# Detection and Classification of Covid-19 from X-Ray Images using SVM-DCNN

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***Abstract***
There is lack of attention on pre-processing the datasets to remove the diaphragm regions, normalize image contrast and reduce image noises. Apart from Covid-19 Perception and classification, the severity of the COVID-19 infection has to be determined by applying deep learning (DL) based segmentation techniques which localizes the infection region. Hence in order to overcome these issues, a detection and classification technique for Covid-19 from X-ray images using Support Vector Machine (SVM) and Deep Convolutional Neural Network (DCNN) is proposed. In the pre-processing stage, a Modified Anisotropic Diffusion Filtering (MADF) method was propelled to remove the noises from the images. After the pre-processing step, the features Histogram-oriented gradient (HOG) and Image profile (IP) are extracted and fused. The fused feature is used then trainedand classified using hybrid SVM-CNN algorithm. It classifies the chest X-ray images into three categories that includes Covid-19, Pneumonia and normal. Experimental results have shown that the proposed SVM-DCNN algorithm attains highest accuracy of 91.8, Precision of 91.9, Recall of 88.5 and F1-score of 94.2 when compared to DCNN and SVM.

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## I. INTRODUCTION

Covid-19 infection has produced groups of deadly pneumonia which greatly look like the SARS-CoV infections. Patients infected with Covid-19 initially feel the symptoms of normal flu such as abnormal body temperature, dry cough, weaker stamina and obstacles in breathing. In some cases with severe infection, it may ends up in acute renal failure causing to death. Apart from these usual symptoms, this virus also has many unique characteristics. Hence early detection of this disease with appropriate infection control is required for the patients infected by Covid-19 (Brunese et al.,2020).

For detection Covid-19, healthcare professional are following additional screening methodslike Chest X-rays and Computed Tomography (CT) imaging which are fast and more effective than the normal tests. These screening methods visually guide through the process detecting the Covid-19 infection (Rahamana et al.,2020). But taking CT scans often is more costly and also dangerous for children and pregnant women due to high radiation.

Hence machine learning (ML) and deep learning (DL) based techniques are applied to detect Covid-19 infection at the earlier stages. Recently DL model have been applied successfully in various medical image analysis and applications such as lung cancer detection, pneumonia detection and brain tumor detection. Hence a DL based training method is applied after extracting the major features from the images (Shadin et al.,2021). The DL based detection and classification techniques help to prevent the spreading of the deadly disease (Alotaibi et al.,2021).

Most of the existing training models involve ImageNet database, which contains color images. But normally Chest X-ray images are in grayscale and hence preprocessing is required to validate their size and structure for training model. Localizing the Covid-19 infected region and segmenting the pneumonia lesions is an important process for accurately detecting the disease. But existing works hardly localize the infected areas from pneumonia lesions in terms of shapes and sizes.

Hence the problem statement of the research work can be defined as: Lock of works on preprocessing the large databases to remove unwanted background regions and noises. Apart from classification, the infected region should be localized and marked.

Hence the main objectives of this research are:

(i) To reduce the image noises by applying pre-processing techniques.

(ii) To apply DL techniques on X-ray images to classify Covid-19 from normal and pneumonia infections.

## II. Related Works

The findings of the DL based classification techniques are presented below:

A set of X-ray and CT scan images are taken by (Rachna Jain et al.,2021) which contains the data of both normal and affected patients. Initially, they have applied data cleaning and data augmentation process on the images. DL based CNN model was then applied for classification. The performance has been compared with Inception V3, Xception, and ResNeXt models. However this method did not guarantee the accuracy of the predictions.

Covid-19 has been detected from X-ray images by (Moutaz Alazab et al.,2020) using CNN model. In addition to CNN, prediction methods based on LSTM networks and autoregressive integrated moving average (ARIAMA) model are used to finalise the exact number of Covid infected patients, countables of patients in serious conditions for the forthcoming period.

