CoVNet-19: A Deep Learning model for the detection and analysis of COVID-19 patients

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ABSTRACT

Background: The ongoing fight with Novel Corona Virus, getting quick treatment, and rapid diagnosis reports have become an act of high priority. With millions getting infected daily and a fatality rate of 2%, we made it our motive to contribute a little to solve this real-world problem by accomplishing a significant and substantial method for diagnosing COVID-19 patients.

Aim: The Exponential growth of COVID-19 cases worldwide has severely affected the health care system of highly populated countries due to proportionally a smaller number of medical practitioners, testing kits, and other resources, thus becoming essential to identify the infected people. Catering to the above problems, the purpose of this paper is to formulate an accurate, efficient, and time-saving method for detecting positive corona patients.

Method: In this paper, an Ensemble Deep Convolution Neural Network model "CoVNet-19" is being proposed that can unveil important diagnostic characteristics to find COVID-19 infected patients using X-ray images chest and help radiologists and medical experts to fight this pandemic.

Results: The experimental results clearly show that the overall classification accuracy obtained with the proposed approach for three-class classification among COVID-19, Pneumonia, and Normal is 98.28%, along with an average precision and Recall of 98.33% and 98.33%, respectively. Besides this, for binary classification between Non-COVID and COVID Chest X-ray images, an overall accuracy of 99.71% was obtained.

Conclusion: Having a high diagnostic accuracy, our proposed ensemble Deep Learning classification model can be a productive and substantial contribution to detecting COVID-19 infected patients.

1. Introduction

The Novel Coronavirus or prominently known as COVID-19, first appeared in Wuhan, the capital of Central China's Hubei province, in 2019 December and globally [1]. On 11th February 2020, "Severe Acute Respiratory Syndrome Coronavirus 2" (SARS-CoV-2) was named COVID-19 by the World Health Organization (WHO). Coronaviruses (CoV) are a large family of vulnerable and hazardous viruses. Coronavirus gets its name from the Crown like structure [2]. This family of viruses includes MERS-CoV (Middle East respiratory syndrome), SARS-CoV-2 (COVID-19), and SARS-CoV (severe acute respiratory syndrome). This virus has become the principal cause of a hundred thousand people's deaths, having a catastrophic effect on the global population [3]. A high magnitude of cases is being experienced in Spain, Italy, China, the USA,

Iran, etc. [4]. On 11th March 2020, it was declared a Pandemic by WHO [5]. With such a high growth rate of COVID-19 instances worldwide, most countries said a complete Lockdown, advising the population to stay indoors to avoid the disease [6].

With millions of people being infected and a minimal number of testing kits and diagnosis systems, many countries' healthcare systems have come to a stage of collapsing. No proper medication and drug or vaccine have been developed till now for the recovery of infected patients. Thus, medical practitioners and government officials rely on diagnosis measures so that infected people can be appropriately quarantined and the spread of pandemic can be controlled. Chest X-ray images of the patients can prove to be a cheap, efficient, and faster method for diagnosis of COVID-19. It is observed in the past that medical practitioners have frequently been using Chest X-ray images to diagnose patients with lung diseases such as Pneumonia, MERS-CoV SARS-CoV, ARDS, etc. Scanned X-ray images can prove beneficial and efficient in diagnosing a person's lung infections, fractures, injuries related to bones, Pneumonia, and tumors. Studies have suggested that

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deformity and abnormality in an individual's X-ray images can be vital in detecting the condition that the concerned person may be suffering. Thus, it can also be possible for them to rely on Chest X-rays to detect positive COVID-19 patients instead of using expensive and dedicated COVID-19 test kits. Our study was based on the fact that chest X-ray images can help identify a COVID-positive person. Due to the limited availability of viral testing kits, hospitals are using chest X-rays, or C.T. Scans to assess and diagnose their patients for the COVID-19 infection. Due to intricate morphological lung patterns, chest X-ray images' diagnosis strongly relies on a radiological expert and can only be done by a highly skilled medical doctor/consultant, which are not present everywhere. The manual reading of Chest X-ray images for diagnosis of patients may take significant time, and also, the radiologists have to familiarize themselves with the X-ray appearance of the Coronavirus infection. Radiologists have to be extremely cautious while practicing this, as the chest imaging can lack specificity and can also overlap with some similar infections such as influenza, SARS, or MERS. Thus, instead of being dependent on a skilled medical practitioner, developing an automated and efficient Chest X-ray diagnosis system can prove to be more beneficial. Our proposed intelligent automated system will take as input the Chest X-ray images of a person, process it through the proposed Deep Learning model, and output whether the person is COVID positive or not. After analyzing a person's Chest X-ray images, if they are suspected of being infected with the COVID-19 virus, they will be quarantined and taken up for further viral specific tests to confirm the infection. This will prove to a rapid and reliable method for COVID-19 screening without using any expensive dedicated test kits and without any medical expert's or highly skilled radiologist's involvement. It will allow the authorities to separate the COVID-19 suspected people from healthy ones, preventing its spread. Along with large hospitals, X-ray machines can easily be set up at small and regional clinics with a flexible architecture generalizing across multiple centers and modalities. It is more versatile and could even be installed in vehicles or portable triage tents for carrying out screening of COVID-19 in remote and village areas where the availability of dedicated COVID-19 testing kits is limited or medical experts are not present. In the present work, we have tried to devise an automated Machine Learning (ML) model to detect whether the patient is COVID-19 positive or not by analyzing its chest X-ray image. ML and Artificial Intelligence (A.I.) can perform this task in seconds and will surely help us deal with exponentially growing COVID-19 cases. Analysis of medical image data using ML can be of great help to the medical association.

With the advancements in A.I. and ML, they are now nearly being used everywhere for solving real-life issues. We also took them as our tools for devising an ML model that can predict positive Coronavirus patients using their Chest X-ray images. We made sure that our proposed model should have the ability to classify among COVID-19, Pneumonia, and a Healthy person's X-ray, with higher accuracy and lower the number of false negatives.

We have developed an automated model for predicting COVID-19 using Deep Convolution Neural Networks (DCNNs) in the following study. Our study aimed to devise a supervised Deep Learning ensemble model to classify the Chest X-ray images belonging to 3 classes. Normal (No-disease, Healthy Person), Non-COVID (i.e., a person infected with Pneumonia), and COVID infected person. Alongside it, we also performed the binary classification of COVID-19 vs. Non-COVID-19 chest X-ray images. For collecting the dataset, multiple open-sourced online sources were referred. These sources were freely available for research purpose. These publicly available dataset has granted us to train complex Deep Neural Networks and provide highly satisfying results.

The proposed Deep Learning ensemble model is called CoVNet-19. It uses pre-trained Deep Convolution Neural Networks (DCNNs) for feature extraction. DCNNs are futuristic and dynamic learning algorithms widely employed in many practical applications, including using computer vision tasks such as pattern detection and image classification. They give the most intuitive way to understand the images and provide with most probable results. After DCNNs for feature extraction, ML algorithm viz. Support Vector Machine (SVM) was used for classification. It is known for its potential in performing the classification of highly non-linear data. Our proposed method unequivocally concludes that X-ray images can be a preferable method for fast and accurate Coronavirus detection. The evaluation metrics chosen to evaluate this Model are Accuracy, F1 Score, Recall, and Precision.

The objective and main contribution of this paper are summarized below:

1. We have proposed a Stacked Ensemble Deep Learning Model called CoVNet-19, which can distinguish among X-rays of COVID-19, Pneumonia, and a healthy patient with an accuracy of 98.28% 3-class and 99.71 on binary class classification. It proved to be a powerful and robust ML model in the classification of medical image data.
2. We collected Five different datasets, consisting of 6214 chest X-ray scans. Out of which 2241 belonged to Pneumonia infected patients, 1628 were COVID-19 positive patients, and 2345 images were of healthy patients.
3. A detailed implementation of our proposed model, "CoVNet-19", and a discussion of the experimental results are provided in the paper.
4. Our proposition's objective was to help medical practitioners and nursing staff deal with exponentially growing COVID-19 cases and perform a faster and automatic diagnosis of patients.

The remaining study is formulated as follows: In Section 2, we have discussed the previously authored works and their drawbacks. We have tried to improve our work and results by building upon those drawbacks. Section 3 explains the fundamental and preliminary concepts required to understand this study. In Section 4, we have discussed the model architecture describing our proposed CoVNet-19 model's architecture for three-class classification. It also refers to the dataset we collected to conduct our experiment. An experimental analysis, results, and discussion are mentioned in Section 5. Sections 6 and 7 consists of future works and conclusions, respectively.

2. Related works

This section interprets the synopsis of previously authored works in the same domain for classification and identification of COVID-19 infected patients using the Chest X-ray images. With the rapid spread of this new disease across the whole world, there are not many much-authored works in detecting COVID-19 using Chest X-ray images. Most of the authors performed three Class classification (COVID-19 vs. Pneumonia vs. Normal) and two-class classification (COVID vs. Non-COVID) using pre-trained DCNNS to extract valuable features and afterward to perform classification. We used these previously authored works to compare the performance of our CoVNet-19 model.

