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Efficient Detection of Covid-19 from Chest X-ray Images using CNN Feature Extraction and an Ensemble of Machine Learning Classifiers

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Abstract

Objectives: The main objective of this work is to detect Covid-19 in radiological chest X-ray images, using Convolutional Neural Network (CNN) as a feature extractor and classify the CNN block-wise features extracted using an ensemble of Machine Learning (ML) classifiers. The classifications of radiological (chest X-ray) images into binary class (Covid-19 and Non-Covid-19) and multi-class (Lungs infected by Covid-19, Normal Lungs and Lungs infected by Pneumonia) are performed in this work. **Methods:** The various six CNN pre-trained models viz. AlexNet, GoogleNet, VGG-16, ResNet-50, SqueezeNet and Inception-V3 and our proposed CoronaNet model are used for feature extraction. Four most popular ML classifiers such as Support Vector Machine (SVM), K-Nearest Neighbours (KNN), Decision Tree (DT) and Naive-Bayes (NB) are used to classify the features extracted from each of the CNN pre-trained and proposed CoronaNet models. The public dataset of chest X-ray images, created by Joseph Paul Cohen and retrieved from GitHub (Covid-19 - Chest X-ray images dataset) is used in our research work. In total, 3785 training samples, 1686 validation samples and 150 testing samples are used in this work. **Findings:** The comparative analysis shows that the proposed CoronaNet model with SVM ML classifier has achieved the highest classification accuracy of 97.7% for binary class classification and 96.6% for multi-class classification. **Novelty:** Exhaustive block wise analysis of the CNN features from the six most popular CNN pre-trained models and the proposed CoronaNet model shows that extracted features in the last layer of each preceding block of CNN models + SVM classifier have resulted in improved classification accuracies, when it is compared to that in the FC /Pool10 layer of CNN models + SVM or Softmax classifier.

Keywords: CNN Deep learning; Machine Learning; Feature extraction; Chest X-ray Images Classification; Covid-19

1 Introduction

COVID-19 has a significant detrimental impact on human existence and produced serious economic challenges for numerous nations. Real-Time Reverse Transcription Polymerase Chain Reaction (RT-PCR) is the primary screening technique for finding COVID-19[1]. Testing and disease diagnosis are delayed due to the significant rise in number of patients and shortage of RT-PCR laboratory equipment in several regions of the world. So, early diagnosis is very essential to prevents spread and reduce fatalities. Radiologists may be able to anticipate COVID-19 from X-ray and CT-scan images with the help of a Computer-Aided Diagnosis (CAD) approach[2]. Pre-trained CNN models have effectively diagnosed breast cancer[3], brain disorders[4] and leukemia[5] in the past. Convolutional neural networks (CNNs) have demonstrated promising outcomes in the domain of computer-aided detection and diagnosis of a number of diseases[6].

In the recent years, several research works and studies have been carried out to identify Covid-19 patients from chest X-ray images. Shervin Minaee et al.[7] have trained four popular CNN models such as ResNet18, ResNet50, SqueezeNet, and DenseNet-121 to detect COVID-19 disease from chest X-ray images. In their work, classification accuracies have been compared, based on sensitivity and specificity. Most of these networks have achieved a sensitivity rate 98 % and a specificity rate 90 % for binary class classification.

Shayan Hassantabar et al.[8] have presented two different algorithms viz. Deep Neural Network (DNN) on the fractal feature of images and Convolutional Neural Network (CNN) methods to detect and diagnosis of Covid-19 from lung X-ray images. The classification results show that the presented CNN architecture has achieved the highest accuracy of 93.2% for binary class classification than that (83.4%) of DNN (with feature extraction) method.

Prabira Kumar Sethy et al.[9] have used ResNet-50+SVM classifier to classify Covid-19 images from chest X-ray images. The deep features are extracted from the FC layer of this model and fed into the SVM classifier and it has achieved an accuracy of 95.33%.

Arnab Kumar Mishra et al.[10] have explored a decision fusion-based approach to detect Covid-19 from chest CT images. The experimental results show that the proposed decision fusion-based approach achieves an accuracy of 86% for binary class classification. Amine Amyar et al.[11] have proposed a new multitask deep learning model to jointly identify Covid-19 and segment Covid-19 lesion from chest CT images which yields the highest accuracy of 94.67%.

Hiam Alquran et al.[12] have employed Texture Features of chest X-ray images and machine learning for classification and detection of Covid -19. The various image processing techniques such as Local Binary Pattern (LBP), Gabor Filter (GF) and Gray-Level Co-Occurrence Matrix (GLCM)have been used to extract features from chest X-ray images. These features have been used in different AI scenarios to distinguish between Normal, Pneumonia and Covid-19 cases. Texture features with an ensemble of ML classifiers have achieved the highest classification accuracy of 93.1%.