A Covid-19 detection method based on feature fusion has been proposed in (Ji D et al.,2021). This method initially performs preprocessing on chest X-rays such as rotation, translation, and transformation. After performing these tasks, this method uses five standard pretraining models for extracting the specific features. However it classifies the images as normal and Covid affected ignoring the severity levels of the diseases.

(Yazan Qiblaweya et al.,2021) have taken CT scan images for detecting Covid-19 infection. In (Lokwani et al.,2021), separate slices of CT scan images are used along with the full images for traning. The U-Net architecture is used to segment the CT slices which mark the affected region from the images. However this technique did not reduce the noises from the images.

In (Qiblaweya et al.,2021), a hierarchical system is proposed for segmenting the CT lung images and detecting the Covid-19 infections.A Deep Encoder-Decoder CNN is applied for classifying the images as mild, moderate, severe and critical based on the % of affected lungs. Moreover, this system confines the infection with respect to different shapes and size. However this technique did not reduce the noises from the images.

(Ali Narin et al.,2020) applied five pretrained DCNN based transfer models for detecting Covid and pneumonia infections from chest X-ray images. They have used 3 binary classifications with 4 classes, using a 5-fold cross validation. They have used x-ray images of 341 Covid patients,2772 bacterial and 1493 viral pneumonia patients. This method yields higher prediction accuracy. However in this method also, the noise is not reduced from the images.

## III. Proposed Methodology

### 3.1 Overview

In this paper, detection and classification technique using SVM-DCNN model for Covid-19 from X-ray images is proposed. A MADF method was applied to remove the noises from the images. After the pre-processing step, we extracted two features: Histogram-oriented gradient (HOG) and Image profile (IP). These two features were fused and trained using the SVM-CNN classification model. The fusion approach provides a vast set of features for accurate detection. Then Hybrid SVM-CNN algorithm classifies the chest X-ray images as: Covid-19, Pneumonia and Normal.

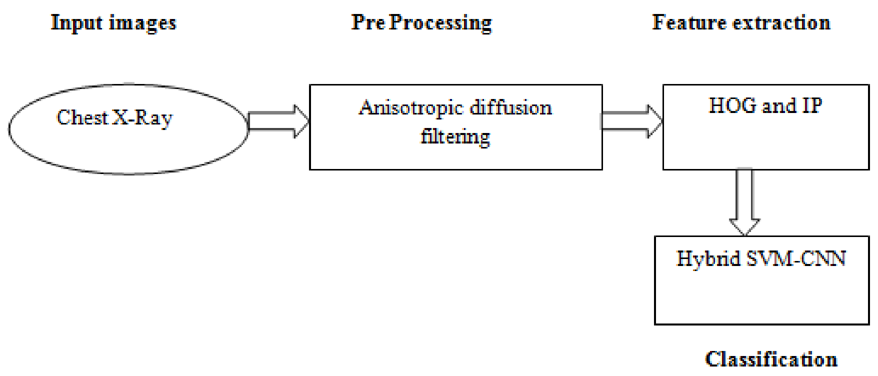


Fig 1 Architecture of Proposed Model

### 3.2 Pre-processing

In this phase, MADF technique is applied for noise removal from the X-ray images. In MADF, the input images are split into multiple sub-images or gradients. These gradients are filtered sequentially after which they are again combined together.

Mostly, this filtering technique eliminates the noises and edge portions of the images. After many iterations, this filter removes the edge information from the images.

An original image O blended with speckle noise n is represented as (Alam N A et al.,2021)

$$O_0 = O.n \quad (1)$$

$$n = \frac{O-G}{\sqrt{G}}$$

G= noise intensity

The mean of noise intensity (m) is computed as follows:

$$m = \sum_{i=1}^{N} G/N \quad (2)$$

The association between both the image and noise classes should be minimum.

The speckle noise removal step is repeated until the noisy portion of the image approaches the Guassian value.