In the study by Ioannis D. Apostolopoulos et al. [7], the authors collected a dataset having 700 images of common Pneumonia, 224 images of positive Covid-19 cases, and 504 images of patients with normal conditions to perform a three-class classification using transfer learning. Results suggested using VGG19 as their classification deep learning CNN model, and they achieved an overall accuracy of 98.75% in the detection of Covid-19 and three

class accuracy of 93.48%. Wang et al. [8] introduced COVIDx, a dataset containing 13,975 chest X-ray images belonging to 3 classes. COVID, normal, and Pneumonia. It was observed that the proposed COVID-Net network architecture achieved a good test accuracy of 93.33%. Asif Iqbal Khan et al. [9] proposed a DCNN model, namely CoroNet, to detect COVID-19 infection using chest X-ray images. The proposed model was based on the Xception model, pre-trained on ImageNet, and fine-tuned on the collected dataset. The proposed model achieved an overall accuracy of 89.6% and 95% for four-class and 3-class classification, respectively, while the binary class classification accuracy was 99%. Narin et al. [10] performed a similar experiment by creating a dataset of 100 chest X-ray images belonging to COVID and Non-COVID patients. The authors used a pre-trained ResNet50 DCNN model and achieved an accuracy of 98% for two-class classification. However, the number of X-ray images was significantly less. In contrast, the experiment conducted by Sethy et al. [11] acquired an overall accuracy of 95.38% for binary class classification. They deployed the ResNet50 CNN model for feature extraction and used SVM for classification purposes. Ozturk et al. [12] collected a dataset comprising 500 Pneumonia, 500 normal, and 125 COVID-19 chest X-ray images. The proposed CNN model, called DarkCovidNet, achieved binary and three-class classification accuracies of 98.08% and 87.02%, respectively.

Shervin Minaee et al. [13] prepared a dataset of 5,000 Chest X-ray images belonging to 3 classes, namely COVID-19, Non-COVID normal, and Non-COVID other diseases. They trained four popular convolutional neural networks, viz ResNet18, ResNet50, SqueezeNet, and DenseNet-121, to perform a three-class classification and achieve an average specificity rate of 90% and a sensitivity rate of 97.5%. Chun-Fu Yeh et al. [14] proposed a deep learning architecture of three-stage cascaded learning for a three-class classification among Normal, COVID-19, Non-COVID (Pneumonia) infected patients. The architecture achieved an AUC of 96.64 at stage 2 and an AUC of 99.88 at stage 3 when trained on open and clinical datasets. Yifan Zhang [15] devised a Deep Domain Adaptation method to diagnose COVID-19 and achieved an AUC of 0.985 and F1-Score of 92.98. The model proposed by the authors transferred the domain knowledge from the well-labeled source domain (i.e., typical Pneumonia) to the partially-labeled target domain (i.e., COVID-19). Ezz El-Din Hemdan et al. [16] extracted 50 X-ray images; 25 for Normal Class and 25 images for COVID positive class, and used pre-trained VGG19 for classification. Their model showed F1 scores of 0.89 and 0.91 for normal and COVID-19, respectively, with 90% accuracy. Y. Pathak et al. [17] used Chest CT Scans to classify COVID-19 patients using deep transfer learning. They collected 413 COVID-19 positive Scans and 439 CT Scans of normal Pneumonia infected patients. ResNet-50 model was used to extract potential features from the collected C.T. images. The Deep Transfer Learning classification model attained a testing accuracy of 93.01%.

Mesut Togaçar et al. [18] collected a chest X-ray dataset of 458 images with 295 images belonging to the COVID-19 class, 65 images for Normal, and 98 Pneumonia class. The authors trained MobileNetV2 and SqueezeNet with the collected dataset and extracted 1000 feature sets that were optimized using Social Mimic Optimization method. Support Vector Machine was used for classification after combining efficient features, and an overall accuracy rate of 99.27% was achieved. Ferhat Ucar et al. [19] proposed a Deep Bayes SqueezeNet model for three-class classification among Normal, Pneumonia, and COVID cases and achieved an accuracy of 98.30%. The authors collected a dataset having 76 COVID-19, 4290 pneumonia, and 1583 normal Chest X-ray images. The study by Ali Abbasian Ardakani et al. [20] collected C.T. Scans of 108 COVID-19 positive patients and 86 patients with other viral diseases. Among all the DCNN models trained

for binary classification, the best result metrics were acquired by ResNet-101 and Xception DCNN models. ResNet101 was attained at the accuracy of 99.51% and AUC of 0.994, while the Xception model achieved an AUC of 0.994 and 99.02% accuracy.

The conclusion from the above works shows that most of the Deep Learning models were built on an unbalanced dataset of X-ray images due to very a smaller number of COVID-19 X-ray scans available. We believe that these results may be improved further by collecting a diversified and balanced dataset and implementing an efficient feature extraction method. Our further work in this research is based on developing a deep learning classification model that can be efficiently used to classify the X-ray images. We have given a detailed comparison report of our proposed methodology with these already done works in literature.

3. Preliminary

This section explains some fundamental concepts that are required to understand and implement our work thoroughly. The following article provides an intuition about Deep Learning, Neural Networks, and the advantages of using the Convolution Neural Network to extract efficient features from an image. This section also notes the pros of using Transfer Learning and Ensemble Learning while building a Deep Neural Network, as we have done in our proposed model.

3.1. Deep learning and convolution neural networks

Neural Networks are the ML algorithms that help us to cluster and classify any structured or unstructured data. Their formation and working are deeply inspired by the human brain and the neurons. They are sophisticated enough to work with all kinds of real-world data like numbers, images, text, and audio. They can tackle the real-life problems related to Image Recognition, Natural Language Processing, and Speech Recognition. Deep Learning is a subdivision of ML, consisting of a robust set of learning algorithms to train and run the Neural Networks [20]. Neurons are the building blocks of neural networks. Fig. 1 shows the structure of a Neuron. A neuron interprets the input data (x_i), combines it with a set of constant weights (w_i) that either intensifies or condenses the input based on its importance, and the resultant is passed through a non-linear activation function (f($\Sigma w_i x_i$). These multiple neurons are stacked together to form a layer of a Neural Network. When placed one after another, three or more such layers include Deep Neural Networks (DNN). When non-linear and large dimensional datasets are passed through these layers, the DNN helps to compute sophisticated high-level features and trends in the data, further used for classification and Clustering of Data. The neurons' optimal weight matrices are calculated using an optimization algorithm to minimize the loss function considering the input data points. A fixed number of epochs are carried out for training the Neural Network after each epoch, the Loss function is reduced and tends to go towards zero.

Convolution Neural Networks have made a prestigious and predominant revolution in the study of computer vision. Manifold objectives like image recognition and classification, image segmentation, object detection can now be undoubtedly solved by Convolution Neural Networks (CNN) [21,22]. Convolution Neural Networks have proved their usefulness to collect valuable features from an image by passing it through a series of convolution layers, non-linear activation functions, pooling (down-sampling), and fully connected dense layers [23]. The convolutional filters, also known as kernels, works by sliding themselves through the image and performing the convolutional operation. These learnable filters can also be referred to as neurons of convolutional layers. They return high-level and complex features called feature
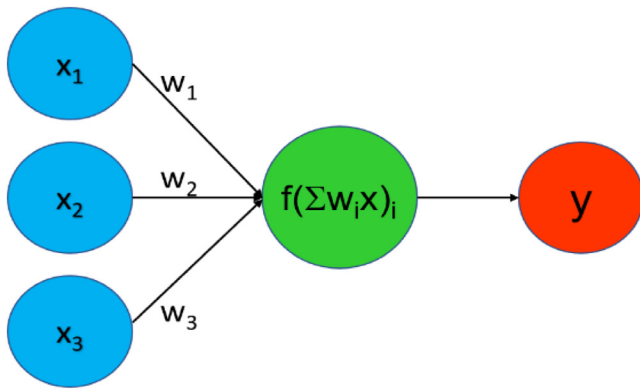
Fig. 1. Neuron: Building blocks of Neural Networks.

maps of activation maps. The filters are nothing but a matrix of weights, which gets multiplied with the pixel values of the image. The hierarchical network of multiple Convolutional layers improves generalization ability, extract high-level activation maps, and identifies more complex patterns in an image. The output feature maps from convolutional layers are fed to a non-linear activation function, i.e., ReLU activation. Max-pooling layers reduce the dimensions of feature maps preserving only the essential information. They reduce the number of parameters and hence the computation power.

3.2. Transfer learning

Transfer learning is a kind of inductive learning and is a popular technique used in Deep Learning. This approach is very significant and helpful when we have a relatively small dataset for training or have minimal computational power, therefore incapable of building the whole model from scratch. This method is majorly used in computer vision and Natural Language Processing tasks. The base intuition behind transfer learning is to take a model previously trained on a large dataset and transfer its knowledge in a smaller dataset. Deep neural network models that are yet trained on large labeled datasets can be imported with their weights. The idea is further to fine-tune them on our smaller datasets [23]. This method was noteworthy as the task of medical image classification was implemented in this study. In our study, two pre-trained Deep Convolutional Neural networks viz VGG19 and DenseNet121, which were previously trained on ImageNet dataset [24], were imported and used for extracting essential image features from X-ray images. These feature matrices that optimally represent the corresponding image were transferred from the pre-trained DCNNs and used for the image classification [25].

