ORIGINAL ARTICLE

Covidense: Providing a Suitable Solution for Diagnosing Covid-19 Lung Infection Based on Deep Learning from Chest X-Ray Images of Patients

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Abstract

Purpose: Coronavirus disease 2019 (Covid-19), first reported in December 2019 in Wuhan, China, has become a pandemic. Chest imaging is used for the diagnosis of Covid-19 patients and can address problems concerning Reverse Transcription-Polymerase Chain Reaction (RT-PCR) shortcomings. Chest X-ray images can act as an appropriate alternative to Computed Tomography (CT) for diagnosing Covid-19. The purpose of this study is to use a Deep Learning method for diagnosing Covid-19 cases using chest X-ray images. Thus, we propose Covidense based on the pre-trained Densenet-201 model and is trained on a dataset comprising chest X-ray images of Covid-19, normal, bacterial pneumonia, and viral pneumonia cases.

Materials and Methods: In this study, a total number of 1280 chest X-ray images of Covid-19, normal, bacterial and viral pneumonia cases were collected from open access repositories. Covidense, a convolutional neural network model, is based on the pre-trained DenseNet-201 architecture, and after pre-processing the images, it has been trained and tested on the images using the 5-fold cross-validation method.

Results: The accuracy of different classifications including classification of two classes (Covid-19, normal), three classes 1 (Covid-19, normal and bacterial pneumonia), three classes 2 (Covid-19, normal and viral pneumonia), and four classes (Covid-19, normal, bacterial pneumonia and viral pneumonia) are 99.46%, 92.86%, 93.91 %, and 91.01% respectively.

Conclusion: This model can differentiate pneumonia caused by Covid-19 from other types of pneumonia, including bacterial and viral. The proposed model offers high accuracy and can be of great help for effective screening. Thus, reducing the rate of infection spread. Also, it can act as a complementary tool for the detection and diagnosis of Covid-19.

Keywords: Covid-19; Deep Learning; Convolutional Neural Network; Transfer Learning; Chest X-Ray Images.

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1. Introduction

Covid-19 infection caused by Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-COV-2) [1-3], since its first appearance in December 2019 [4-6], it has been spreading across the world, and to this date, it has been confirmed in 216 countries with over 2,560,995 confirmed deaths, and over 115 million confirmed cases until March 5th, 2021 [7]. The first confirmed cases of this infection were observed in Wuhan, China [8], which then swiftly spread to the rest of the world, and finally, on March 11, 2020, the World Health Organization (WHO) declared Covid-19 as a pandemic [2,6]. Covid-19, like Severe Acute Respiratory Syndrome (SARS) and Middle East Respiratory Syndrome (MERS), causes similar lung abnormalities, but still, its extent and clinical indications are different [4,5]. Patients infected with Covid-19 may present flu-like symptoms, including cough and fever [3], and appears as bilateral and peripheral opacities on radiographic images [3, 5]. Since there is still no confirmed drug to cure pneumonia caused by this virus [8, 9], wearing masks and social distancing are advised by the WHO to be able to at least decrease the rate of disease spread.

Screening the infected individuals and finally isolating them can be an effective measure of avoiding further disease spread [1, 3, 8, 9] and lowering the burden on the healthcare system in most of the countries, especially with the surge of the confirmed cases and inability of the health care service providers to accommodate to the needs of this increasing patient number specifically in developing countries. Today, the primary procedure used for screening patients supposedly infected with Covid-19 is real-time Reverse Transcription-Polymerase Chain Reaction (real-time RT-PCR). However, this method still poses a challenge of patient comfortability and shortage of test kits [3, 5, 8-11]. Chest imaging (including Chest Radiographs/ X-Rays (CXR) and CT Scans) can be an alternative method of screening with the advantages of fast diagnosis and a more comfortable process [3]. The mentioned imaging procedure offers multiple advantages like availability and multiple analysis of patients leading to an increase in patient throughput and effectiveness of the screening concept itself [3]. CT offers higher sensitivity and soft tissue differentiating capability [9] but needs to be sterilized after each patient, or otherwise, it will be the cause of hospital-acquired infections. Another imaging modality is CXR imaging using portable or stationary units [2, 10]. The American College of Radiology (ACR) disapproves CT-Scan as the first choice of screening process due to cross-infection probability, which can be appropriately addressed using chest X-rays, especially portable Radiography facilities [10]. Another advantage of the chest X-ray is its lower radiation dose, and visual indexes observed in CXR are correlated with Covid-19. Thus, making CXR the first choice of radiologists.

Artificial intelligence systems, especially machine learning and deep learning methods, have attracted much attention in Computer Vision problems like denoising, segmentation, classification, and, more importantly, diagnosis in medical imaging like Computed Assisted Diagnosis (CAD) [6, 10]. Deep learning methods, including Convolutional Neural Network (CNN), have eliminated the process of hand-crafted feature extraction [3, 8-9]. This feature of deep learning methodology is critical, especially in Covid-19 Detection, since most of its indications in images are still unknown.

The reviewed studies presented low performance and have used a lower number of chest X-ray images for training and testing. We have chosen the models of two studies, A. I. Khan *et al.* [3] and Ozturk *et al.* [12], for further analysis and have tested their performance on our dataset.

Also, in this paper, we propose a model for multiple modes of detection, including classifications of two classes (Covid-19 and normal), three classes 1 (Covid-19, normal, bacterial pneumonia), three classes 2 (Covid-19, normal, viral pneumonia), and finally four classes (Covid-19, normal, bacterial pneumonia, and viral pneumonia). Our model is based on the pre-trained model DensNet-201, which is modified to accommodate the study's aim. We used public repositories to train and validate the model. We aim to be able to differentiate, at first, normal CXR from Covid-19 infected cases. Then we use this model to identify bacterial or viral pneumonia separately from normal, and Covid-19 induced pneumonia, and, Finally, we are introducing four-classes classification (Covid-19, normal, bacterial pneumonia and, viral pneumonia).