The kurtosis value k is given by

$$k = \frac{\frac{1}{N}\sum_{i=0}^{N}(G-m)^4}{\left[\frac{1}{N}\sum_{i=0}^{N}(G-m)^2\right]^2} - 3 \quad (3)$$

Since all the image features will be removed if value of k becomes 0, the filtering process is repeated until the value of k becomes 0.001 to get an accurate filtered image.

### 3.3 Feature Extraction

After the pre-processing step, we extracted two features: Histogram-oriented gradient (HOG) and Image profile (IP).

The image window is split into tiny spatial portions or ‘‘cells,’‘which collect a local 1-D histogram of edge orientations across pixels in each cell. The picture is built up entirely of the sum of the histogram's component values. To normalize all the cells in a block, add up the local ‘‘energy’‘ from histograms taken from much bigger spatial areas (‘‘blocks’‘). The normalized descriptor blocks will be referred to as Histogram of Oriented Gradients (HOG) descriptors. The cell histograms of each pixel are combined with a gradient L2-norm to create a direction-based histogram channel. These channels are produced by computing an unsigned gradient on the rectangular portions (i.e. R-HOG). The final feature vector's cells add up more than once since they overlap by half their area.

The artifacts which present in X-ray images can be easily detected by extracting the image profiles. In the same way, the accuracy of the reconstructed images can be evaluated by visualizing the IPs of sharp edges.

Since fusing various image features results in more number of features for accurate detection, both the HOG and IP features are fused. The fused features are then trained using the classification model.

HOG and IP are extracted features respectively.

$$f_{HOG1\times n} = \{HOG_{1\times 1}, HOG_{1\times 2}, HOG_{1\times 3}, \ldots\ldots HOG_{1\times n}\}$$

$$f_{IP1\times m} = \{IP_{1\times 1}, IP_{1\times 2}, IP_{1\times 3}, \ldots\ldots IP_{1\times n}\}$$

$$Fused\ (featurevector) = \{HOG_{1\times n}, IP_{1\times n}\} \quad (4)$$

Thus the HOG and IP features are fused into 7876 features among which 116 features are selected based on the maximum entropy value.

If i = 1, it takes HOG features and if i = 2, it takes IP features which are added together at the end.

### 3.4 Classification using Hybrid SVM-DCNN

#### 3.4.1 Architecture of DCNN

A DCNN uses filters on the original pixel of an image to gather details pattern compared to global pattern using a conventional neural net.

A DCNN contains the following layers:

**Convolutional layer** (CL): It uses n number of filters to the feature map. After the intricacy, a Relu stimulation function is used to include non-linearity to the network.

**Pooling layer** (PL): Max pooling is the traditional method to divide the feature maps into sub regions (with a 2x2 size) and retains only the extreme values.

**Completely connected layer**: The whole neurons from the preceding layers are associated to the subsequent layers. The DCNN will categorize the labels based on the aspects from the CLs and abridged with the PL.

Table 1 illustrates the details of the DCNN architecture

**Table 1 Detailed Parameters of Proposed DCNN**

| Layer | Function | Weight Filter Size | Activation function |
|---|---|---|---|
| Input | | | |
| Conv1 | Convolutional | 32:5 x 5 | Relu |
| Pooling1 | Max pooling | 5:2 x 2 | Relu |
| Conv2 | Convolutional | 64:5 x 5 | Relu |
| Pooling 2 | Max pooling | 5:2 x 2 | Relu |
| Conv3 | Convolutional | 128:5 x 5 | Relu |
| Pooling 3 | Max pooling | 5:2 x 2 | Relu |
| Conv4 | Convolutional | 64:5 x 5 | Relu |
| Pooling 4 | Max pooling | 5:2 x 2 | Relu |
| Conv5 | Convolutional | 32:5 x 5 | Relu |
| Pooling 5 | Max pooling | 5:2 x 2 | Relu |
| Dense | Fully connected | 1024 | Relu |
| Dense | Fully connected | 1024 | Softmax |

### 3.4.2 SVM-CNN

The Hybrid SVM-CNN algorithm [12] classifies the chest X-ray images as: Covid-19, Pneumonia and normal.