Abhir Bhandary et al.[13] have used two different Deep Learning (DL) methods; first DL method is termed as modified AlexNet (MAN) to classify chest X-ray images into Normal and Pneumonia classes. SVM is used for classification and the performance of SVM is compared with Softmax classifier. The second DL method is a fusion of handcrafted and extracted deep features from the MAN. The benchmark lung cancer CT images are used to test the effectiveness of this DL method and has achieved the classification accuracy of 97.27%.

Bejoy Abraham and Madhu S. Nair[14] have used kernel SVM to extract features from an ensemble of five different CNN models, viz. MobilenetV2, Shufflenet, Xception, Darknet53 and EfficientnetB0 to diagnose the Covid-19 from CT scans. This method has achieved the highest accuracy of 91.6 %.

A.M. Ismael and A. Sengur[15] have suggested a deep learning-based approach for classification of Covid-19 and Normal from chest X-ray images. Three methods have been employed for detection of Covid-19 such as i) deep feature extraction using pre-trained CNN models, ii) fine-tuning of pre-trained CNN models and iii) end-to training of a newly developed CNN model. Five pre-trained deep CNN models such as ResNet18, ResNet50, ResNet101, VGG16 and VGG19 have been used for deep feature extraction. The extracted deep features have been classified using SVM classifier with various kernel functions viz. Linear, Quadratic, Cubic and Gaussian. The deep features, extracted from the ResNet50 model and SVM classifier with the Linear Kernel function have achieved the highest accuracy of 94.7%.

The literature survey shows that the use of ML algorithms with CNN feature extraction for classification and detection of Covid-19from chest X-ray images has not been fully investigated empirically. Feature extraction plays a key role in image processing. Along with other tools, this technique is used to detect features in digital images such as edges, corners, shapes, or motion. Feature extraction identifies the most discriminating features /characteristics in images, which a machine learning or a deep learning algorithm can more easily consume. Once these features are identified, the data can be processed to perform various tasks related to analyzing an image. In general, the feature extraction has some important advantages over deep learning such as-

- Accuracy improvements[16]

- Speed up in training[16]
- Overfitting risk reduction[17]
- Improved data visualization[18].

The objectives of our study is to extract deep features from Fully Connected (FC) layer and last layer of each block of CNN pre-trained and proposed CoronaNet models for instantaneous detection of Covid-19 infection from chest X-ray images and ii) to choose the best classifier among the Machine Learning (ML) algorithms [Support Vector Machine (SVM), K-Nearest Neighbours (KNN), Decision Tree (DT) and Naive-Bayes (NB)] for the accurate classification of Covid-19, Normal and Pneumonia.

This paper is organized as follows. Section 2 briefly describes the details of the work such as flow diagram, chest X-ray images dataset, feature extraction process and its implementation. In Section 3, we present our results and discussion on a) Softmax classifier b) feature extraction from FC layer and classification c) feature extraction from last layer of each block and classification d) confusion matrices of proposed CoronaNet model plus SVM classifier with highest accuracy e) comparison of maximum classification accuracies between the existing studies and our present work based on CNN feature extraction and ML classifiers. In Section 4, principal outcome of the work.

2 Methodology

2.1 Flow diagram

The flow diagram of our present work is illustrated in Figure 1. The extracted features from the pre-trained models and proposed CoronaNet model[19] are fed into four most popular Machine Learning (ML) algorithms/classifiers such as SVM, KNN, DT and NB for classifications. In this study, both binary class classification (Covid-19 and Non-Covid-19) and multi-class classification (Covid-19, Normal and Pneumonia) are done using features extracted from the last layers of each block and also from the fully-connected (FC) layer of CNN models. The performance metrics such as Accuracy (Acc), Precision (Pre), Sensitivity (Sen), Specificity (Spec) and F1-Score have been used as evaluation criteria.