2. Related Works

A. I. Khan *et al.* [3] have proposed a deep convolutional neural network called CoroNet, which is based on Xception architecture to detect Covid-19 infection automatically, offering an overall accuracy of 89.6%. The authors pre-trained their model initially of ImageNet Dataset and then employed end-to-end training on a dataset of Chest Radiographs of different diseases, including Covid-19 and other pneumonia types. The precision and recall rate measures were calculated for 4-class classifications, which give these results 93% and 98.2%, respectively. Domain Extension Transfer Learning (DETL) is a new concept proposed by Base *et al.* [8], which is employed alongside a pre-trained deep convolutional neural network for the aim of four classes classification on chest X-ray images to detect and differentiate Covid-19 from other types of pneumonia and by doing so, achieved an overall accuracy of 90.13% ± 0.14 [8]. Using Transfer learning, Minaee *et al.* [9] trained four different CNN architectures, namely SqueezeNet, DenseNet-121, ResNet-18, and ResNet-50, on a Dataset containing roughly 5000 Chest Radiograms (2000 training and the remaining 3000 were used for evaluation) to identify Covid-19 infection on chest X-ray Images. A certified radiologist specified Covid-19 infected radiographs. Most of the mentioned networks could achieve an overall sensitivity rate of 98% (±3%) and specificity of around 90% [9]. Also, generated heat maps of Covid-19 infected regions were in good match with regions suspected to be infected and were specified by radiologists. Ramadhan *et al.* [10] proposed a deep learning model to detect pneumonia cases related to Covid-19 Based on chest X-ray images. Model accuracy, sensitivity, and specificity were tested, and 98.44%, 100%, and 96.97% results were achieved [10]. Ozturk *et al.* [12] developed a model with two types of classification: binary and multiclass. The accuracy of their classification modes is 98.08% and 87.02%. The authors employed different filtering on each layer of 17 convolutional layers, and the classifier used in this model was the DarkNet model. CovXNet, a deep convolutional neural network, introduced by Mahmud *et al.* [13] using depth-wise convolution and efficient feature extraction through changing dilation rates, could achieve an accuracy of 90.2% for multiclass (bacterial or viral pneumonia, Covid-19, and normal) classification [13]. Rahimzadeh and Attar [14] trained multiple CNN on two open-access datasets of Chest X-ray images to classify them into Covid-19, normal, and pneumonia classes. The authors introduced a concatenated model composed of Xception and ResNet50-V2 and tested it on 11302 images. The overall average accuracy of the proposed model was 91.40% in all classes.

3. Materials and Methods

3.1. Data Set

In this paper, we have gathered 200 chest X-ray images of Covid-19 patients acquired from a public GitHub repository [15], 360 normal chest X-ray images, 360 bacterial pneumonia chest X-ray images, and 360 viral pneumonia chest X-ray images from an open access Kaggle repository [16] to create our dataset. Our dataset, as shown in Table 1, is created from the combination of the listed datasets above. The size of all images is 224 × 224 pixels as we have resized them to be. We have used a 5-fold cross-validation method, with 80% of the dataset for training and 20% for testing. Sample chest X-ray images as identified in the datasets are shown in Figure 1.

Table 1. The total number of images in our dataset

Illness	Number of Images
Covid-19	200
Normal	360
Bacterial pneumonia	360
Viral pneumonia	360

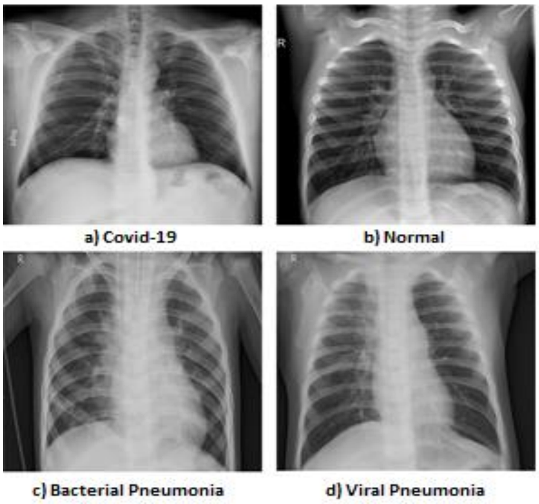

Figure 1. Chest X-ray image samples from different classes, including a) Covid-19, b) Normal, c) Bacterial pneumonia, and d) Viral pneumonia are selected from created datasets and are shown above

3.2. Data Preprocessing

To prevent the model from being over-fitted and provide more generalization, input images were shuffled and Data Augmentation methods were employed including

Horizontal and Vertical flipping, randomly zooming up to 15 %, rotating up to 50 degrees, width and height shifting up to 20 %.

3.3. Convolutional Neural Network (CNN)

A CNN [17] is a deep learning algorithm that receives the input image and assigns importance to each object in the image (learnable weights and bias), which gives the ability to distinguish them from each other. The CNN algorithm requires less pre-processing than other classification algorithms. With enough training, CNN can learn these filters or features.

An image is nothing more than a matrix with pixel values. CNN can use linked filters to capture temporal and spatial relationships in an image accurately and have a better architecture due to the reduced number of parameters and weight reuse. In other words, the network can be further trained to understand complex images better.

Extracting required features for the classification of a new disease is not an easy procedure. Also, working on large images requires a long time and immense computational power. Therefore, we need to reduce image sizes without losing their essential data. After each block of convolution and pooling layers, the input images are decreased in size and pass the essential details to the next block. These blocks can be chained to extract most of the possible required features of images and use them for classification. Then, these feature maps get flattened into a vector to be used as input for the fully-connected layers, which are responsible for training the unknown algorithm for the aim of classification of unseen images into defined classes.