The SVM-CNN classifier has the advantages of both SVM and DCNN algorithms. The best features are processed by dividing into training and testing features along with the labelled results. The steps involved in this algorithm are as follows:

**SVM-CNN:Algorithm**

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**Input: Train_feature {TrF}, Test_feature {TeF}and Labels**
**Output: Classified labels**

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```
1.  For each tef ∈ {TeF}
2.          SizeF = Size of (TrF}
3.           Get the class values
4.          S(m,n) = Size of(TeF}
5.          For i in (1..m)
6.             For j in (1..n)
7.               Train_t = tef(i,j)
8.               unique_class = unique(Label)
9.                L = length(Unique_class)
10.       Determine SVM Struct
11.       If (N>1)
12.              iTrain = 1
13.              classes =0
14.      Condition = Maximum(class_label)-Minimum(class_label)
15.      If (Label == unique_class(iTrain)
16.           Class_new = Label
17.      Svmtrain(TrF, Class_new, 'svm kernel', 'rbf')
18.      Determine TrF based on SVM struct
19.      For X in (1..size(TrF,1)
20.          Train1(X)=scalefactor of svmstruct* TrF(X)
21.      For X in (1..size(Train_t,1)
22.            Trainst1(X)=scalefactor of svmstruct * Train_t(X)