3.3. Ensemble learning

Ensemble learning is a keynote topic under ML techniques that can significantly improve the classification performance by sophisticated combinations of different classifiers. Bias, Variance, and Noise are the main error factors that can affect the ML model's proper training. Ensembles play a considerable role in eliminating these errors by complementing each model and, at the same time, utilizing the individual benefit of each candidate mode. Ensemble methods increase the overall stability, and the errors are reduced effectively. Our proposed CoVNet-19 model is a stacked ensemble model that combines two pre-trained DCNNs for feature extraction at base level and finally uses Support Vector Machine (SVM) for classifying the medical X-ray images in the final level. The complete architecture of our proposed model is explained in the upcoming section.

4. "CoVNeT-19" model and implementation

Our devised framework's primary purpose is to differentiate between X-ray images of COVID-19 positive patients, Pneumonia patients, and a healthy person. This section has discussed the in-depth knowledge about our proposed "CoVNet-19" model and its implementation.

CoVNet-19 model is based on the Deep CNN framework to detect COVID-19 positive patients using Chest X-ray images. Given the limitation in the availability of X-ray images of COVID-19 patients, it can be difficult to train a DCNN from scratch. Hence, to subjugate this issue, we decided to use the transfer learning approach and then fine-tune the pre-trained DCNNs on our collected Chest X-ray dataset. The main objective of using DCNNs was to extract essential and valuable features from image data. The proposed model is a 2-leveled stacked ensemble ML model. A stacked ensemble model combines multiple classification models to form a heterogeneous combination that can interpret the same data in different ways. In level 1 or base-level model of the CoVNet-19 model, we combined two pre-trained DCCNs viz. VGG19 (Visual Geometry Group) [26] and DenseNet121 [27]. Both the models were imported with pre-trained weights matrices, which were trained on the ImageNet Dataset. ImageNet [24] is an image database belonging to more than 20 thousand categories, having more than 14 million images. Models pre-trained on the ImageNet Dataset are proved to give tremendously successful results in image classification tasks [28]. We selected DenseNet121 and VGG-19 pre-trained models because of their exceptionally well performance in the classification of X-ray images. Combinational features from two DCNNs were used to deal with noise present in medical image data and extract contrasting image features to make our whole model generalized and accurate. Both models' complex architecture deals wisely with the vanishing gradient descent problem and minimizes noise and variance problems. The motivation to use the Ensemble ML model was to allow better predictive performance and robustness in comparison to a single DCNN classification model. Both the DCNNs were separately trained on the collected dataset to perform the classification task. The input given to them is a (224,224,3) dimensional Chest X-ray image. While at Level 2 of the stacked ensemble model, an SVM ML model was trained to perform multi-class classification and binary classification. It was trained on the features extracted from the base model.

Fig. 2 illustrates the detailed pictorial representation of our proposed DCNN ensemble model. CoVNet-19 architecture gives an optimum intuition of VGG19 and DenseNet121 models with our proposed technique's working procedure and architecture. Unlike VGG19, the visualization of DenseNet121 is a little bit complex. Therefore, we have tried to show a simple blueprint of the architecture of DenseNet121. The operating procedural algorithm, of our proposed deep learning classification method, is illustrated in Algorithm 1. The same model architecture was developed and trained separately to perform binary classification also i.e., two separate VGG-19 and DenseNet121 were trained for binary and ternary class feature extraction along with two separate SVM models for the final classification. Three additional layers were added at the end of both the DCNNs. They included two fully-connected dense layers having 64 and 32 nodes, respectively, that were activated by Relu activation Function and a final SoftMax layer to predict the class probabilities. Models were trained and validated on training and validation datasets formed.

4.1. DCNN Model: DenseNet121

The DenseNet121 was first trained for both three and two-class classification and then finally used as a feature extractor alongside VGG19. It consists of 121 layers and has several

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Algorithm 1: X-Ray classification using "CoVNet-19" Model

Input: (224x224x3) dimensional Chest X-Ray images.

Output: Predicted class label for the image (0: COVID-19, 1: Normal, 2: Pneumonia).

Steps:

1. Extracting features from the image

    1.1 Image is passed through multiple Convolutional, ReLU Activation and Max Pooling Layers of

    DenseNet121

    Convolution Operation between the Filter (K) of size (m x n) and Image (I) to give Feature Map (F):

    $$F(i, j) = (I \ast K)(i, j) = \sum_m \sum_n I(i + m, j + n) K(m, n)$$

    ReLU Activation Function to introduce non-linearity:

    $$f(x) = \max(0, x)$$

    Max Pooling:

    It is a Down-sampling layer to reduce the dimension of feature maps.

    Returns: (32x1) Feature Vector: $X_1 = [\alpha_0, \alpha_1, \alpha_2 \ldots, \ldots, \ldots, \alpha_{32}]^T$

    1.2 Image is passed through multiple Convolution, Max Pooling and Relu Activation Layers of VGG19

    Returns: (32x1) Feature Vector: $X_2 = [\beta_0, \beta_1, \beta_2 \ldots, \ldots, \ldots, \beta_{32}]^T$

2. Augmentation of both Feature Vectors

    $$X = (X_1{}^T | X_2{}^T) = [\alpha_0, \alpha_1, \alpha_2 \ldots, \ldots, \ldots, \alpha_{32}, \beta_0, \beta_1, \beta_2 \ldots, \ldots, \ldots, \beta_{32}]$$

    Returns: (64x1) Feature Vector

3. The formed feature vector is given as input to SVM ML model to perform Classification.

    The trained SVM model returns the class label.

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compelling advantages, such as encouraging feature reusing and solving the vanishing gradient problem. It has substantially reduced the trainable parameters compared to an equivalent CNN model with the same number of layers. Each layer of DenseNet12 uses the activation-maps of the previous layers as inputs. In contrast, the layer's activation-maps are used as inputs to the succeeding layers. The pre-trained DenseNet121 DCNN model was imported, and the weights were trained on the ImageNet [24] dataset. This model was fine-tuned separately for both three-class classification (COVID-19, Normal, and Pneumonia) and then for two-class classification (COVID-19 vs. Non-COVID-19). After the complete training of DenseNet121, the last SoftMax layer used for predicting the class probabilities was removed. The output from the second last layer, i.e., Dense layer with 32 nodes, i.e., is a (32×1) dimensional feature vector, was used as input to SVM. These feature vectors gave a significant representation of the corresponding X-ray image, which could efficiently be used further for classification.

4.2. DCNN Model: VGG19

Visual Geometry Group Network, i.e., VGG19, consists of 19 layers, including 16 convolutional layers and three fully connected dense layers. It has five max-pooling layers. VGG19 was

also imported along with the weights trained on the ImageNet Dataset. Similar to DenseNet121, VGG-19 was also firstly fine-tuned separately for three-class and two-class classification and then used as a feature extractor in CoVNet-19. The last layer, i.e., the SoftMax layer, was removed after training. The output from the second last layer, i.e., the Dense layer with 32 nodes, was used as the feature vector to be given as input to SVM for classification purposes.

4.3. Stacked ensemble model: CoVNet-19

Level 2 of CoVNet-19 was SVM. SVM is a supervised ML algorithm used in classification and regression problems. SVM, when used for classification purposes, is called Support Vector Classifiers (SVC). For classifying the data points, SVC forms a hyper-plane to separate the classes based on the input features. The hyper-plane line is calculated by observing the critical data points that are difficult to classify, making it one of the most prominent and robust ML classification algorithms. The data points are allotted to the corresponding classes based on the distance concerning the Hyper-plane. Linear Support Vector Classification (Linear SVC) was used to perform binary and three-class classification. Linear SVC is a faster implementation of SVC using a linear kernel function. It implements a "one versus the
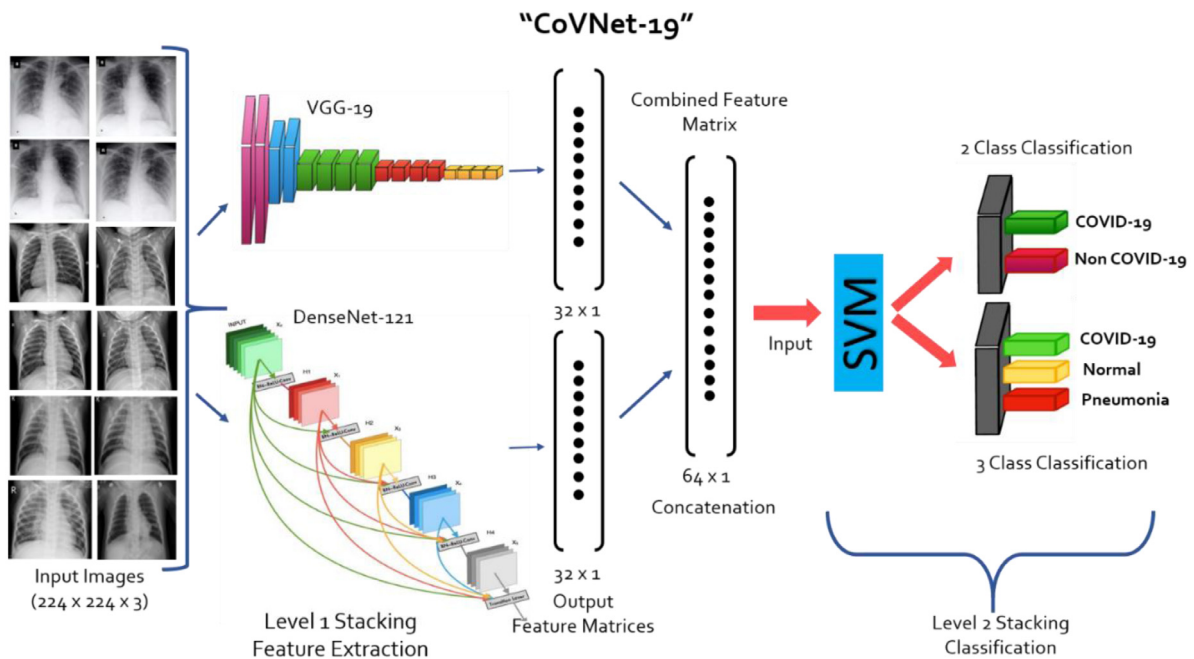
Fig. 2. CoVNet-19 architecture.

