



Deep Learning ResNet101 Deep Features of Portable Chest X-Ray Accurately Classify COVID-19 Lung Infection

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Received: 08 November 2022; Accepted: 30 January 2023

Abstract: This study is designed to develop Artificial Intelligence (AI) based analysis tool that could accurately detect COVID-19 lung infections based on portable chest x-rays (CXRs). The frontline physicians and radiologists suffer from grand challenges for COVID-19 pandemic due to the suboptimal image quality and the large volume of CXRs. In this study, AI-based analysis tools were developed that can precisely classify COVID-19 lung infection. Publicly available datasets of COVID-19 (N = 1525), non-COVID-19 normal (N = 1525), viral pneumonia (N = 1342) and bacterial pneumonia (N = 2521) from the Italian Society of Medical and Interventional Radiology (SIRM), Radiopaedia, The Cancer Imaging Archive (TCIA) and Kaggle repositories were taken. A multi-approach utilizing deep learning ResNet101 with and without hyperparameters optimization was employed. Additionally, the features extracted from the average pooling layer of ResNet101 were used as input to machine learning (ML) algorithms, which twice trained the learning algorithms. The ResNet101 with optimized parameters yielded improved performance to default parameters. The extracted features from ResNet101 are fed to the k-nearest neighbor (KNN) and support vector machine (SVM) yielded the highest 3-class classification performance of 99.86% and 99.46%, respectively. The results indicate that the proposed approach can be better utilized for improving the accuracy and diagnostic efficiency of CXRs.



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The proposed deep learning model has the potential to improve further the efficiency of the healthcare systems for proper diagnosis and prognosis of COVID-19 lung infection.

Keywords: COVID-19; deep learning (DL); lung infection; convolutional neural network (CNN)

1 Introduction

Severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2), associated with COVID-19 is a single-stranded ribonucleic acid (RNA) virus was found in Wuhan, China, in December 2019 [1,2]. The highly transmissible disease quickly gained global attention and was declared a “public health emergency of international concern” by the World Health Organization (WHO) in January 2020. By March, the disease was officially declared a global pandemic [3]. As of 2nd August 2021, the disease was responsible for 4.2 million confirmed deaths and had affected more than 198 million people worldwide [4]. The virus causes pneumonia with symptoms similar to that of the seasonal flu, which includes fever, dry cough, and fatigue, amongst others.

To date, a standard of care to detect SARS-CoV-2 infection uses Reverse Transcription Polymerase Chain Reaction (RT-PCR) [4]. This method has high specificity but relatively low sensitivity and is usually performed with a nasopharyngeal swab-based sample. The results produced have turnaround times ranging from a few hours to days. Antibody tests also used to predict SARS-CoV-2 infection [1,2].

Portable chest X-ray (CXR) was one of the primary tools to triage patients associated with SARS-CoV-2 infection before RT-PCR being as reliable it is today. To date, CXR is primarily used to assess the extent of lung infection in emergency room settings as well as to evaluate the severity of lung infection in intensive care units (ICU) and to evaluate intubation tube placement in invasive mechanical ventilation. Portable CXR is still widely used in developing countries to detect and evaluate infection. The CXRs have several advantages as it is readily available, cost-effective, and have faster turnaround than other modalities. Moreover, it can provide the extent and location of SARS-CoV2 infection, amongst others. These characteristics are still useful for triaging patients promptly, on time for isolation as well as assisting in ICU care [5]. However, computed topography (CT) is more sensitive and offers more information than CXR. The CT is less assessable, more expensive, and more susceptible to cross-contamination and is not extensively utilized in COVID-19 settings, except earlier in China [1,2].

Artificial intelligence (AI) methods have widely been utilized for the diagnosis and prognosis of different cancer diseases. In this current pandemic, various counties encounter a lack of experienced health professionals for proper diagnosis of the disease. Thus, AI techniques in diagnosing COVID-19 have rapidly gained traction over the past year. The computer-aided diagnosing (CAD) frameworks use graphical processing units (GPUs) to process medical images and to provide a rapid diagnosis of COVID-19. Deep learning (DL) and CAD have been used in combination for many medical imaging applications, including the analysis of COVID-19 [5]. Furthermore, Convolutional neural networks (CNNs) are often used for processing radiological images. As a result, CNN frameworks and DL can also be promising areas of exploration for COVID-19 diagnosis.

The deep learning methods have diverse applications, including liver diseases [6], lung cancer [7], breast cancer [8], brain tumor [9], colon cancer [10], skin cancer [11], pneumonia [12], and more recently COVID-19 analysis exclusive of any human involvement. The principal reason for applying deep learning in disease diagnosis is because, unlike classical machine learning, deep learning (DL) methods learn by forming more abstract representations of data as the network continues to grow deeper. Moreover, deep learning algorithms maximize model accuracy by specifying features through different nonlinear functions organized in a combinatory fashion. Consequently, deep learning models can automatically extract features leading to higher accuracy and precision results [13]. Moreover, deep learning methods focus intensely on automatic extraction and image classification, this has conferred more accurate and efficient predictions and diagnoses [1,2]. By integrating computer-aided diagnosis (CAD) into healthcare systems, doctors will not only be able to reduce their workload, but also give a more exact diagnosis, especially in times of crisis where there will be an inevitable lack of doctors and healthcare personnel [14]. An additional limitation is that in many developing countries, radiologists might be scarce; AI has the potential to solve this issue by providing an immediate diagnostic interpretation or, at the least, offering a second opinion as well as prioritizing a reading list. This will allow for improved workflow, and accessibility Convolutional Neural Networks (CNNs) need trained on the ImageNet dataset that is comprised of images from diverse sources [15,16]. Due to prior training, transferred learning lowers the need for large dataset and, consequently, calculation costs [17].