Various CNN architectures play a crucial role in linking artificial intelligence to other scientific fields. One of these areas, in which much work has been done is the use of CNN models to detect, segment, and classify X-ray images in various cases such as breast cancer diagnosis [18], post-stroke pneumonia [19], etc.

3.4. Transfer Learning

Transfer learning is a method that uses a pre-trained model to solve problems other than the problem it was initially trained to solve. This method is generally used in situations where little data is available to model the new phenomenon. Therefore, it is possible to make use of the deep learning models that have already been trained on the larger and more general dataset and have a common ground with the new phenomenon under study, and the transfer learning model is based on the knowledge gained from the previous model.

3.5. Architecture of Proposed Case Studies

For better understanding and more detailed study, we have selected two article models [3, 12] for the case study. DarkCovidNet [12] model was used for modes two classes (Covid-19 and normal) and three classes (Covid-19, normal, and bacterial pneumonia), and CoroNet [6] model was used for four classes (Covid-19, normal, Bacterial pneumonia, and viral pneumonia) classification which have been tested on our database. CoroNet [3] is a Convolutional Neural Network based on a pre-trained architecture called Xception with 71 layers. Additional to having Depth wise separable convolution layers with "Skip Connections" as residual connections, which is a trait of Xception architecture, CoroNet also employs one dropout and two fully connected layers. Xception, being previously trained on the ImageNet dataset, was trained on an additional dataset with a total number of 1251 images. The learning rate, batch sizes, and numbers of epochs were 0.0001, 10, and 80, respectively [3]. DarkCovidNet [12] is based on the DarkNet model with 17 convolutional layers and offers different filtering in each layer. Their proposed model used a linear layer for classification. DarkCovidNet was trained with a total number of 1125 images. The learning rate and the number of epochs were 0.003 and 100, respectively [12].

3.6. Architecture of Proposed Model

Covidense is a CNN architecture designed to identify Covid-19 using chest X-ray images. It is based on the DenseNet-201 CNN architecture. DenseNet [20] is a convolutional neural network architecture used to detect objects in images. This architecture is quite similar to the ResNet architecture, but there are substantial differences. DenseNet architecture has the upper hand compared to ResNet in terms of lower Graphics Processing Unit (GPU) computational resources and has proved its higher performance on the ImageNet dataset while having a lower number of parameters [21]. DenseNet-201 is a pre-trained CNN model with 201 layers of depth, and it has 20 million parameters, which are trained on over one million images from the ImageNet database. Schema of the pre-trained DenseNet-201 model that is used for prediction is shown in Figure 2. DenseNet had a surprising performance in benchmark tasks of recognizing objects [22]. Concatenating feature maps of previous layers and providing it as an input for proceeding layers, leads to advantageous characteristics of DenseNet architecture, which are being trained easily and efficiency of parameters [22]. The size of the feature maps stays the same as a result of the integration of closely connected Dense Blocks [22].

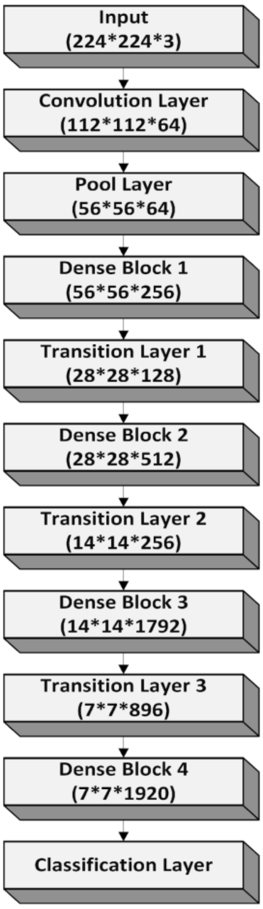

Figure 2. Schema of the pre-trained DenseNet-201 model

The proposed model uses pre-trained DenseNet-201 as the base model with two fully connected layers and a dropout layer having about 30 million parameters. Architectural details and output of the Covidense model are shown in Figure 3.

3.7. Experimental Implementation of Models

We implemented the DarkCovidNet [12] and CoroNet [3] models on our dataset by taking the same steps as authors [3, 12] to detect Covid-19 from chest X-ray images without any alterations in their respective codes. All values are the same as those mentioned in the studies, and no changes have been made to them. For DarkCovidNet classification of two classes and three classes, we used our “Covid-19 and normal” and “Covid-19, Normal, and Bacterial pneumonia” chest X-ray images, respectively. In the case of CoroNet four classes classification, we used our “Covid-19, Normal, Bacterial pneumonia, and Viral pneumonia” chest X-ray images.

Also, we have implemented four modes of Covidense for Covid-19 detection using chest X-ray images. In this model, we use the pre-trained DenseNet-201 model as a base model for four different classifications: two classes (Covid-19 and normal), three classes 1 (Covid-19, normal, and bacterial pneumonia), three classes 2 (Covid-19, normal, and viral pneumonia) and four classes (Covid-19, normal, bacterial pneumonia, and viral pneumonia).

