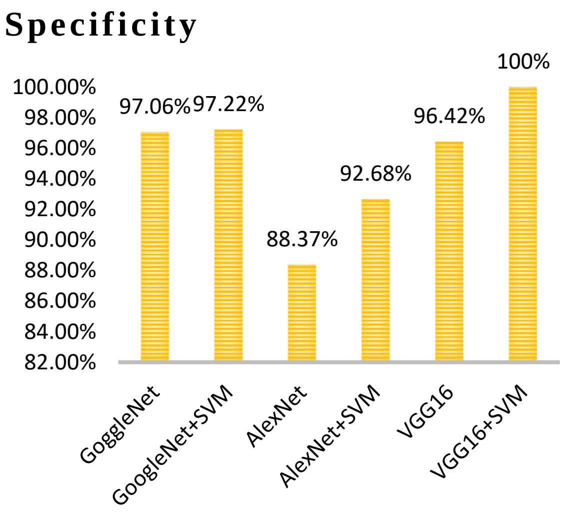


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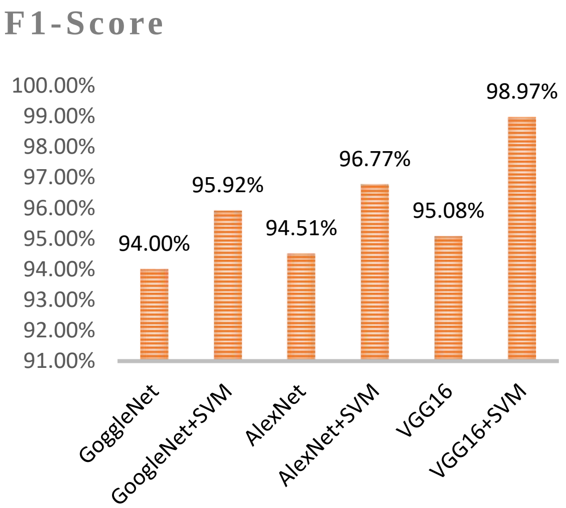


E

Figure 11: Performance evaluation of the models.

Based on the results, we can observe that the model generated through the proposed CNN-SVM architectures obtained the best performance in diagnosing COVID-19, the focus of this study. The proposed CNN-SVM architectures obtained a result superior to CNN in all the metrics analyzed. Because it achieves a higher hit rate (accuracy) than using CNN alone, The proposed CNN-SVM becomes a feasible choice of architecture to be further explored in future works. It is important to emphasize that this study has as its premise to serve as an alternative way of screening patients in the future. From this study, new possibilities can be explored. To optimize and improve the previous proposal, it will be necessary to use more databases containing images of patients diagnosed with COVID-19 or other diseases that can be diagnosed through x-ray images to enhance and generalize the model. A WEB system can be developed to serve as a test environment for the trained model. The user will be able to upload an x-ray image of the chest of a patient with suspected COVID-19, and the model will generate a possible pre-diagnosis of the image.

## 7 Conclusion

The COVID-19 pandemic is a unique pandemic caused by a coronavirus, and the only currently accessible preventative strategies are social isolation and early discovery. DL models are learned to recognize and categorize x-rays for early identification and prevention of dissemination. Since the COVID-19 epidemic separation, few data are available for training DL algorithms. Researchers generated unique datasets by integrating many data repositories to address this deficiency. We utilized the transfer learning technique in our models. Furthermore, on the ImageNet dataset, we used innovative designs using transfer learning and some approaches, such as deep feature extraction using hierarchical classification algorithms and deep learning architecture. The evaluation was based on and without using SVM. The findings demonstrated models empowered SVM superiority in classifying COVID-19 patients perfectly.

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