CNN models extract features from the input images according to the designed architecture and then classify them via the fully-connected (FC) layers using ML algorithms. In literature survey, it is found that various ML algorithms are applied due to their different advantages. It is important to identify the ML algorithms that offer the best performance according to the applications. The powerful classifying algorithms, commonly preferred in the literature, are SVM, KNN, DT and NB[20]. Hence, these algorithms are used in our research work.
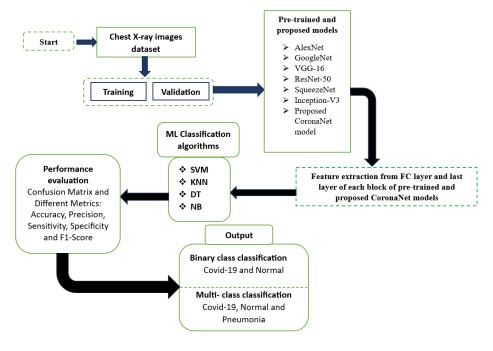

Fig 1. Flow diagram of our present work

2.2 Chest X-ray images dataset

A chest X-ray image is one of the primary procedures, performed during a lung examination when a respiratory condition is suspected. The public dataset of chest X-ray images, created by Joseph Paul Cohen and retrieved from GitHub (Covid-19 - Chest X-ray images dataset) is used in our research work[21]. The original (fundamental) dataset consists of X-ray and CT Scan images. In this work, only X-ray images are used for classification of Covid-19, Normal and Pneumonia. Table 1 provides a dataset summary. The sample X-ray images are as shown in Figure 2.

The process of performing a set of operations on the fundamental dataset to increase the amount of data samples is known as data augmentation. In this work, rotation, scaling, noise adding and horizontal flipping operations are performed for data augmentation. The X-ray images are rotated by $45°$, $90°$ and $180°$. Scaling is used to alter or change the size of images. A matrix of random numbers, frequently derived from a Gaussian distribution, are injected during the "noise addition" process. The horizontal axis flipping operation is both rows and columns of matrix (of an image) flip horizontally[22].

Table 1. Summary of dataset

Disease	No. of samples in the fundamental dataset	No. of samples after augmentation	No. of training samples	No. of validation samples	No. of testing samples
Covid-19	1441	1860	1249	561	**50**
Normal	1435	1890	1282	558	50
Pneumonia	1459	1871	1254	567	50
Total	4335	5621	3785	1686	150

Fig 2. Sample X-ray images

2.3 Feature extraction

Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. Many of the recent research studies have worked on models, based on pre-trained CNNs as feature extractors[7–15]. In this work, pre-trained CNNs and CoronaNet are used as feature extractors. Table 2 shows the description of the pre-trained CNN models such as AlexNet, GoogleNet, VGG-16, ResNet-50, SqueezeNet, Inception-V3 and proposed CoronaNet model that are used as a block (layer)-wise feature extractors in this work. CNN models can learn hierarchical features layer by layer automatically. Deep learning (CNN) models extract relevant features from the data automatically[23].

The process of feature extraction in this work encompasses the following steps:

1. **Pre-trained CNN model selection:** Most popular pre-trained models such as AlexNet, GoogleNet, VGG-16, ResNet-50, SqueezeNet and Inception-V3 are used for training the large dataset.
2. **Input data preparation:** Resize the input data depending on the specific model requirements. The input size of AlexNet and SqueezeNet are 227*227 whereas that of GoogleNet, VGG-16 and ResNet-50 are 224*224. The input size of Inception-V3 is 299*299 and that of proposed CoronaNet is 256*256 as given in Table 2.
3. **Feature extraction:** This process involves passing the data through CNN layers and capturing activations of a specific layer, usually just before the Softmax classifier, which is FC layer. In this work, the features are extracted from FC layer of classification block and the last layer of its preceding blocks of pre-trained CNN and CoronaNet models.

4. **Feature representation:** Once the features are extracted, they need to represent in a suitable format for further analysis. In this work, the extracted features are represented by numerical vectors. Commonly these vectors are 1-dimensional array.

5. **Classification :** The extracted features are used for classification process which is carried out by using the ML algorithms/classifiers namely SVM, KNN, DT and NB.

Table 2. Structure of the CNN pre-trained models [24] and proposed CoronaNet model [19] used in our present work

Structure of models		
CNN Models	**Input size**	**Description of model**
AlexNet	224,224,3	5 convolutional and 3 fully connected layers
GoogleNet	224,224,3	21 convolutional and 1 fully connected layers
VGG 16	224,224,3	13 convolutional and 3 fully connected layers
ResNet-50	224,224,3	49 convolutional and 1 fully connected layers
SqueezeNet	224,224,3	15 convolutional and 3 fully connected layers
Inception-V3 [25]	299,299,3	41 convolutional and 1 fully connected layers
Proposed CoronaNet	256,256,3	5 convolutional and 1 fully connected layers

2.4 Implementation

Two distinct classification approaches, viz. binary class (Covid-19, non-Covid-19) and multi-class (Normal, Covid-19, Pneumonia) classifications, are used to evaluate the performance of features extracted from chest X-ray images using the pre-trained and CoronaNet models in detecting Covid-19. We split our dataset for training (70%) and validation (30%). We have used pre-trained models such as AlexNet, GoogleNet, VGG-16, ResNet-50, SqueezeNet, Inception-V3 and CoronaNet model to extract features from last layer of each block. All the runs (simulations) of CNN pre-trained and CoronaNet models for different hyper-parameters are carried out in **MatlabR2022b**. Hyper-parameters are the explicitly specified parameters viz. learning rate, dropout, batch size, epoch and optimizer that control the training process. They are essential for optimizing the model.