Our proposed model was implemented in Python programming language and Keras programming Application Programming Interface (API) for TensorFlow. Our models used Categorical cross-entropy loss function and learning rate, batch size, and the numbers of epochs are 0.00001, 10,

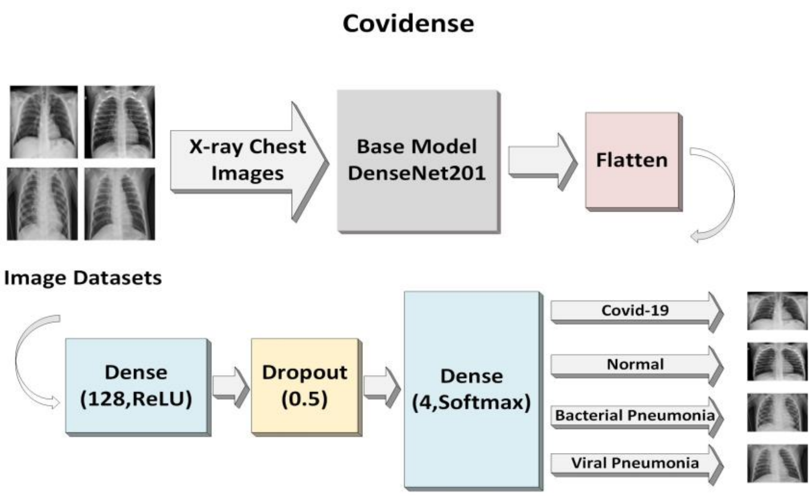

Figure 3. Diagram of our proposed model and its details

and 50, respectively. In this paper, we have used the Nvidia GPU GEFORCE GTX 1650 and the Intel Central Processing Unit (CPU) CORE i7 9850H.

The 5-fold cross-validation method was used to measure the classification performance of the proposed model. Five equal subsets were created after the random division of the training dataset. Four subsets were used to train the CNN model, and testing was done using the remaining set, which contained 256 images (40 Covid-19 images, 72 Normal images, 72 Bacterial pneumonia images, and 72 Viral pneumonia images). This procedure was repeated five times by changing the “train and test datasets”. In other words, we divided the main dataset into five subsets of the same size. One-fifth of each dataset was used for testing, and the rest was dedicated to training; this has been done five times in a row.

4. Results

The classification results of all Covidense modes in each fold are stored and averaged. The average performance of all Covidense classification modes in all folds of cross-validation represented in the form of a confusion matrix is shown in Figure 4. To measure the performance of all Covidense classification modes, we have used standard measurement formulas in deep learning [23] for further investigation:

1. Accuracy: Accuracy means how close the measured value is to the actual value.

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

2. Recall or Sensitivity: Recall or Sensitivity means the fraction of positive responses that have been correctly identified.

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

3. Precision: Precision for consecutive measurements of a value indicates how close the measurement values are.

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

4. F1-score: The F1-score is a measure that acts as an average for precision and recall parameters.

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

5. Specificity: specificity means a fraction of the negative answers that have been correctly identified.

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

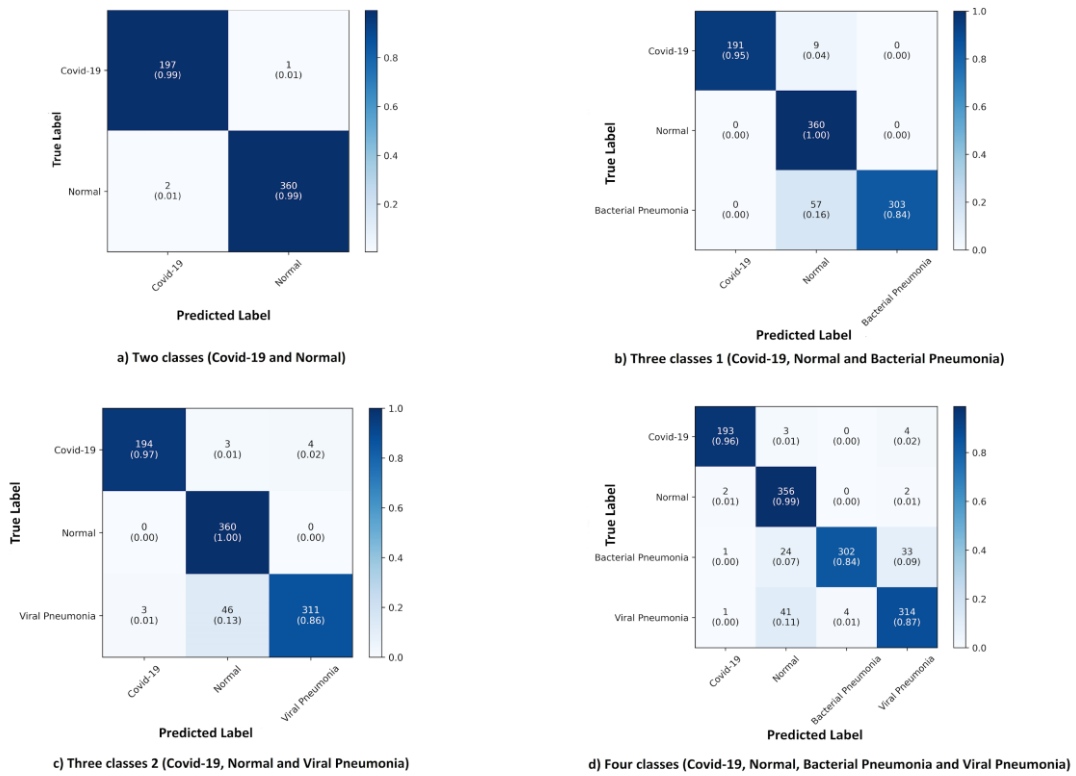

Figure 4. Average Confuse matrix of all Covidense classification modes

When comparing the accuracy of a screening test to "The Gold Standard", two main statistical metrics are considered [24]: Positive Predictive Value (PPV) and Negative Predictive Value (NPV). Positive Predictive Value increases if the number of patients with positive testing results who are diseased increases [23]. Similarly, Negative Predictive Value increases when the proportion of healthy people among patients with negative test results increases [23]. If the values of the metrics mentioned above reach 100%, then the test is as good as the Gold Standard [23]. There is a direct correlation between both of the predictive values (PPV and NPV) and prevalence of the disease [23]; however, this connection is of type Direct Proportionality for PPV, but in the case of NPV, they have an inverse relationship [23]. As mentioned in [23], the formulas for calculating the PPV and NPV are as follows (Equation 6, 7):

$$Positive\ Predictive\ Value\ (PPV) = \frac{TP}{(TP + FP)} \tag{6}$$

$$Negative\ Predictive\ Value\ (NPV) = \frac{TN}{(TN+FN)} \tag{7}$$

The average Positive Predictive Value and Negative Predictive Value of all folds of Covidense classification modes are presented in Table 2.