rest" multi-class classification strategy. We trained two separate SVCs to perform the final binary and ternary classification. The output from both the trained DCNNs for both binary and ternary classification was a (32×1) feature vector corresponding to each image. The two feature vectors, one from each DCNN, were concatenated to form a (64×1) dimensional feature vector. This combinational high-level feature vector was used as an input to the SVM model, with the corresponding output to be the class label of that image. For the three-class classification, the class labels were 0: COVID-19, 1: Normal, and 2: Pneumonia, and for the two-class classification, the class labels were 0: COVID-19 and 1 for Non-COVID-19 X-ray images. We used L2 regularization to prevent overfitting while training the SVM model. Using the feature output from highly accurately trained DCCNs, the SVC combined the best features of both of them to make the final predictions.

For performing binary classification of COVID-19 vs. Non-COVID-19, a subset from the collected dataset was extracted. The healthy and Pneumonia X-ray were combined in equal proportion to form the Non-COVID-19 class, while the COVID-19 class was the same as used for three-class classification. The training and testing for both binary and ternary CoVNet-19 models were carried out separately on their respective datasets, and the experimental result metrics were observed. Our trained models' result metrics were compared with the other state-of-the-art models, and a detailed discussion report was formulated, details of which are given in the next section.

5. Experimental analysis and results

The fifth section of our paper discusses the Datasets, CoVNet-19 hyperparameters, performance analysis, and the proposed CoVNet-19 model results. The part is thereby divided into five sub-sections. The first sub-section characterizes our Chest X-ray image dataset belonging to Normal (Un-diseased person), COVID-19, and Pneumonia patients. It was collected from multiple online sources, which are made available for the sole purpose of research and implementation. The second and third sub-sections explain the Evaluation Metrics and hyperparameters of the CoVNet-19

model used, respectively. The fourth sub-section contains a detailed, comprehensive analysis of the resultant evaluation metrics of the CoVNet-19 model, achieved after three and two-class classification. The fifth and the last sub-section presents a brief comparison report of our proposed model with the other state-of-the-art methods discussed in Section 2 (i.e., Related Works) of this study.

5.1. Dataset description

The training and testing of our proposed CoVNet-19 model were done on the combined five different datasets. We referred to five other publicly available dataset repositories to perform an unbiased and neutral experimental analysis. From there, we collected Chest X-ray images belonging to three classes viz. Normal (Un-diseased), COVID-19, and Pneumonia. All the selected repositories are updated regularly by their respective authors, and the number of images may increase in the future. While collecting images for our dataset, we tried to get the maximum possible number of images to build a more robust Deep Learning model having high multi-class classification accuracy and F1 score. Our collection of medical images from five different was randomly divided into our Training, Validation, and test set to conduct and evaluate our experiment. This Train/Validation/Test set distribution from five different datasets helped us better generalize our model and evaluate it over a larger dataset. As cited in Section 2 (Related Work), most of the studies worked on a relatively smaller and unbalanced dataset. Thus, having a more extensive and balanced dataset gave us a predominance to train a more generalized and well-fitted ML model balancing the Bias–Variance Tradeoff. The validation set was used to tune some important hyperparameters like Learning Rate, Number of Epochs, Batch Size, etc. Test Set was a purely unseen dataset that was used to evaluate our model finally. The five repositories accessed for creating our dataset are as follows:

1. "COVID-19 Radiography Database" [29] from Kaggle, collected by a research team present at Qatar University and collaborators from Malaysia and Pakistan. This dataset contained 1341 Chest X-ray images of a healthy person, 219

Table 1
Dataset used in CovNet-19.

Dataset	Reference	COVID-19	NORMAL	PNEUMONIA
1	[29]	219	1341	1345
2	[30]	0	1000	1000
3	[31]	457	0	0
4	[32]	50	0	0
5	[33]	72	0	0
	Total	**798**	**2341**	**2345**

Table 2
Three-class classification dataset distribution.

	Training set	Validation set	Test set
COVID-19	1198	154	276
NORMAL	1187	154	1000
PNEUMONIA	1191	154	1000
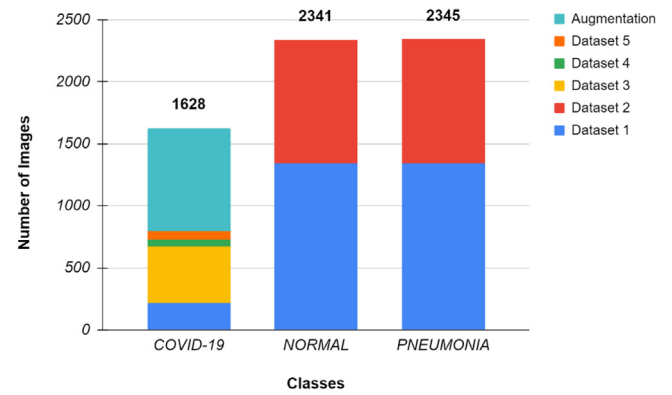
Fig. 3. Dataset distribution for CoVNet-19.

Table 3
Two-class classification dataset distribution.

	Training set	Validation set	Test set
COVID-19	1198	154	276
Non-COVID-19	1218	154	776

images for COVID-19, and 1341 images of a Pneumonia infected person.

2. "Chest Xray images (Pneumonia)" [30] Dataset from Kaggle contained a large number of X-ray images of Healthy and pneumonia infected patients. So, from this dataset, 1000 images belonging to both classes were extracted.

3. "COVID-chestxray-dataset", [31] a GitHub repository by a researcher named Joseph Paul Cohen that has a mix of chest X-ray and C.T. scan images of patients who are COVID-19 positive or infected by any other viral or bacterial pneumonia. From this repository, we were able to collect 457 Chest X-ray Images of positive COVID-19 patients.

4. "Fig. 1 COVID-19 Chest X-ray Dataset Initiative", [32] GitHub repository, from which we extracted 50 X-ray images of positive COVID-19 patients.

5. "COVID-19 X-ray dataset", [33] from Kaggle, helped us to get 72 Chest X-ray images of positive COVID-19 patients.

Table 1 displays the number of images for each class that we collected from the datasets mentioned above. A total of 5,484 Chest X-ray images were obtained from these five Datasets. Out of them, 798 images belonged to COVID-19 infected patients, 2345 were of Pneumonia infected patients, and the rest of 2341 was Chest X-ray images of a healthy person. All five of these Datasets are open-sourced and fully accessible to the research community. The X-ray images for COVID-19 patients are relatively low compared to pictures collected for Normal and Pneumonia classes. Thus, to cater to this issue, we used Data Augmentation to fabricate the transformed version of COVID-19 images. The Augmentation techniques used were Width Shift, Height Shift, Zooming, Shearing, and Rotation by a small angle. Approximately a 2-fold increase in COVID-19 X-ray images was done using augmentation. 830 Augmented images were added to the COVID-19 class making a total of 1628 images.

Fig. 3 shows the Bar-Plot for distributing images concerning each class extracted from the different Datasets. After obtaining a nearly balanced dataset, we shuffled and divided the images into Train, Validation, and Test Set. The training and validation sets were made equitable for each class to have even-handed and impartial training and model validation. The distribution of images to each class in Train, Validation, and Test sets can be seen in Table 2. All the images were distributed randomly to make a proper unbiased dataset

A subset of the above-collected dataset was formed for performing the binary classification between COVID-19 and Non-COVID. Images from Normal and Pneumonia classes were randomly selected in equal proportion to create the Non-COVID class. Simultaneously, the photos in the COVID-19 category were the

same as the one formulated for three-class classification. The distribution of this subset is shown in Table 3. Fig. 4 shows a few examples of Chest X-ray images from the collected dataset. Each column in Fig. 4 corresponds to two images belonging to respective classes, as mentioned in the image.