23.   Train the CNN using Conv_layer and Sub-sampling Layer
24.       Find the batch size of tef
25.       CNN_res = test_y(cnn_out)
26.  Stop
```

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Features form the Images are taken in to account. Obtain the size of the training feature matrix. Calculate the SVN Struct. If (N<1), training feature= 1, Classes = 0. Estimate the training feature based on SVM structure. Train the convolution neural network. Fetching the  batch size of the test feature .Once the nodules are detected, they are classified as severe, moderate and very severe by applying CNN algorithm.

## IV. Simulation Results

### 4.1Input Data Set

The proposed SVM-DCNN based classification model has been implemented in Python. The COVID-19 X-ray image dataset is fetched from https://github.com/ieee8023/COVID-chestxray-datasetdeveloped by Cohen JP. The database http://openaccess.thecvf.com/content_cvpr_2017/papers/Wang_ChestX-rayof Wang et al. was applied for normal and pneumonia images.

Fig.2 shows the input images from normal, Covid-19 and pneumonia databases.

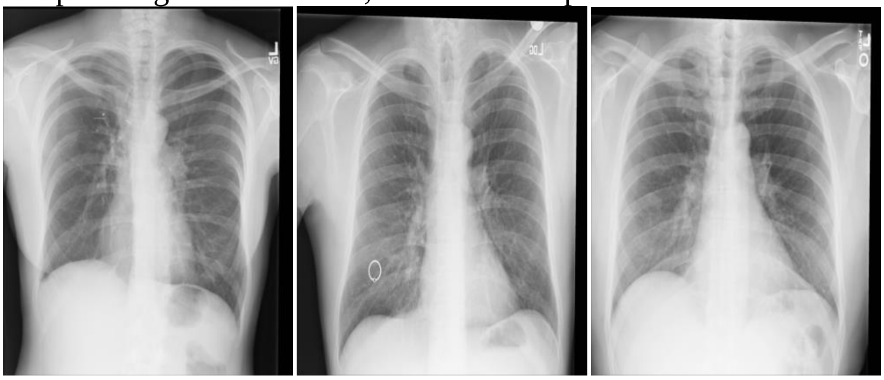


**Fig 2 (a) Normal Images**

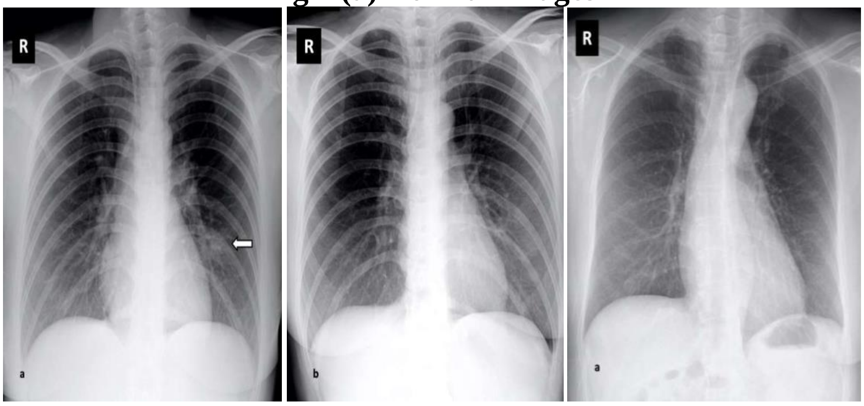


**Fig 2 (b) Covid-19 Affected Images**

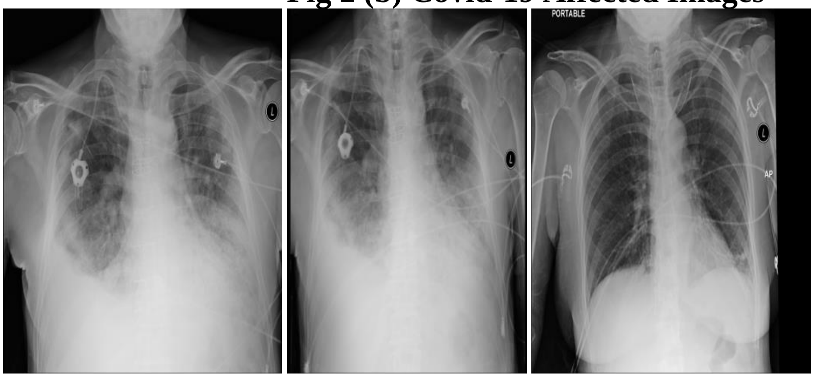