The best learning rate of a model will be chosen, based on the minimum loss. Hence, the learning rate will be chosen to be 0.0001, since this value is used especially for ADAM optimizer in most of the CNN model studies. Each layer learns at the same learning rate of 0.0001. ADAM optimizer is employed here for the training. Each model is trained with dropout rate 0.2, batch size 64 and epoch value 50 for binary class classification whereas respective parameter values are 0.5, 32 and 30 for multi-class classification [19].

Subsequently, extracted features are fed into ML classifiers such as SVM, KNN, DT and NB. The performances of the pre-trained and CoronaNet models are assessed from the confusion matrices. The various metrics such as accuracy, precision, sensitivity, specificity and F1-score are calculated from these confusion matrices. Figure 3shows the block diagram representation of feature extraction and classification using four ML classifiers.

3 Results and discussion

This section includes the computer experimental results and discussion on the performance of feature extraction based Covid-19 detection system. The classification accuracies of our present work and previously published works (existing works) [9,12,15,20] for binary class and multi-class classifications are compared.

3.1 Softmax classifier

Softmax classifier is a crucial component in a CNN model for classification process. In this process, the input data is fed directly into the CNN models. The CNN output layer is the last layer of the classification block containing Softmax classifier and it directly gives the classification results. [16]

Table 3 demonstrates the classification accuracies of both CNN pre-trained and proposed CoronaNet models for binary class and multi-class classifications. Using Softmax classifier, the proposed CoronaNet model has achieved the highest accuracy of 96.4% for binary class classification and 94.4% for multi-class classification than that of six CNN pre-trained models.
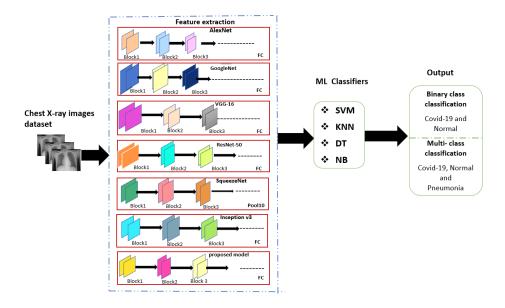
Fig 3. Block diagram representation of feature extraction and classification using four ML classifiers

Table 3. Classification accuracies in the CNN pre-trained models and proposed CoronaNet model with Softmax classifier for binary class and multi-class classifications

Existing study	CNN Models	Classifier	Binary class classification	Multi-class classification
	AlexNet		95.90%	93.90%
	GoogleNet		92.80%	83.89%
	VGG-16		96.30%	92.60%
Asha et al. [19]	ResNet-50	Softmax classifier	93.70%	89.80%
	SqueezeNet		94.80%	89.40%
	InceptionV3		92.70%	89.70%
	CoronaNet		**96.40%**	**94.40%**

3.2 Feature extraction from FC layer and classification

In extracting features from specific layer of the CNN models, commonly used approach is to extract features from the FC layers of the model. The FC layers are typically located at the end of the CNN architecture and are responsible for performing the final classification. The extracted features from the FC layers are fed into the Machine Learning (ML) classifiers.

Table 4. The performance metrics calculatedfor binary class and multi-class classifications of features extracted from FC layers of CNN models with ML classifiers

Models	No of Layers	Last layer feature extraction of each model	Acc (%)	Pre (%)	Sen (%)	Spec (%)	F1-Score (%)	Acc (%)	Pre (%)	Sen (%)	Spec (%)	F1-Score (%)
							SVM classifier					
			Binary class classification					Multi-class classification				
AlexNet	8	FC	95	92	96	92	94	92	91	95	89	95
GoogleNet	22	FC	94	92	93	94	**92**	**89.9**	89	83	95	94
VGG-16	16	FC	95.4	94	96	95	96	91.5	90	91	92	93
ResNet-50	50	FC	96	96	97	96	95	89.9	73	95	88	87
SqueezeNet	18	Pool10	95.9	95	97	95	96	91.1	93	92	91	82
InceptionV3	42	FC	95	94	93	92	98	90.3	91	94	91	89