Table 2. Average NPV and PPV of all Covidense models

Model	NPV (%)	PPV (%)
Two classes (Covid-19 and normal)	99.38	99.38
Three classes 1 (Covid-19, normal and bacterial pneumonia)	94.96	96.50
Three classes 2 (Covid-19, normal, and viral pneumonia)	95.32	96.45
Four classes (Covid-19, normal, bacterial pneumonia, and viral pneumonia)	92.95	96.89

True positive and True negative parameters state that a prediction made is true while on the other hand False positive and False Negative inform us of a wrong prediction. By using Equations 1-5, the performances of all Covidense classification modes through all folds are examined in Table 3. Also, the average test accuracy of DarkCovidNet modes and CoroNet are examined in Table 4.

Table 3. Performance of all Covidense modes on each fold

Modes	Folds	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)	Specificity (%)	Sensitivity (%)
Two Classes (Covid-19 and Normal)	Fold 1	100	100	100	100	100	100
	Fold 2	100	100	100	100	100	100
	Fold 3	100	100	100	100	100	100
	Fold 4	98.75	99.31	99.02	99.11	99.31	99.31
	Fold 5	98.61	97.62	98.07	98.21	97.62	97.62
	Average	99.47	99.38	99.41	99.46	99.38	99.38
Three Classes 1 (Covid-19, Normal, and Bacterial Pneumonia)	Fold 1	91.66	94.57	92.60	92.39	96.59	94.57
	Fold 2	93.14	94.57	93.31	92.39	96.30	94.57
	Fold 3	95.37	95.93	95.35	94.57	97.26	95.93
	Fold 4	90.46	93.04	90.81	89.67	95.15	93.04
	Fold 5	95.46	96.29	95.65	95.11	97.54	96.29
	Average	93.21	94.88	93.54	92.82	96.56	94.88
Three classes 2 (Covid-19, normal, and viral pneumonia)	Fold 1	96.02	95.69	95.83	96.20	98.08	95.69
	Fold 2	91.85	93.46	92.15	91.30	95.78	93.47
	Fold 3	91.29	95.93	93.46	94.57	94.58	95.93
	Fold 4	90.46	93.04	90.79	89.67	95.15	93.04
	Fold 5	98.14	98.24	98.14	97.83	98.94	98.24
	Average	93.55	95.27	94.07	93.91	96.50	95.27
Four Classes (Covid-19, Normal, Bacterial Pneumonia, and Viral Pneumonia)	Fold 1	93.47	93.49	93.23	92.97	97.64	93.49
	Fold 2	89.65	91.25	89.67	88.67	96.30	91.25
	Fold 3	90.07	91.45	90.31	89.45	96.52	91.45
	Fold 4	91.11	92.41	91.37	90.62	96.88	92.41
	Fold 5	93.81	94.68	93.89	93.36	97.82	94.68
	Average	91.62	92.65	91.69	91.01	97.03	92.65

Table 4. Average test accuracy of DardCovidNet and Coronet

Model	Classification	Average accuracy (%)
DarkCovidNet	Two classes	85.20
DarkCovidNet	Three classes	80.20
CoroNet	Four classes	90.06

The proposed Covidense model has averaged the precision, recall, F1-score, specificity, sensitivity values for two classes (Covid-19 and normal) of 99.47%, 99.38%, 99.41%, 99.46%, 99.38%, and 99.38%, respectively. Moreover, the proposed Covidense model has averaged the precision, recall, F1-score, specificity, sensitivity values for three classes 1 (Covid-19, normal and bacterial pneumonia) of 93.21%, 95.54%, 93.54%, 92.82%, 96.56% and 94.88%, respectively. Moreover, the proposed Covidense model has averaged the precision, recall, F1-score, specificity, sensitivity values for three classes 2 (Covid-19, normal, and viral pneumonia) of 93.55%, 95.27%, 94.07%, 93.91%, 96.50%, and 95.27%, respectively. And finally, Covidense model has averaged the precision, recall, F1-score, specificity, sensitivity values for the four classes (Covid-19, normal, bacterial pneumonia, and viral pneumonia) of 91.62%, 92.65%, 91.69%, 91.01%, 97.03%, and 92.45%, respectively. Accuracy and Loss plots for all Covidense classification modes in fifth fold cross-validation are shown in Figure 5.

When comparing averages of two different groups, it is common to use the t-test statistical method [25]. In particular, when using paired sample t-test, we compare means of samples chosen from the same population to accept or reject the Null Hypothesis.

P-value and T-score are results of this test. P-value determines whether our results are in compliance with the Null Hypothesis or not, and common sense is that if the P-value is near 0.05, it is said that the value of t is significant. T-score represents the difference between two groups so that as the T-score value increases, the difference between two groups becomes more significant.

We used the t-test method for a better comparison of our proposed model with DarkCovidNet and CoroNet models that we test on our dataset. The results of this comparison using the t-test method, including the T-score and P-value, are given in Table 5 and Figure 6.

Table 5. The training and testing computational times of models.