5.2. Evaluation metrics

Evaluation metrics are the mathematical functions that provide constructive feedback and measure an ML model's quality. The performance evaluation of training and testing of the CoVNet-19 Classification Model was done using metrics such as F1 Score, Precision, Recall, Accuracy, Matthews Correlation Coefficient (MCC), and Confusion Matrix. Formulas are briefly summarized below in Eqs 1–5, and Matrix 1.

1. **Accuracy:** A ratio between total correctly classified observations upon the total number of predicted observations (Eq. (1)). The ratio between the summation of True Negatives and True positives upon summating all values in a Confusion Matrix.

$$Accuracy = \frac{No.\ of\ images\ correctly\ classified}{Total\ no.\ of\ images} \times 100 \quad (1)$$

2. **Precision:** This metric indicates the confidence we have in our predictions. The ratio of True Positive Predicted observation and all positively predicted observation (Eq. (2)).

$$Precision = \frac{Sum\ of\ all\ True\ positives\ (TP)}{Sum\ of\ all\ True\ Positives\ (TP) + All\ False\ Positives\ (FP)} \quad (2)$$

3. **Recall:** It tells us about what proportion of actual positive observations we could predict correctly (Eq. (3)).

$$Recall = \frac{Sum\ of\ all\ True\ positives\ (TP)}{Sum\ of\ all\ True\ Positives\ (TP) + All\ False\ Negatives\ (FN)} \quad (3)$$

4. **F1 Score:** It is an overall evaluation metric formed by a combination of Precision and Recall. It is represented by
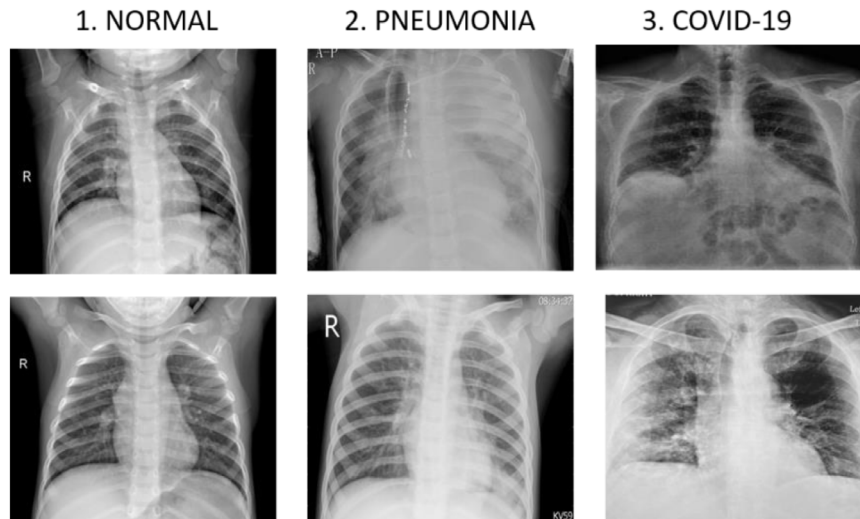
1. NORMAL   2. PNEUMONIA   3. COVID-19

Fig. 4. Random images from the dataset.

the Harmonic mean of Precision and Recall (Eq. (4)).

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (4)$$

5. **Confusion Matrix:** It is a performance measurement matrix comparing the actual and predicted observations through the values of False Positives, True Negatives, True Positive, and False Negative labels (Matrix 1). Summation of True Positives and True Negatives are the total correct predictions, while summation of False Positive and False Negatives are the incorrect predictions.

$$\begin{bmatrix} True\ Positive\ (TP) & False\ Negative\ (FN) \\ False\ Positive\ (FP) & True\ Negative\ (TN) \end{bmatrix} \quad (\text{Matrix 1})$$

- True Positives: Cases where the predictions are positive to a class and are correct.
- True Negatives: Cases where the predictions are negative to a class and are correct.
- False Positive (Type 1 Error): Cases where the predictions are positive to a class but are incorrect.
- False Negatives (Type 2 Error): Cases where the predictions are negative to a class but are incorrect.

6. **Matthews Correlation Coefficient (MCC):** It is a single value performance measurement metric that summarizes the whole Confusion Matrix. It produces a more informative and truthful score than accuracy and F1 score in evaluating classification problems. It produces a high score only if the prediction results are useful in all four confusion matrix categories.

$$MCC = \frac{TN \times TP - FP \times FN}{\sqrt{(TN + FN)(FP + TP)(TN + FP)(FN + TP)}} \quad (5)$$

The aforementioned metric evaluation formulas were used by mostly all other authors mentioned in Related works to evaluate their ML model's performance. Thus, building upon that, we also used the same metrics to conduct a fair comparison with them.

5.3. Model hyperparameters

DenseNet121 and VGG19 were optimized using Adam Optimizer, having a learning rate of 0.001 decayed by a factor of 10 after each epoch. We used Adam Optimizer [34] as it is one of the best Stochastic Gradient Descent algorithm combining the best properties of AdaGrad [35] and RMSProp. It can easily handle noise problems and sparse gradients during training. It works faster and is more reliable in reaching the global minimum with the default hyperparameters. Categorical cross-entropy and binary cross-entropy was chosen as the loss function while training for three class and two-class classification, respectively. The training batch size was set to 32. All the Convolutional layers of DenseNet121 were made non-trainable during training, and the pre-trained ImageNet weights were used. Only the externally added two fully connected Dense layers and a SoftMax layer were trained. For ternary classification SoftMax layer consisted of 3 nodes belonging to three classes. Out of 10,251,011 total parameters, just 3,213,507 were trainable. Unlike DenseNet121, in VGG19, some convolutional layers closer to output were made trainable. At the same time, all other convolutional layers were made non-trainable. Out of 21,632,259 total parameters it had 3,967,683 trainable parameters. The number of training epochs was selected by observing the model's validation accuracy to prevent potential overfitting. For binary classification VGG19 and DenseNet121, both models were fine-tuned for five epochs, with a batch size of 32. In Binary classification, the number of training parameters of both the DCNNs was fewer as the last SoftMax layer had only 1 Node.

Python Programming Language (Python 3.6) [36] using the Keras API [37] along with TensorFlow [38] at the backend was used to build and implement the Deep Learning models of CoVNet-19. Scikit-Learn [39] was used to implement the ML model Linear SVC. The evaluation metrics such as MCC Score, Confusion Matrix, F1 Score, Precision, Recall, and Accuracy were also computed using the Scikit-Learn library in Python. The computations were done on Intel(R) Core (i5 8250U CPU 1.60 GHz) processor, Windows 10, using the graphical processing unit (NVIDIA MX 130 of 2 GB and RAM 8 GB). For some of the massive computations, Google Collab Notebook [40] was used.

5.4. Result discussion

Building the proposed CoVNet-19 model was followed by the training and testing phase on the collected dataset. This section discusses the resultant evaluation metrics obtained. Both the three and two-class classification models were trained and tested separately on their respective datasets. First, the classification evaluation metrics obtained after fine-tuning the DCCNs are discussed, and then the improvement achieved in classification

Table 4
DenseNet121: Three class classification.

	TRAINING				VALIDATION				TEST			
	P	R	F1	ACC.	P	R	F1	ACC	P	R	F1	ACC
COVID-19	1.00	1.00	1.00		1.00	0.97	0.99		0.98	0.98	0.98	
NORMAL	0.94	0.99	0.97	**97.79%**	0.91	0.99	0.95	**95.67%**	0.94	0.99	0.96	**96.30%**
PNEUMONIA	0.99	0.94	0.97		0.97	0.90	0.94		0.99	0.93	0.96	

results by using CoVNet-19 is stated. All the results are compared based on their performance in the test set. This section is thereby further divided into two sub-sections examining the results of each classification model.

5.4.1. Three-class classification

After fine-tuning the two pre-trained DCNNs, the training and validation accuracies achieved by DenseNet121 were 97.79% and, 95.67% respectively. While on the other hand, training and validation accuracies achieved by VGG-19 were 96.17% and 96.32%, respectively. DenseNet121 achieved a test set accuracy of 96.30%, and the test set accuracy reached by VGG19 was 96.08%. All the resultant metrics related to training, validation, and testing in Accuracy, Precision, Recall and F1 Score of DenseNet121 and VGG19 are given in Tables 4 and 5, respectively (P: Precision, R: Recall, F1: F1 Score, Acc: Accuracy). The confusion matrices on the test set of DenseNet121 and VGG19 are shown in Figs. 5 and 6. Figs. 8–11 shows the curves for training and validation accuracies and losses for both DCNNs. Sudden fluctuations can be seen in the graph of Validation Accuracy and Loss for both the DCNNs. During the model training small changes are made to the model's training parameters near the decision boundary. The small changes in those training parameters are made to optimize the training accuracy, but sometimes the validation accuracy gets more affected than the training accuracy resulting in its high fluctuation and variance. This is also due to relatively small size of the validation set in comparison to the training set. Although, these random fluctuations in the validation accuracy do not generalize to the whole CoVNet-19 model and also do not affect the performance of the model.