Continued on next page

Table 4 continued

Model		Depth	Layer										
Proposed Coro-naNet	Coro-naNet	26	FC	**96.5**	93	99	93	95	**95.4**	95	95	90	94
						KNN classifier							
AlexNet		8	FC	89	86	88	91	93	88.3	87	86	89	92
GoogleNet		22	FC	88.6	93	85	83	91	88.6	**85**	94	93	83
VGG-16		16	FC	89.9	84	92	85	90	87.7	82	86	82	84
ResNet-50		50	FC	88.9	80	97	83	86	89	89	93	86	95
SqueezeNet		18	Pool10	90.6	83	98	85	90	82.7	82	84	91	85
InceptionV3		42	FC	87	85	83	85	82	84.7	68	93	86	84
Proposed Coro-naNet	Coro-naNet	26	FC	**89.4**	91	96	92	90	**89.3**	95	93	86	85
						DT classifier							
AlexNet		8	FC	87.1	84	91	83	90	82	78	87	86	87
GoogleNet		22	FC	84.8	83	85	93	80	80.2	**73**	85	88	77
VGG-16		16	FC	83.1	81	85	82	83	82.3	76	87	89	84
ResNet-50		50	FC	83.6	82	85	82	84	80.4	74	74	93	82
SqueezeNet		18	Pool10	84.9	82	87	83	82	82.7	82	84	91	88
InceptionV3		42	FC	82	80	81	84	82	76	65	73	83	69
Proposed Coro-naNet	Coro-naNet	26	FC	**87.3**	89	85	88	83	**83**	82	86	87	83
						NB classifier							
AlexNet		8	FC	85.7	87	86	84	83	80	87	88	76	87
GoogleNet		22	FC	84.5	86	85	83	82	84	**80**	83	85	84
VGG-16		16	FC	71.2	81	73	72	80	83.2	81	81	91	79
ResNet-50		50	FC	83.3	81	85	82	83	85	83	87	92	86
SqueezeNet		18	Pool10	85.9	80	88	83	86	80.4	74	74	93	82
InceptionV3		42	FC	84	89	79	80	85	81	80	83	85	84
Proposed Coro-naNet	Coro-naNet	26	FC	**86**	88	84	86	87	**85.8**	87	86	91	90

Table 4 illustrates the performance metrics, calculated for binary class and multi-class classifications of features extracted from FC layers of CNN models with ML classifiers. In this process, CoronaNet +SVM classifier has achieved the highest classification accuracy of 96.5% for binary class and 95.4% for multi-class classifications. Based on the analysis, out of four classifiers (SVM, KNN, DT and NB), SVM has demonstrated the highest accuracy both in binary class and multi-class classifications. Precision (Pre), Sensitivity (Sen), Specificity (Spec) and F1-Score values for the CoronaNet model are 93%, 99%, 93% and 95% for binary class classification and 95%, 95%, 90% and 94% for multi-class classification respectively.

3.3 Feature extraction from last layer of each block and classification

Deep features of CNN models are extracted from a specific layer of each model. The layers, used for feature extraction can produce a different number of outputs(features), depending on the CNN models. By feeding these features into ML classification algorithms, the models are able to learn patterns and make predictions. The computer experiment and analysis of CNN models are typically conducted to determine the most efficient layer or combination of layers by using feature extraction and classification methods. Here, four blocks are utilized for the feature extraction analysis.

Table 5. Classification accuracies (in %) of CoronaNet with ML classifiers for binary class and multi-class classifications

(a) CoronaNet + ML for binary class classification					(b) CoronaNet + ML for multi-class classification				
Block	**CoronaNet + ML**				**Block**	**CoronaNet + ML**			
	SVM	**KNN**	**DT**	**NB**		**SVM**	**KNN**	**DT**	**NB**
2	94	94	86	85	2	95	90	85	83
3	96.4	**95.5**	85	**88.9**	3	**96.6**	91	**87.8**	84
4	**97.9**	95	**89.9**	87	4	94	**92.6**	83	85
5	96.5	94	88	86	5	**95**	92	84	**85.8**

Table 5**(a)** presents the results of block-wise feature extraction and binary class classification of the proposed CoronaNet model. Block 4 of the proposed CoronaNet model has achieved the highest classification accuracy of **97.9%** with SVM classifier. In the cases of KNN, DT and NB, block 3 with KNN has achieved the highest accuracy of 95.5%, block 4 with DT has achieved the highest accuracy of 89.9% and block 3 with NB has achieved the highest accuracy of 88.9% respectively.

Table 5**(b)** presents the results of block-wise feature extraction and multi-class classification of the proposed CoronaNet model. Block 3 of the proposed CoronaNet model has achieved the highest classification accuracy of **96.6%** with SVM classifier. In the case other classifiers, block 4 with KNN has achieved the highest accuracy of 92.6%, block 3 with DT has achieved the highest accuracy of 87.8% and block 5 with NB has achieved the highest accuracy of 85.8% respectively.