**Fig 2 (c) Pneumonia affected Images**

### 4.2 Results

The preprocessing results using anisotropic diffusion filtering technique are shown in Fig. 3.


**Fig 3 Pre processed Images**

Table2 shows the Covid-19 classified  images from the test dataset.

**Table 2 Classified X-ray images**

| Input | Processed | Class | Accuracy | Precision | Recall |
|---|---|---|---|---|---|
|  |  | Normal | 95.67 | 93.47 | 92.59 |
|  |  | Covid | 95.43 | 93.72 | 91.49 |
|  |  | Pneumonia | 94.27 | 91.34 | 90.78 |

The training and validation curves of SVM-DCNN for 10 epochs are shown in Fig. 4.

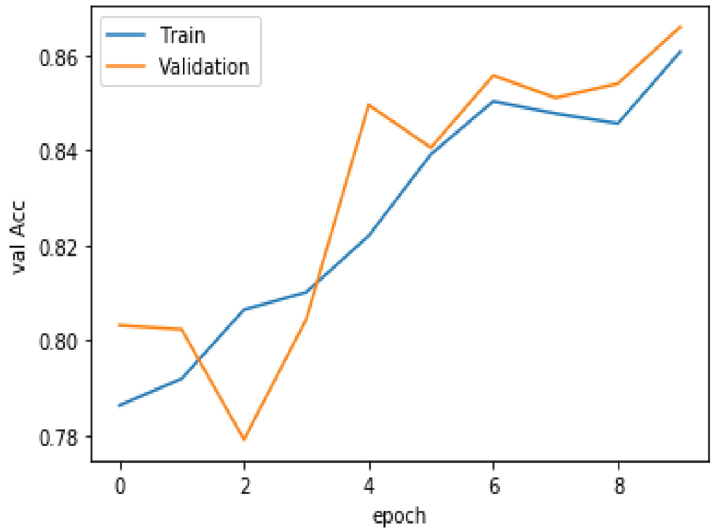
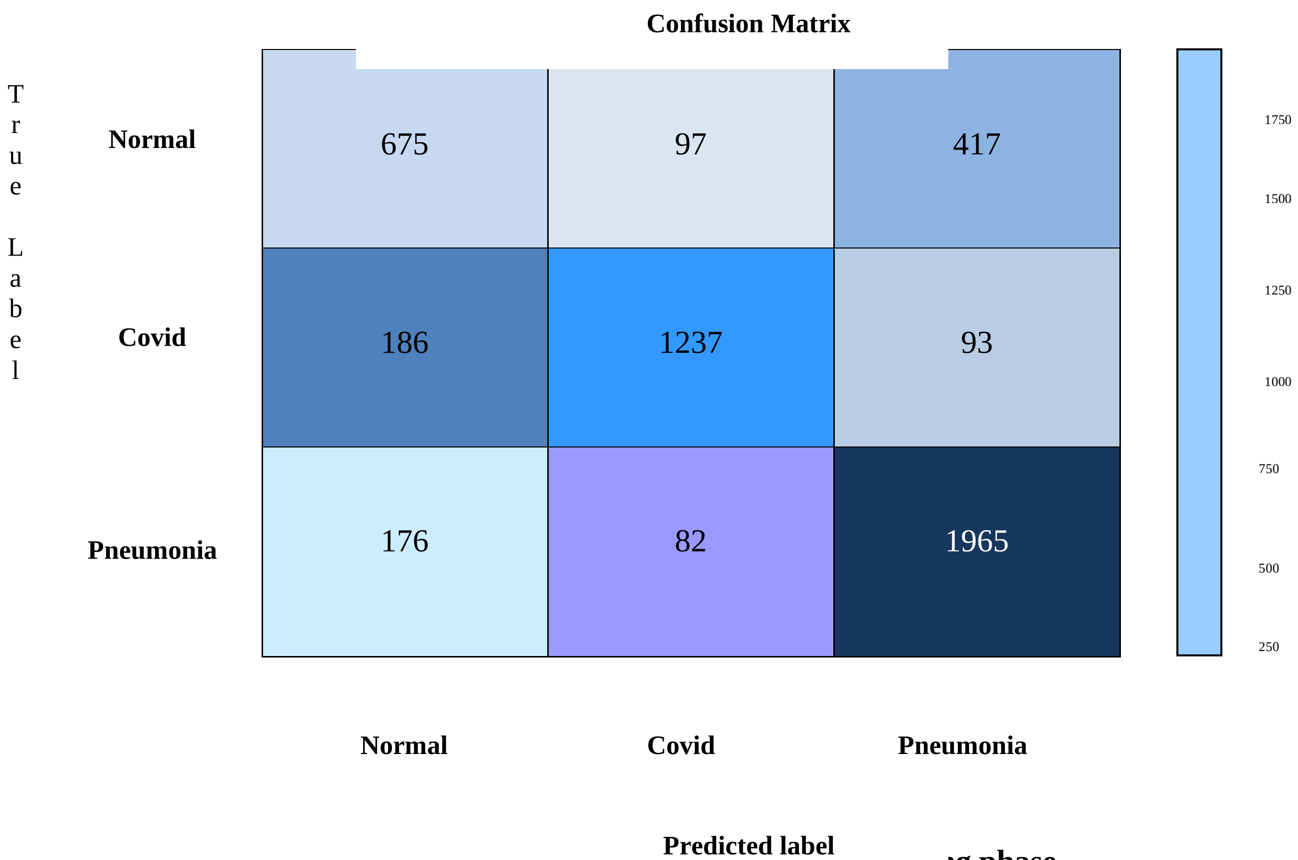



**Fig.4 Training Vs Validation for SVM-DCNN**

Fig.5 shows the confusion matrix for the training phase.




**ıg phase**

From this confusion matrix, the following things can be inferred:

**(i)** Out of total 4928 data sets, 675+186+176= 1037 are predicted as normal, 97+1237+82=1416 are predicted Covid and 417+93+1965=2475 are predicted as pneumonia.

**(ii)** The actual number of normal cases are 675+97+417=1189 , actual number of Covid cases are 186+1237+93=1516 and actual number of pneumonia cases are 176+82+1965=2223

The accuracy of proposed hybrid SVM-DCNN classifier is compared against the SVM and DCNN classifiers in terms of the metrics Accuracy, Precision, Recall and F1- score.