We achieved an overall three-class classification accuracy of around 96% from both DCNNs models. The metric results were exceptionally improved in Accuracy, Precision, Recall, and F1 Score when the image feature matrix from them was combined and used by SVC for ternary classification forming our proposed CoVNet-19 model. Table 6 displays the detailed result metrics of CoVNet-19. The training and validation accuracies achieved by CoVNet-19 are 99.02% and 97.40%, respectively. CoVNet-19 increased the training and validation accuracies by around 2%. The overall test set accuracy achieved by CoVNet-19 was 98.28%, having an approximate increment of 2% compared to the accuracies achieved from DenseNet121 and VGG19 models on the test set.

Comparing the CoVNet-19's test set confusion matrix in Fig. 7 with confusion matrices of DenseNet121 (Fig. 5) and VGG19 (Fig. 6), we can conclude a considerable reduction in the number of misclassifications. Out of 2276 images in the test set, CoVNet-19 misclassified 39 of them. (including all False Positives and False Negatives). The number of misclassifications done by DenseNet121 and VGG19 was 84/2276 and 89/2276, respectively. For the COVID-19 class, CoVNet-19 predicted 3 False Negatives (Type 2 Error) and 3 False Positives (Type 1 Error). The number of False Positives and False Negatives of Pneumonia and Normal classes also decreased considerably in CoVNet-19 compared with the ones resulting from the predictions of VGG19 and DenseNet121 models. It is also observed that most of the misclassifications were when X-ray images belonging to the Pneumonia class were classified as Normal. We could reasonably conclude
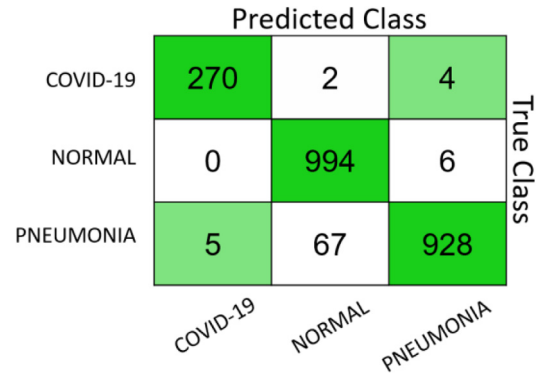

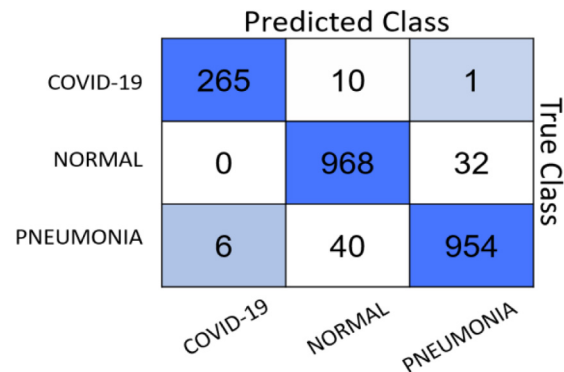**Fig. 5.** DenseNet121 confusion matrix (Test Set)

Fig. 6. VGG19 confusion matrix (Test Set)

that our proposed stacked ensemble model precisely performed a sophisticated combination of both DCNNs and reduced the misclassifications done by the DCNNs by eliminating the error and noise factors.

CoVNet-19 achieved an F1-score of 99% for the COVID-19 class and 98% for the Normal and Pneumonia class. It showed an improvement in the F1-score by 2% for the Normal and Pneumonia classes and by an average of 1.5% for the COVID-19 class on the test set. It is also observed that the overall average Precision, Recall, and F1-score of CoVNet-19 for all three classes is 98.33%. For a more in-depth exploration of the performance of CoVNet-19, we also observed the Matthews Correlation Coefficient. The MCC of our model for ternary classification was 0.9715. A high MCC score and F1 score signifies the better prediction ability of our model.

Based on these results, it can be concluded that CoVNet-19 performs well as a whole in classifying the Chest X-ray images. We also observed the Gradient Weighting Class Activation Mapping study the X-ray images' comprehensive visual analysis (Grad-CAM). Grad-CAMs visually analyze and understand the region of interest where our DCNN model is looking for classifying the images [41]. We examined the gradients flowing into the last convolution layer and highlighted the picture's localized regions, which are crucial for class prediction. It acts as a core component

Table 5
VGG19: Three class classification.

	TRAINING				VALIDATION				TEST			
	P	R	F1	ACC.	P	R	F1	ACC	P	R	F1	ACC
COVID-19	1.00	0.98	0.99		1.00	0.96	0.98		0.98	0.96	0.97	
NORMAL	0.93	0.96	0.94	**96.17%**	0.91	0.99	0.95	**96.32%**	0.95	0.97	0.96	**96.08%**
PNEUMONIA	0.96	0.95	0.95		0.99	0.94	0.96		0.97	0.95	0.96	

Table 6
CoVNet-19: Three class classification.

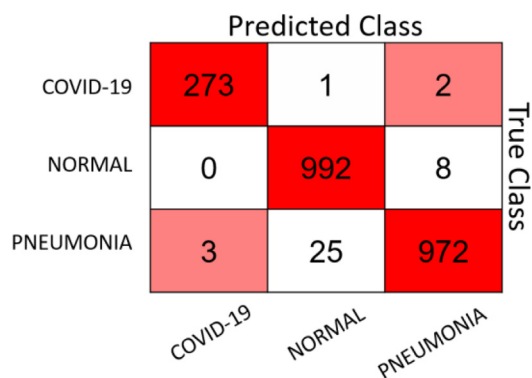|	TRAINING				VALIDATION				TEST			
	P	R	F1	ACC.	P	R	F1	ACC	P	R	F1	ACC
COVID-19	1.00	1.00	1.00		1.00	0.99	0.99		0.99	0.99	0.99	
NORMAL	0.98	0.99	0.99	**99.02%**	0.95	0.98	0.96	**97.40%**	0.97	0.99	0.98	**98.28%**
PNEUMONIA	0.99	0.98	0.99		0.97	0.95	0.96		0.99	0.97	0.98	

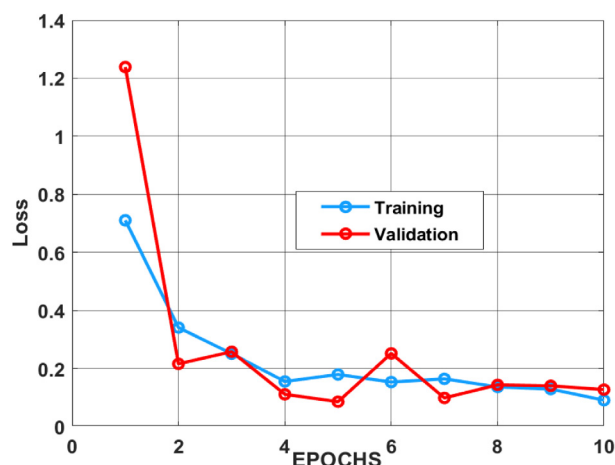**Fig. 7.** CoVNet-19 confusion matrix (Test Set)

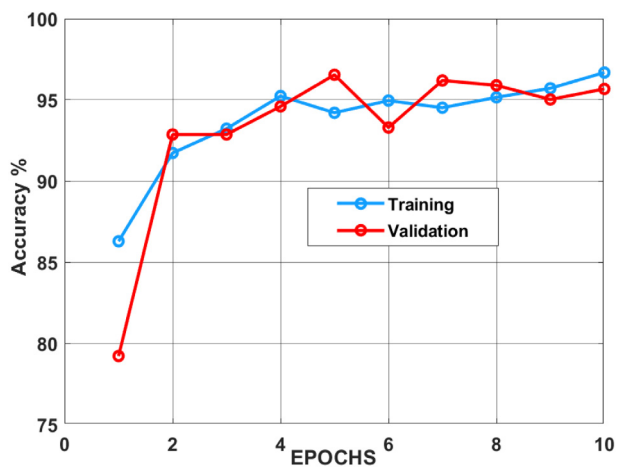**Fig. 9.** Three classes: DenseNet121 (Loss).

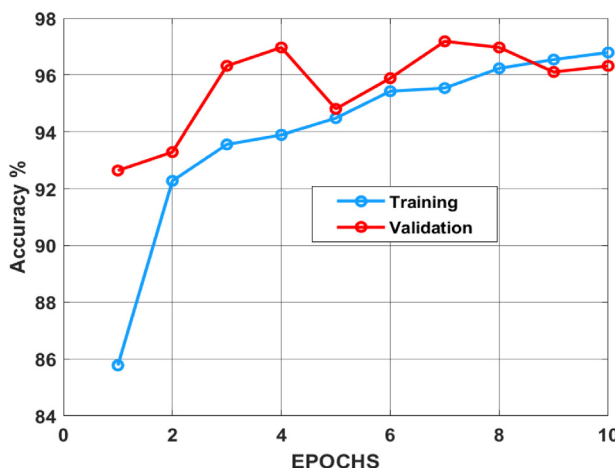**Fig. 8.** Three classes: DenseNet121 (Accuracy).