Model	classification	Time (second)
DarkCovidNet	Two classes	5500
DarkCovidNet	Three classes	12000
CoroNet	Four classes	11600
Covidense	Two classes	4750
Covidense	Three classes	5750
Covidense	Four classes	6750

DarkCovidNet and CoroNet all models, which are Grad-Cam is a well-known method used to generate a heat map for a specific class of a Convolutional Neural Network trained with input images [26]. Gradient-weighted Class Activation Mapping (Grad-Cam) works with finding the last Convolutional layer and analyzing Gradient descent data in that specific layer.

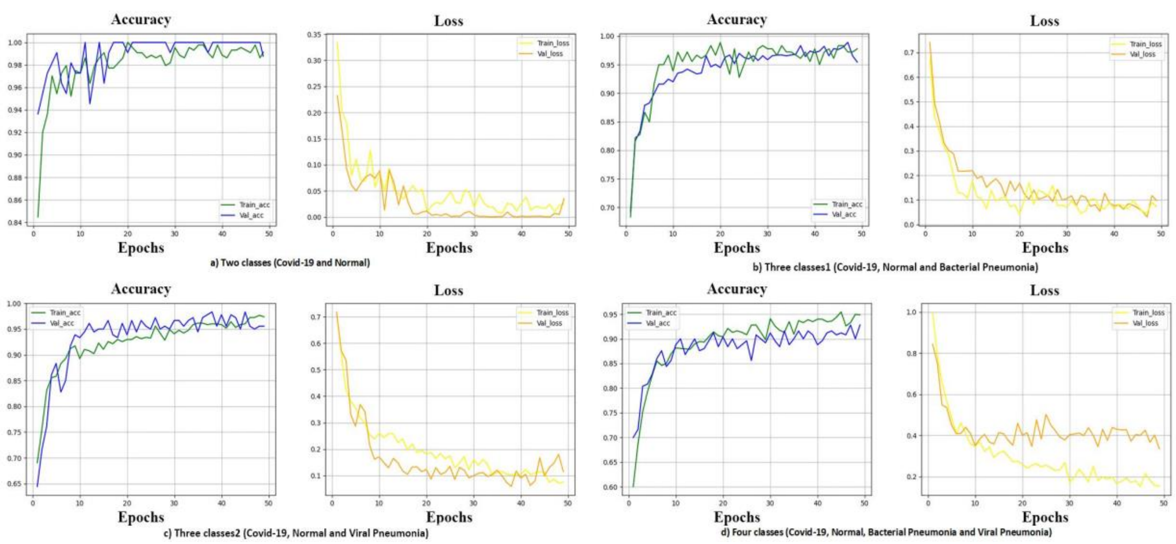

Figure 5. Accuracy and loss of all Covidense classification modes on fold 5

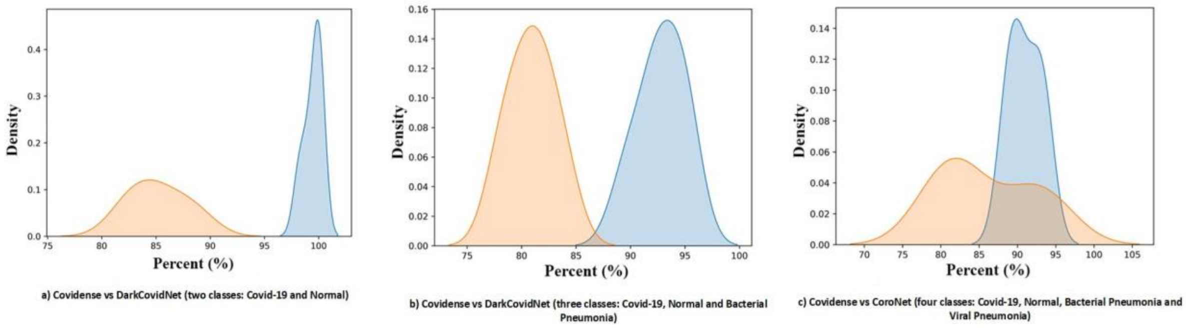

Figure 6. T-test Comparison of Covidense with DarkCovidNet and Coronet (Blue: Covidense, Orange: Compared model)

The Grad-Cam output is a representation and illustration of a Heat map for a specific class [26]. We used the Grad-Cam explainability tool to demonstrate how the model makes its decision, and the areas of involvement in the lungs of patients according to each disease have been shown in Figure 7.

We compare the training and testing computational times of different modes of our proposed model with presented in Table 6. It can be seen that the proposed model of this study requires lower computational time for training and testing compared with the reviewed articles.

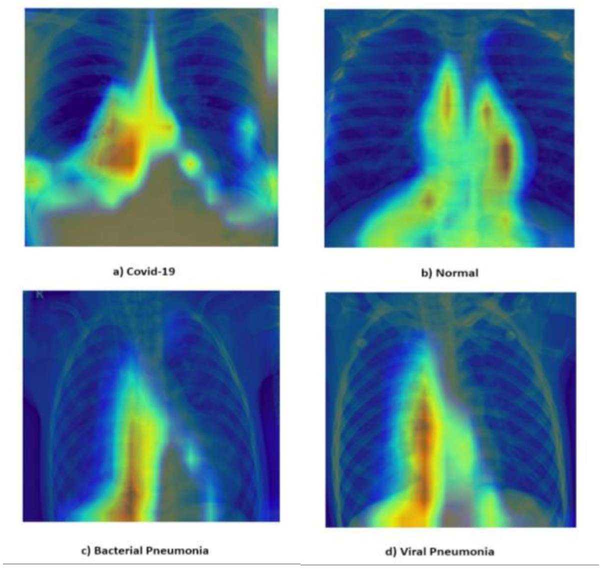

Figure 7. Grad-Cam demonstration of Covidense four classes classification

5. Discussion

In Covidense, we used the pre-trained DenseNet-201 model because of its ability to reuse features of different layers as an input for the next layer and thus improving performance. Therefore, we use a dense network to detect Covid-19 using chest X-ray images. It could be said that using this dense network had a very high impact on this study. Better results acquired using DenseNet-201

Table 6. Comparison results between our proposed model and DarkCovidNet and Coronet models using t-test statistical method.