Table 6 provides the best performance results of six pre-trained models and proposed CoronaNet model using various ML classifiers for binary class and multi-class classifications. Here, the blocks with maximum accuracies in each model +ML classifiers are tabulated. In the binary class classification, the proposed CoronaNet model with block4 last layer as the feature extraction layer has achieved the highest accuracy of 97.9% while using SVM as the ML classifier. Also, in the multi-class classification, that model with block3 has achieved the highest classification accuracy of 96.6% while using the same SVM as the ML classifier.

3.4 Confusion matrices of proposed CoronaNet model plus SVM classifier with the highest accuracy
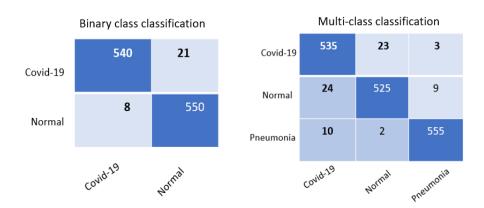

Fig 4. Confusion matrices for binary class and multi-class classification of features extracted with highest accuracy respectively from the last layer of block 4 and that of block 3 of the proposed CoronaNet model + SVM classifier

Figure 4 shows the confusion matrices for binary class and multi-class classifications of features extracted with highest accuracy respectively from the last layer of block 4 and that of block 3 of the proposed CoronaNet model + SVM classifier. In the confusion matrix of binary class classification, shown in Figure.6, among the 561 Covid-19 images, 21 images are misclassified as Normal, while among 558 Normal samples, 8 chest X-ray images are misclassified as Covid-19. In the confusion matrix of multi-class classification, as shown in Figure 4,535 among 561 Covid-19 samples, 525 among 558 Normal samples and 555 among 567 Pneumonia samples are correctly classified; totally 26 Covid-19 samples are misclassified as Normal and Pneumonia, totally 33 Normal samples are misclassified as Covid-19 and Pneumonia and totally 12 Pneumonia samples are misclassified as Covid-19 and Pneumonia. Overall, the accuracy, achieved by binary class classification is **97.7%** and that achieved by multi-class classification is **96.6%**.

3.5 Comparison of maximum classification accuracies between the existing studies and our present work based on CNN feature extraction and ML classifiers

Table 7 demonstrates the comparison between existing studies and our present work based on the classification accuracies of CNN features extracted with ML classifiers. Prabira Kumar Sethy et al. [9] are classifying Covid-19 images from chest X-ray images using a ResNet-50+SVM classifier and achieve an accuracy of 95.33%. Hiam Alquran et al. [12] are implementing a Texture Feature with machine learning model for classification and detection of Covid -19 from chest X-ray images. Texture feature with ensemble classifier achieves the highest classification accuracy of 93.1% for multi-class classification. A.M. Ismael and A. Sengur [15] useResNet-50+SVM classifier for deep feature extraction and classification of Covid-19 and Normal from

Table 6. Summary of best performing blocks with maximum classification accuracy in each model by using feature extraction and ML classifiers for binary class and multi-class classifications