Fig. 10. Three classes: VGG19 (Accuracy)

in the interpretation and understanding of the model. Grad-CAMs are used to visually verify that our model is looking and activating correct patterns in the image. The output is a heatmap visualization. Heat Map visualization of Grad-CAMS [41] is shown in Fig. 16, where the first row shows the original X-ray images of each class from our dataset, and the second-row shows their corresponding Grad-CAM Heatmap.

5.4.2. Two-class classification

Similar to the three-class classification, we implemented CoVNet-19 for the binary classification to distinguish between COVID-19 and Non-COVID-19 chest X-ray images. Figs. 12–15 shows the curves for training and validation accuracies and losses

for both the DCNN models. Training, Validation, and Test set efficiencies achieved by DenseNet121 were 99.87%, 99.35%, and 99.60%, respectively. Training, Validation, and Test set efficiencies achieved by VGG19 were 98.47%, 99.03%, and 99.61%. Table 7 shows the Accuracy and Loss metrics for both the DCNNs. An improvement in all the evaluation metrics was seen with CoVNet-19 for binary classification—Table 8 displays all the training, validation, and testing evaluation metrics of CoVNet-19. Fig. 17 shows the confusion matrix of CoVNet-19 on the test set. The overall training and validation accuracies achieved by CoVNet-19
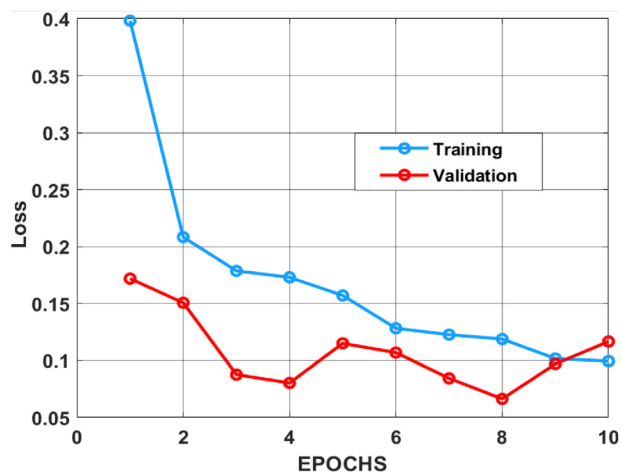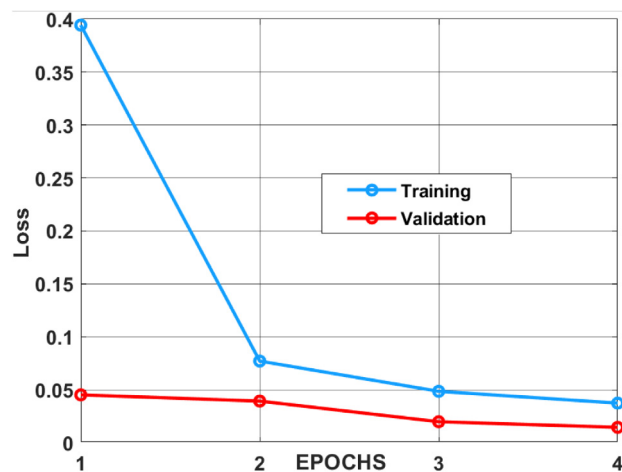
Fig. 11. Three classes: VGG19 (Loss)
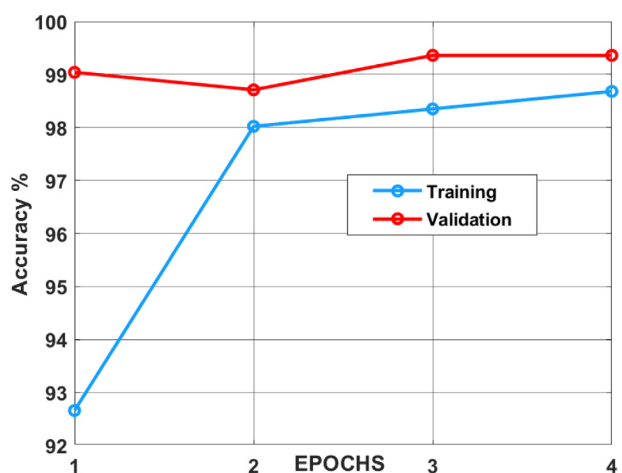

Fig. 13. Two classes: DenseNet121 (Loss)

Fig. 12. Two classes: DenseNet121 (Accuracy)
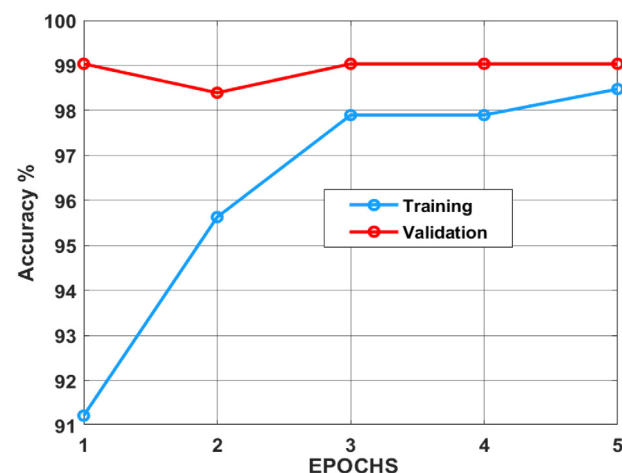

Fig. 14. Two classes: VGG19 (Accuracy)

Fig. 15. Two classes: VGG19 (Loss)

for binary classification are 100% and 99.03%, respectively, while it achieved a test set accuracy of 99.71%. The model achieved F1 Scores of 99% and 100% for detecting COVID-19 and Non-COVID, respectively. Out of 276 COVID-19 X-ray scans, the model predicted 274 correctly, and out of 776 Non-COVID X-ray scans, 775 were predicted correctly. The model resulted in 1 False Positive (Type 1 Error) and 2 False Negative (Type 2 Error). MCC achieved by CoVNet-19 for the binary classification was 0.9926. Similar to ternary classification, CoVNet-19 attained a High MCC and F1 score for binary classification. It depicts the high classification and generalization power of our model.

5.5. Model interpretation and comparison

Table 9 demonstrates a comparison of our Novel "CoVNet-19" model with other ML models acknowledged in Section 2, i.e., Related Work of this study. We have compared our proposed work with various deep learning-based studies mentioned previously in the literature review section of this study [7–12,16,18, 19,42]. We performed a direct comparison of our results with these works due to our and their datasets' considerable resemblance. We collected our dataset from the same open-sourced repositories used by most of the other authors in their studies. We collected and compiled images from all those open-sourced repositories available to us and presented them as one single dataset in our study. We tried to fill all the gaps in previous
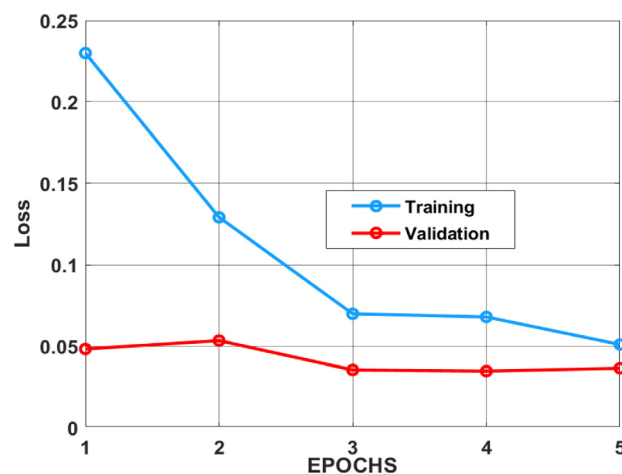
studies on COVID-19 detection using Deep Learning with our proposed methodology. We can certainly see that our trained model out-performs all other binary class classification models, while for three-class classification, we have achieved considerably high accuracy surpassing nearly all of the previously done works. Mesut Tougaçar et al. [18] achieved a higher ternary classification

Table 7
Two-class classification: DCNNs evaluation metrics.

Metrics	TRAINING		VALIDATION		TEST	
	Accuracy	Loss	Accuracy	Loss	Accuracy	Loss
DenseNet121	99.87%	0.009	99.35%	0.014	99.60%	0.019
VGG19	98.47%	0.023	99.03%	0.022	99.61%	0.021

Table 8
CoVNet-19: 2-class classification.