Model	Classification Mode	T-score	P-value
Covidense vs DarkCovidNet	Two classes	2.6864	0.05
Covidense vs DarkCovidNet	Three classes	7.8597	0.001
Covidense vs CoroNet	Four classes	14.362	0.0001

architecture compared to its predecessors, including DenseNet-121, DenseNet-161, and DenseNet-169 is indicating its better performance and necessitates its priority over prior architectures [27].

Covidense achieved promising results in four classes classification (Covid-19, normal, bacterial pneumonia, and viral pneumonia), and according to Table 7, outperforms most of the studies reviewed. CoroNet, a deep Convolutional Neural Network, proposed by Khan *et al.* [3], used chest X-ray images to detect Covid-19 infection and differentiates it from other types of pneumonia with an overall accuracy of 89.6%. CoroNet is an Xception based model with 33 million parameters.

Mahmud *et al.* [13] proposed a depth-wise convolution for efficient feature extraction using chest X-ray images. Their model was initially trained with a lot of normal and pneumonia images, then transfer learning with an additional number of Covid-19 and other pneumonia patients. For the aim of differentiating different types of pneumonia from each other, discriminative localization based on Gradient was utilized.

Thus, achieving 90.3% accuracy for multiple class classification (normal, Covid-19, bacterial pneumonia, or viral pneumonia). Covidense offers outstanding performance in two classes, three classes 1 and 2 compared to other models' and its comparison to other studies can be seen

Table 7. Comparison of four class classification results

Model Name	Accuracy	Sensitivity	Specificity	F1-Score	Precision	Number of Parameters (in million)	Number of Epochs	Number of chest X-ray images
Khan *et al.* [3] "CoroNet"	89.6%	89.92%	96.4%	89.8%	90%	33	80	1251
Mahmud *et al.* [13] "CovXNet"	90.3%	89.9%	89.1%	90.4%	90.8%	-	-	1220
Proposed Model "Covidense"	91.01%	92.65%	97.03%	91.69%	91.62%	~ 30	50	1280

Table 8. Comparison of Covidense with other studies

Study	Architecture	Accuracy two classes	Accuracy three classes	Number of parameters (in million)	Number of chest X-ray images
Khan *et al.* [3]	CoroNet (Xception)	99%	89.6%	33	1251
Ramadhan *et al.* [10]	CovidNet	98.44%	-	-	-
Mahmud *et al.* [13]	Stacked Multi-resolution (CovXNet)	97.40%	-	-	1220
Ozturk *et al.* [12]	DarkCovidNet	98.08%	87.02%	-	1125
Narin *et al.* [28]	ResNet-50	98%	-	36	100
Sethy *et al.* [29]	ReNet-50/SVM	98%	-	-	50
Proposed Model	Covidense (DenseNet-201)	99.46%	Covid-19, normal and bacterial pneumonia 92.86%	~ 30	1280
			Covid-19, normal and viral pneumonia 93.91%		

in Table 8. To demonstrate the proposed models' superior performance over previous studies, we chose two models introduced in prior works, including DarkCovidNet [21] and CoroNet [6], for further analysis by exploring their performance on our dataset. The results of this comparison can be seen in Table 4.

6. Conclusion

Covidense is one of the most accurate models to date, offering multiple advantages, including better performance while having a relatively lower number of parameters and lower number of epochs value during model training and testing. While being a more comprehensive model compared to other studies, the proposed model still offers better performance in terms of average accuracy. It should be noted that the choice of a more appropriate pre-trained Architecture (DenseNet-201) acting as the basis for developing the model had a profound effect on the success of the study. Our proposed model has fewer parameters than other trained models, which is one of the notable lower number of epochs of this model compared to other models. In other words, with a parameter number of about 30 million and 50 epochs, this model has been points in this work. Another important point is the able to show very high accuracy, precision, recall, F1-score, sensitivity, and specificity in all classification modes of this model.

Covid-19 stated as a pandemic by the WHO is currently infecting more and more people day by day. Multiple vaccines have been introduced and tested against Covid-19 virus but not one of them have had 100 percent efficacy against one specific strain and considering multiple mutations of the virus, the efficacy of the vaccines varies for different strains and in some occasion may not be effective at all. Plus, there is still a vaccine shortage and not all of the countries have the same access to the introduced vaccines. Although, there is no verified drug to encounter Covid-19 infection until this date. Thus, Social distancing and Screening of infected patients using an automatic procedure like Covidense which diagnoses Covid-19 infections using Chest X-ray images with high accuracy can decrease the surging number of deaths and infected patients.

References

1- S. B. Desai, A. Pareek, and M. P. Lungren, “Deep learning and its role in COVID-19 medical imaging,” Intell Based Med, vol. 3, no. 100013, p. 100013, 2020.

2- Litmanovich D. E., Chung M., Kicska G., “Review of Chest Radiograph Findings of Covid-19 Pneumonia and Suggested Reporting Language.” *Journal of Thoracic Imaging*, 2020.

3- Khan A. I., Shah J. L., Bhat M. M., “CoroNet: A deep neural network for detection and diagnosis of Covid-19 from chest x-ray images.” *Computer Methods and Programs in Biomedicine*, 105581, 2020.

4- Sun Z., Zhang N., Li Y., Xu X., “A systematic review of chest imaging findings in Covid-19.” *Quantitative Imaging in Medicine and Surgery*;10(5):1058, 2020.