CNN pre-trained and proposed CoronaNet models	Block with maximum accuracy in each model	Binary class classification					Block with maximum accuracy in each model	Multi-class classification				
		Acc (%)	Pre (%)	Sen (%)	Spec (%)	F1 Score (%)		Acc (%)	Pre (%)	Sen (%)	Spec (%)	F1 Score (%)
						SVM classifier						
AlexNet	Block5	96.8	95	96	99	98	Block4	95.5	97	97	98	97
GoogleNet	Block9	97.5	97	98	95	96	Block7	96.1	98	99	99	96
VGG-16	Block7	96.4	97	95	98	97	Block7	94.8	99	98	98	97
ResNet-50	Block35	96.7	98	93	95	99	Block40	95.9	98	97	97	98
SqueezeNet	Block9	97.2	97	96	95	99	Block7	95.6	97	97	98'	95
InceipetionV3	Block25	96.4	98	95	94	98	Block20	95.9	98	93	95	93
Proposed CoronaNet	Block4	**97.7**	98	99	97	98	Block3	**96.6**	98	99	98	97
						KNN classifier						
AlexNet	Block7	94.3	90	99	91	90	Block5	91.1	89	98	95	96
GoogleNet	Block6	93.4	89	98	90	90	Block9	91.2	94	93	91	95
VGG-16	Block4	93.7	94	99	94	90	Block5	89.9	89	96	95	94
ResNet-50	Block35	94.4	94	95	94	95	Block35	91	91	96	96	92
SqueezeNet	Block5	95.4	93	98	93	98	Block6	89.7	91	96	98	87
InceipetionV3	Block20	90.4	83	99	84	90	Bloc15	90.4	83	99	84	90
Proposed CoronaNet	Block3	**95.5**	93	98	93	97	Block4	**92.6**	86	89	86	90
						DT classifier						
AlexNet	Block5	88.8	89	91	89	90	Block5	84.4	88	83	94	89
GoogleNet	Block5	86	82	89	83	85	Block9	85.8	83	87	92	90
VGG-16	Block6	88.3	86	89	86	85	Block6	85.1	81	88	91	90
ResNet-50	Block15	88.9	80	97	83	89	Block10	84.6	83	85	92	89
SqueezeNet	Block4	87.8	86	89	90	89	Block4	84.6	83	85	84	85
InceipetionV3	Block30	87.2	94	82	97	90	Block25	86.4	83	99	84	90
Proposed CoronaNet	Block4	**89.9**	86	89	86	85	Block3	**87.8**	86	89	86	90
						NB classifier						
AlexNet	Block5	88.8	91	90	91	92	Block4	83.4	81	85	91	80
GoogleNet	Block10	85.9	89	89	86	95	Block7	85.2	85	85	80	79
VGG-16	Block4	89.3	83	91	84	90	Block6	84.5	85	85	83	87
ResNet-50	Block45	87	86	89	86	90	Block25	82	80	76	82	81
SqueezeNet	Block8	83.5	86	85	83	88	Block6	87.7	81	83	80	82
InceipetionV3	Block25	81.5	88	81	79	83	Block30	83.4	83	82	84	80
Proposed CoronaNet	Block3	**88.5**	73	79	88	82	Block5	**85.8**	86	85	80	87

chest X-ray images and achieve an accuracy of 94.7%. M.F. Aslan et al. [17] extract the features from four pre-trained models such as AlexNet, GoogleNet, ResNet-50 and InceptionV3 and classify them with SVM classifier. InceptionV3 achieves the highest classification accuracy of 95.58%for binary class classification. Comparing the existing studies with our present study show that proposed CoronaNet features, extracted from the FC layer + SVM classifier achieve the highest classification accuracy of **96.5%** for binary class and **95.4%** for multi-class classifications.

As shown in the Table 7, our present work shows that the highest classification accuracies of features extracted from specific blocks of the CNN models with SVM classifier are obtained in both classifications. Here also, comparing with pre-trained models, CoronaNet + SVM classifier has achieved the highest classification accuracy of **97.7%** for binary class classification and **96.6%** for multi-class classification.

Table 7. Comparison between existing studies and our present work based on CNN feature extraction and classification accuracies

Existing studies and our present work	Models	ML algorithms/classifiers	Binary class classification		Multi-class classification	
			Feature extraction block maximum accuracy	Accuracy	Feature extraction block maximum accuracy	Accuracy
Prabira Kumar Sethy et al. [9]	ResNet-50	ResNet-50 +SVM	FC	95.33%	-	-
Hiam Alquran et al. [12]		Machine Learning	Texture Features			93.10%
A.M. Ismael and A.Sengur [15]	ResNet-50	ResNet-50 +SVM	-	94.70%	-	-
	AlexNet		FC8	95.05%	Fc8	
M.F.Aslan et al. [20]	GoogleNet	SVM	Pool5	95.05%	Pool5	-
	ResNet-50		FC100	95.23%	Fc100	
	Inception-V3		Predictions	95.58%	Predictions	
Our present work	Proposed CoronaNet	SVM	FC	**96.50%**	FC	**95.40%**
	AlexNet		Block5	96.8	Block4	95.5
	GoogleNet		Block9	97.5	Block7	96.1
	VGG-16		Block7	96.4	Block7	94.8
Our present work	ResNet-50	SVM	Block35	96.7	Block40	95.9
	SqueezeNet		Block9	97.2	Block7	95.6
	Inception-V3		Block25	96.4	Block20	95.9
	Proposed CoronaNet		Block4	**97.7**	Block3	**96.6**

3.6 Research findings

Deep learning models, CNNs like AlexNet, are designed to automatically learn hierarchical features. In these models, initial layers capture low-level features, while deeper layers capture high-level which may be more abstract features. By extracting features at various blocks and then using machine learning classifiers, it becomes easier to visualize and interpret the learned features, which can be crucial in medical image analysis for identifying Covid-19.