Table 3 and Fig.6 show the comparison results of the performance metrics for all the 3 algorithms.

**Table 3 Comparison of Performance metrics for all the approaches**

| Metrics | SVM | DCNN | SVM - DCNN |
|---|---|---|---|
| Accuracy | 91 | 91.2 | 91.8 |
| Precision | 85 | 89.3 | 91.9 |
| Recall | 87 | 87.5 | 88.5 |
| F1 - Score | 85 | 90.4 | 94.2 |

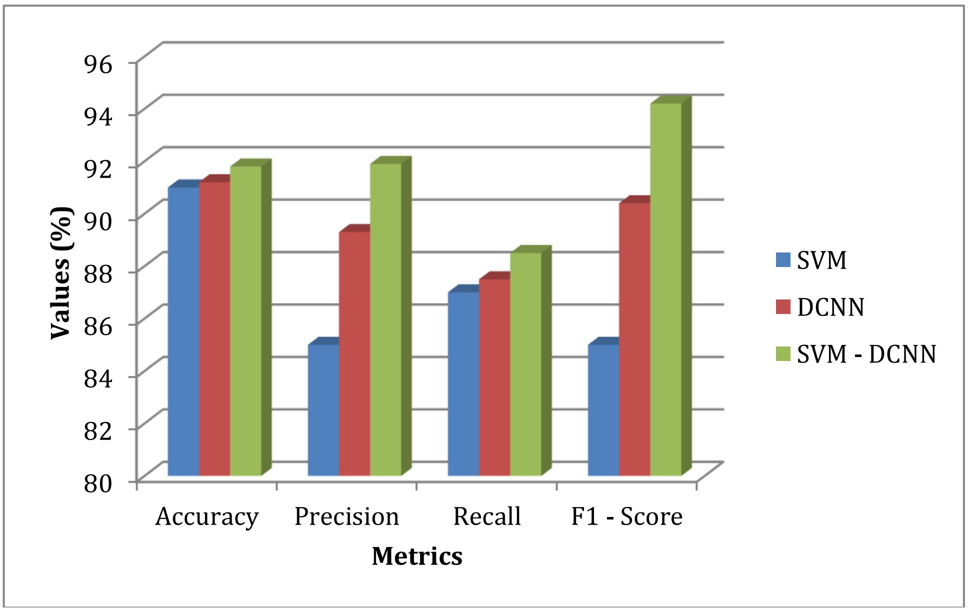



**Fig. 6 Performance comparison for all the techniques**

As seen from the Fig, the accuracy of SVM-DCNN attains the highest of 91.8 followed by DCNN (91.2) and SVM (91). Similarly, the proposed SVM-DCNN outperforms the other two algorithms for other metrics also.

## V. Conclusion

In this paper, we have proposed to detect and classify Covid-19 from X-ray images using SVM-DCNN technique. AMADF technique is applied to eliminate multiplicative noise from the testing images. After the pre-processing step, we extracted two features: HOG and IP. These two features are fused and trained using the classification model. Then Hybrid SVM-DCNN algorithm classifies the chest X-ray images into three categories of Covid-19, Pneumonia and normal. Experimental results have shown that the proposed SVM-DCNN algorithm attains highest accuracy of 91.8, Precision of 91.9, Recall of 88.5 and F1-score of 94.2 when compared to DCNN and SVM.

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