5- Brunese L., Mercaldo F., Reginelli A., Santone A., “Explainable deep learning for pulmonary disease and coronavirus Covid-19 detection from X-rays.” *Computer Methods and Programs in Biomedicine*; 196:105608, 2020.

6- Khalifa N. E. M., Taha M. H. N., Hassanien A. E., Elghamrawy S., “Detection of coronavirus (Covid-19) associated pneumonia based on generative adversarial networks and a fine-tuned deep transfer learning model using chest X-ray dataset.” *arXiv preprint arXiv*: 200401184, 2020.

7- WHO Coronavirus Disease (Covid-19) Dashboard | WHO Coronavirus Disease (Covid-19) Dashboard, https://Covid19.who.int, 5nd March 2021.

8- Basu S., Mitra S., “Deep Learning for Screening Covid-19 using Chest X-Ray Images.” *arXiv preprint, arXiv*:200410507, 2020.

9- Minaee S., Kafieh R., Sonka M., Yazdani S., Soufi G. J., “Deep-Covid: Predicting Covid-19 from chest x-ray images using deep transfer learning.” *arXiv preprint arXiv*: 200409363, 2020.

10- Ramadhan M., Faza A., Lubis L., Yunus R., Salamah T., Handayani D., *et al.*, “Fast and accurate detection of Covid-19-related pneumonia from chest X-ray images with novel deep learning model.” *arXiv preprint arXiv*:200504562, 2020.

11- Zhang J., Xie Y., Liao Z., Pang G., Verjans J., Li W., *et al.*, “Viral pneumonia screening on chest X-ray images using confidence-aware anomaly detection.” *arXiv*: 200312338, 2020.

12- Ozturk T., Talo M., Yildirim E. A., Baloglu U. B., Yildirim O., Acharya U. R., “Automated detection of Covid-19 cases using deep neural networks with X-ray images.” *Computers in Biology and Medicine*, 103792, 2020.

13- Mahmud T., Rahman M. A., Fattah S. A., “CovXNet: A multi-dilation convolutional neural network for automatic Covid-19 and other pneumonia detection from chest X-ray images with transferable multi-receptive feature optimization.” *Computers in biology and medicine*; 122:103869, 2020.

14- Rahimzadeh M., Attar A., “A modified deep convolutional neural network for detecting COVID-19 and pneumonia from chest X-ray images based on the concatenation of Xception and ResNet50V2.” *Informatics in Medicine Unlocked*; 19:100360, 2020.

15- GitHub – “ieee8023/Covid-chestxray-dataset: We are building an open database of Covid-19 cases with chest X-ray or CT images.” https://github.com/ieee8023/Covid-chestxray-dataset

16- Kaggle – “CoronaHack-Chest X-Ray-Dataset.” https://www.kaggle.com/praveengovi/coronahack-chest-xraydataset

17- Indolia S., Goswami A. K., Mishra S., Asopa P., “Conceptual understanding of convolutional neural network-a deep learning approach.” *Procedia computer science*;132: pp. 679-688, 2018.

18- Sun W., Tseng T., Zhang J., Qian W., “Enhancing deep convolutional neural network scheme for breast cancer diagnosis with unlabeled data.” *Computerized Medical Imaging and Graphics*, Vol. 57, pp. 4-9, Apr. 2017.

19- Ge Y., Wang Q., Wang L., Wu H., Peng C., Wang J., *et al.*, “Predicting post-stroke pneumonia using deep neural network approaches.” *International Journal of Medical Informatics*, 2019;132:103986.

20- Huang G., Liu Z., Van Der Maaten L., Weinberger K. Q., “Densely connected convolutional networks.” *Proceedings of the IEEE conference on computer vision and pattern recognition*; 2017.

21- Zhang, C., Benz, P., Argaw, D.M., Lee, S., Kim, J., Rameau, F., Bazin, J.C. and Kweon, I.S., Resnet or densenet? introducing dense shortcuts to resnet, *In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pp. 3550-3559, 2021.

22- Yu X., Zeng N., Liu S., Zhang Y. D., “Utilization of DenseNet201 for diagnosis of breast abnormality.” *Machine Vision and Applications*; 30(7-8): pp. 1135-1144, 2019.

23- Parikh R., Mathai A., Parikh S., Chandra Sekhar G., Thomas R., “Understanding and using sensitivity, specificity and predictive values.” *Indian J Ophthalmol*;56(1): pp. 45-50, 2008.

24- Guirguis-Blake J., Wolff T., Crichlow R., Wilson J. E., Meyers D., “Chapter 6 - Preventive Health Care, in Textbook of Family Medicine (Eighth Edition)”, Rakel R. E. and Rakel D. P., Eds. Philadelphia: W.B. Saunders, pp. 73-99, 2011.

25- Mishra P., Singh U., Pandey C. M., Mishra P., Pandey G., “Application of student's t-test, analysis of variance, and covariance.” *Annals of cardiac anaesthesia*; 22(4):407, 2019.

26- R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, D. Batra, “Grad-cam: Visual explanations from deep networks via gradient-based localization.” *In Proceedings of the IEEE international conference on computer vision*, pp. 618-626, 2017.

27- Bressem, K.K., Adams, L.C., Erxleben, C., Hamm, B., Niehues, S.M. and Vahldiek, J.L., “Comparing different deep learning architectures for classification of chest radiographs.” *Scientific reports*, 10(1), pp. 1-16, 2020.

28- Narin A., Kaya C., Pamuk Z., “Automatic detection of coronavirus disease (Covid-19) using x-ray images and deep convolutional neural networks.” *arXiv preprint arXiv*:200310849, 2020.

29- Sethy P. K., Behera S. K., “Detection of coronavirus disease (Covid-19) based on deep features.” *Preprints*, 2020;2020030300:2020.