3.6.1 AlexNetwith ML classifiers for binary class classification

As a further investigation, AlexNet with ML classifiers for binary class classification is taken as an example. The graphical representation of block–based feature extraction and classification accuracies of AlexNet with ML classifier for binary class classification is as shown in Figure 5.

a). In the case of AlexNet model, 6 blocks are used for feature extraction and classification process. The initial block (block 3) focuses on learning low-level features such as edges, corners, and texture of regions of the image as referred in Ref. [26]. The
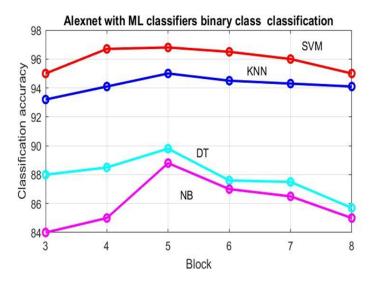
Fig 5. Graphical representation of block–based feature extraction and classification accuracies of AlexNet with ML classifier for binary class classification

extracted features from this block are visualized as shown in Figure 6. These features serve as basic patterns which form the foundation for learning higher-level features. Low-level features such as edges, corners, and textures are essential but may not provide enough information for solving complex classification tasks. Since, the initial layers of the CNN are too shallow or lack of expressiveness, they might not capture the intricate patterns in the data. This leads to under fitting and lower classification accuracy (Figure 6). Hence, in this case, block3 of AlexNet model has achieved lower accuracy.

Fig 6. Output (8x8 channels) visualization of the features, extracted from block 3 of the AlexNet model

b). The intermediate blocks can learn the low-level features and high-level features of the image simultaneously. The high-level features are size, shape and texture/pattern of the image. These features can be more complex patterns than that of the initial block. Therefore, the intermediate block (block 5) has demonstrated the maximum classification accuracy in the AlexNet model. This block is particularly efficient in identifying the Covid-19 infected images. The corresponding image, generated out of these extracted features is as shown in Figure 7.

c). The final block is the classification block (which contains FC layer) can learn high-level features. However, employing FC layers for feature extraction and classification increases the risk of overfitting and potentially leads to diminishing accuracy. Hence, lower accuracy is achieved when it is compared with the intermediate blocks.

Similarly, the above block-wise feature extraction method is systematically implemented in the other CNN pre-trained and proposed CoronaNet models. Importantly, each block within these CNN models comprises different layers. Exhaustive block-wise analysis of the CNN features from the six most popular CNN pre-trained models and the proposed CoronaNet model shows that blockwise extracted features + SVM classifier have resulted in improved classification accuracies, when it is compared to that with the FC /Pool10 layer of CNN models + SVM or Softmax classifier. It indicates that intermediate features are highly
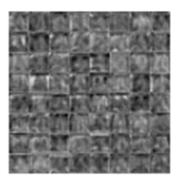
Fig 7. Output (8x8 channels) visualization of the features, extracted from block 5 of the AlexNet model
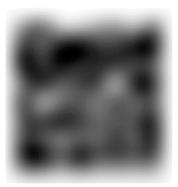

Fig 8. Output (8x8 channels) visualization of the features, extracted from block 7 (FC layer) of the AlexNet model

suitable for the classification process as observed from Table 6.

4 Conclusions

In this work, the efficiency of features extracted from CNN models for detecting Covid-19 from chest X-ray images have been analysed. Classification processes have been carried out using the most popular ML classifiers such as SVM, KNN, DT and NB. It is found from Table 4 that among all the classifiers, the SVM classifier has achieved the highest classification accuracy, calculated from the FC /Pool10 layer features extracted in all the CNN models. From Table 5, it is observed that as we progress through the blocks, the accuracy initially increases and reaches a maximum and then decreases. This indicates that there is a specific block within each CNN model that performs best for accurate classification using this feature extraction method. The accuracies, obtained from feature extraction at different blocks of each CNN model, show an interesting trend.

Exhaustive block-wise analysis of the CNN features from the six most popular CNN pre-trained models and the proposed CoronaNet model show that the extracted features in the last layer of each preceding block of CNN models + SVM classifier have resulted in improved classification accuracies, when it is compared to that in the FC /Pool10 layer of CNN models + SVM or Softmax classifier. It indicates that intermediate features are highly suitable for the classification process as observed from Table 6.

Again, it is found from Table 7 that the proposed CoronaNet model + SVM classifier has achieved the highest classification accuracy in both classifications than that of all pre-trained CNN models. In the proposed CoronaNet model + SVM classifier, the accuracy is **97.7%** for binary class and **96.6%** for multi-class classifications. It is clearly seen from the results of our present work while comparing with our previous study[19] using the same dataset, CNN feature extraction and an ensemble of ML classifiers together create a significant difference in improving classification performance.

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