CoVNet-19	TRAINING				VALIDATION				TEST			
	P	R	F1	ACC.	P	R	F1	ACC	P	R	F1	ACC
COVID-19	1.00	1.00	1.00	**100%**	0.98	1.00	0.99	**99.03%**	1.00	0.99	0.99	**99.71%**
Non-COVID-19	1.00	1.00	1.00		1.00	0.98	0.99		1.00	1.00	1.00	
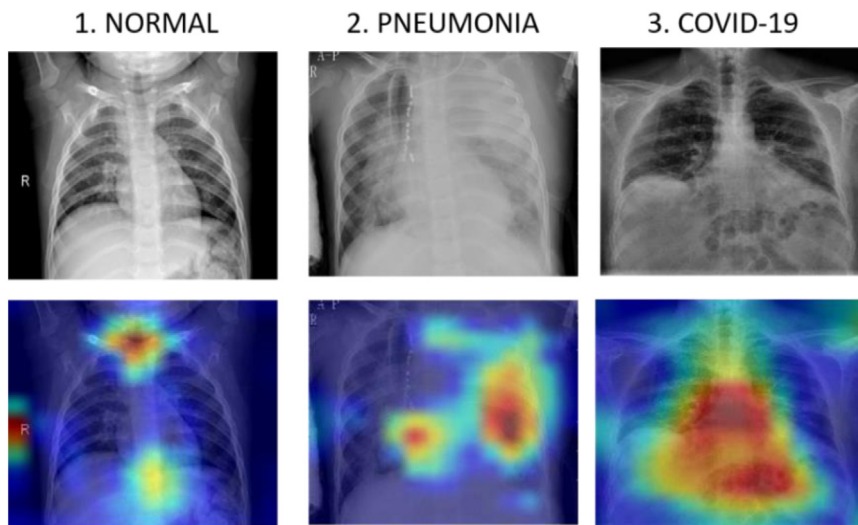
Fig. 16. Gradient weighted class activation mapping visualization.

Fig. 17. CoVNet-19 confusion matrix (Test Set)

accuracy of 99.27%, but the author's dataset was relatively small compared to ours. A small dataset may not thoroughly explain the higher generalizability of the model. The assuring and favorable results obtained from CoVNet-19 signifies it to be an efficient deep learning method for detecting COVID-19 using Chest X-ray images. CoVNet-19 outperformed the works discussed in literature due to its complex ensemble architecture along with a well-balanced training dataset.

Some salient and novel features of CoVNet-19 can be summarized as:

1. Our dataset comprised 6214 X-ray images, formed from the reasonable homogeneity of five different Datasets. It allowed our model to be robust and influential, showing highly accurate results. Our model's results were better due to the availability of a relatively larger and balanced dataset used for training.

2. Our proposed CoVNet-19 model proved to be an efficient deep learning model for the classification of COVID-19 Chest X-ray images. Using two powerful DCNNs, we extracted valuable and significant image features, making our model generalized and accurate.

3. CoVNet-19 clearly distinguished between X-ray images of a Normal, COVID positive, and Pneumonia infected person with an F1 score of 98.33% and MCC of 97.15%. In COVID-19 detection, CoVNet-19 produced 3 False Negative (Type 2 Error), 3 False Positives (Type 1 Error) in Ternary Classification, and 2 False Negatives, 1 False Positive in Binary Classification out of 276 True Positive Cases of COVID. It implies that CoVNet-19 can efficiently be used in clinics and hospitals to analyze Medical and Radiographic Images.

4. Using automated Artificial Intelligence-based methods to diagnose the patients for COVID-19 infection can be time and cost-effective. Many people can be analyzed using their Chest X-ray images when there is limited availability of Testing kits and other medical resources in remote places. Machines for X-rays and Radiography can easily be made available in small clinics and installed in moving vans.

6. Conclusion

The results showed that our CoVNet-19 classification model could distinguish between COVID-19 amid pneumonia diseases along with a regular person with steep accuracy, Precision, and

Table 9

Comparison of CoVNet-19 with other state-of-the-art methods.

Reference study	Model architecture	X-ray dataset	2-Class accuracy	3-Class accuracy
Ioannis D. et al. [7]	VGG19	224 COVID +, 504 Normal. 700 Pneumonia	98.75%	93.48%
Wang et al. [8]	COVID-Net network	183 COVID +, 8066 Normal, 5538 COVID -	N/A	93.33%
Asif Iqbal Khan et al [9]	CoroNet	290 COVID +, 1203 Normal. 1590 Pneumonia	99.00%	95.00%
Narin et al. [10]	ResNet50	50 COVID +, 50 COVID -	98.00%	N/A
Sethy et al. [11]	ResNet50 + SVM	25 COVID +, 25 COVID -	95.38%	N/A
Ozturk et al. [12]	DarkCovidNet	127 COVID +, 500 Normal, 500 Pneumonia	98.08%	87.02%
Ezz El-Din Hemdan [16]	VGG19	25 COVID +, 25 COVID -	90.00%	N/A
Mesut Tougaçar et al. [18]	MobileNetV2+ SqueezeNet + SVM	295 COVID +, 65 Normal, 98 Pneumonia	N/A	99.27%
Ferhat Ucar et al. [19]	Deep Bayes SqueezeNet	76 COVID +, 1583 Normal, 4290 Pneumonia	N/A	98.30%
Mahesh Gour [42]	Stacked CNN	270 COVID +, 1139 Normal, 1355 Pneumonia	N/A	92.74%
Proposed Model	**CoVNet-19**	**1628 COVID + 2341 Normal, 2345 Pneumonia**	**99.71%**	**98.28%**

**N/A: Authors did not perform the specified classification.

Recall. The results suggest that the DCCNs viz. VGG19 and the DenseNet121 helped us to achieve the best classification accuracy by extracting valuable sophisticated features. Hence an automated Deep Learning accession for diagnosis of COVID-19 using chest radiography tablatures can be beneficial for medical institutions. CoVNet-19 model is trained on X-ray images dataset from various sources and has attained a high overall three-class classification accuracy of 98.28% and MCC of 97.15%. Alongside that, CoVNet-19 has achieved an overall accuracy of 99.71% for two-class classification and an MCC of 99.26%. CoVNet-19 achieved an F1-score of 99% for detection of COVID-19 in both ternary and binary classification. A proper medication or a vaccine is not available to humanity; it is of primary importance to correctly detect all the positive COVID-19 cases and stop its rapid spread. Due to the high increase rate of this pandemic, no particular conclusive case must file anonymously. With millions of people getting infected, this pandemic has out-run the medical resources and testing-kits in many countries. We believe that CoVNet-19 will provide significant assistance and support to the medical practitioners and nursing staff to deal with exponentially growing COVID-19 cases and perform a faster and automatic diagnosis of patients. This fatal disease is still a standing danger for millions of people and should be dealt with wisely by strong-arming ourselves with everything we can do in our reach.

7. Future work

According to the formulated results, it can thus be established that using Deep Convolutional Neural Networks can help us extract valuable features from images that can be further used to diagnose and detect COVID-19 infected patients. Further research work can be carried based on our proposed study by eliminating the limitations of our work. The notably more reliable in-depth analysis can be done with much more patient data, specifically of the patients affected with COVID-19. Using chest X-ray images, the patient's other characteristics and physiological characteristics can be observed and used as input features to the Deep Learning Classification model. In this study, apart from COVID-19, only Pneumonia cases were taken into consideration. A better and broad scaled classification model can be built by including other similar viral and pneumonia-based diseases like SARS, MERS. All the Convolutional layers of the pre-trained DCNNs were not fine-tuned due to limited computational power. Classifications results may improve if the whole DCNN is fine-tuned with the training data. Rather than extracting a (32×1) feature vector from one DCNN, the number of features can be increased to 64 or 128 for multi-class classification tasks having three or more distinct classes. As we have used an ensemble model of 2 DCNNs and an SVC Model, CoVNet-19 can be optimized and transformed into its lighter version. It can then be made to run on lower power devices like Smart Phones and Arduinos efficiently. In smartphones, the Camera can be used to capture the X-ray image and detect COVID-19. This will enable the population to check the diagnosis results on their smartphones by capturing the X-ray image photo. The presented work thereby commits to the achievability of a cheaper, faster, and more efficient mode of diagnosing the disease automatically and can be an excellent aid for medical practitioners and nursing staff to deal with exponentially rising COVID-19 cases. This technique can play a significant role in controlling the rapidly increasing cases via timely informing the infected person to stay quarantined and prevent others from coming in contact.

CRediT authorship contribution statement

Priyansh Kedia: Worked on the Conceptualization of the Idea to reach the research goals and aims, Conducting a research and

investigation process, Conceived and designed the Deep Learning-based Artificial Intelligence model's methodology and creation, Worked on Collecting the required Dataset, performed its analysis and implementation of the computer code and supporting algorithms, and tested existing code components, Analyzing the obtained results and defining its importance and applications of the research in real life, Drafting and writing of the research manuscript. **Anjum:** Validation, Formal analysis of the research idea, Analysis of the collected Dataset and implementation of the computer code, Preparation for the manuscript's presentation, Management, and coordination responsibility for the research activity planning and execution, Technical help, Performed analysis, Writing and editing assistance, General support. **Rahul Katarya:** Oversight and leadership responsibility for the research activity planning and execution, including mentorship and Research guidance, Validation, Formal analysis of the research idea, Preparation for presenting the manuscript, Management, and coordination responsibility for the research activity planning and execution. Technical help, Performed analysis, Writing and editing assistance, General support.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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