Recently, researchers utilized different deep learning methods to predict COVID-19 using chest X-ray images [13,18–20] and to utilize CT images [14,21–35]. Some studies even used lung dataset for detecting and diagnosing COVID-19 [4,36], while others used limited dataset with CNN for detecting COVID-19 from chest X-rays, as detailed in [37,38]. Several other researchers took an interest to detect COVID-19 by differentiating it from other chest diseases like pneumonia [5,8,16,20,39]. It was also noted by authors [37] that X-ray images have little impetus in the early stages of the disease, while CT scans prove valuable even earlier symptoms appear. However, one issue associated with chest CT images and chest X-rays is the possibility of overlap in diagnosing COVID-19, chest cancer, and pneumonia. This is especially the case when the healthcare worker diagnosing the patient is inexperienced or lacks patient history files. Since classification models for classifying the three lung diseases have not been heavily explored, this allows to present a model that can automate diagnosing patients to confirm scrupulously whether a patient has one of the three diseases.

This study is aimed to improve the multiclass (COVID-19, normal, pneumonia including viral and bacterial) classification to detect COVID-19 on publicly available dataset recently used in the studies [13,14,38,39]. Though few prior studies have used two-class classification, most of which analyze CT images that are less suitable for contagious disease, our multiclass classification is robust for performance improvement by employing Residual network 101 (ResNet101) with Softmax for classification using (i) default parameters, (ii) optimized hyperparameters, (iii) extraction of in depth features from ResNet101 and fed into k-nearest neighbor (KNN) and support vector machine (SVM) classification algorithms rather than simply using Softmax for classification, from the last pooling layer of ResNet101, the images are retrained. The hyperparameters optimization enhanced the multiclass detection performance. Moreover, the high order features with machine learning classification algorithm provided excellent detection performance because multiclass chest x-ray images are first automatically enhanced learning with the deep learning feature learning approach. The in-depth features are then fed to machine learning algorithms and trained further to enhance performance.

This section below will attempt to cover ongoing attempts of utilizing CXR images to diagnose COVID-19, highlighting attempts of automatic frameworks utilizing CNN. Hemdan introduced COVIDC-Net, a unique network that analyzes normalized forces in CXR images to analyze the positivity of the COVID-19 virus. It combines seven deep convolutional neural networks, including VGG19 and the second form of Google MobileNet [40]. DenseNet and VGG19 networks were seen to detect COVID-19 automatically. Furthermore, Khan proposed CoroNet, a DCNN model with a similar goal [41]. Similarly, Li proposed Covid-MobileXpert, a mobile-based DL network framework [42]. Narin et al. proposed a deep convolutional neural network (CNN) based pre-trained model on chest X-ray images. The deep learning pre-trained models used to classify patients as normal (healthy), COVID-19 infected, bacterial, or viral pneumonia patients are as follows: ResNet50, ResNet101, ResNet152, InceptionV3, and InceptionResNetV2 [14].

1.1 Recent Work

Researchers recently developed Artificial intelligence (AI) based CAD tools that automated the detection of COVID-19 and improved the healthcare system. Shahin et al. [43] proposed a machine learning-based CAD system, which comprised of CT lungs screening collection, pre-processing to improve the ground glass opacities (GGOs), segmentation and modifying the machine learning algorithms. Rehman et al. [44] conducted a systematic review to summarise the machine learning and deep learning algorithms for COVID-19 classification, prediction, and detection using clinical and radiological dataset. The outcomes can be helpful for healthcare practitioners and radiologists for improved diagnosis and prognosis. Chen et al. [45] developed a method based on medical screening and isolation measures numerical methods for assessing and simulating the virus's transmission and spread. Hou et al. [46] proposed a deep learning (DL) model with six-layers by combing batch normalization, max pooling and Adam algorithm for improving the COVID-19 detection. Agrawal et al. [47] developed deep learning model for improving COVID-19 detection. Gupta et al. [48] improved COVID-19 detection by utilizing deep learning models. Abir et al. [49] proposed a CovNet model based on Long Short-term Memory Variational Autoencoder (LSTM-VAE) to detect COVID-19 infection with wearable devices i.e., fitness trackers and smartwatches in the pre-symptomatic stage from resting heart rate (RHR).

Previously, the researchers not considered most of the factors to detect COVID-19. In this study, deep learning models were proposed to detect COVID-19 from multiclass (i.e., COVID-19, normal, pneumonia; COVID-19, normal, viral, COVID, bacterial, normal) with multi-approach. First, different pre-processing methods were utilized, such as normalization, augmentation, resizing and splitting. The ResNet101 model was pre-trained on the ImageNet dataset using the transfer learning approach, which is trained on 1000 classes. In this case, the last three layers were removed i.e., {'fc1000', 'prob', 'ClassificationLayer_predictions'} and replaced with the new classes of the current study. Secondly, the ResNet101 features were extracted from the last average pooling layer with default parameters. Thirdly, the ResNet101 features, by optimizing the hyperparameters were computed from the last average pooling layer. Fourthly, the extracted features from ResNet101 obtained from the last average pooling layers were fed into machine learning KNN and SVM as detailed in Fig. 1. Below. The Section 2 summarizes the methodology, Section 3 describes the results, and discussions and Section 4 show the conclusions.

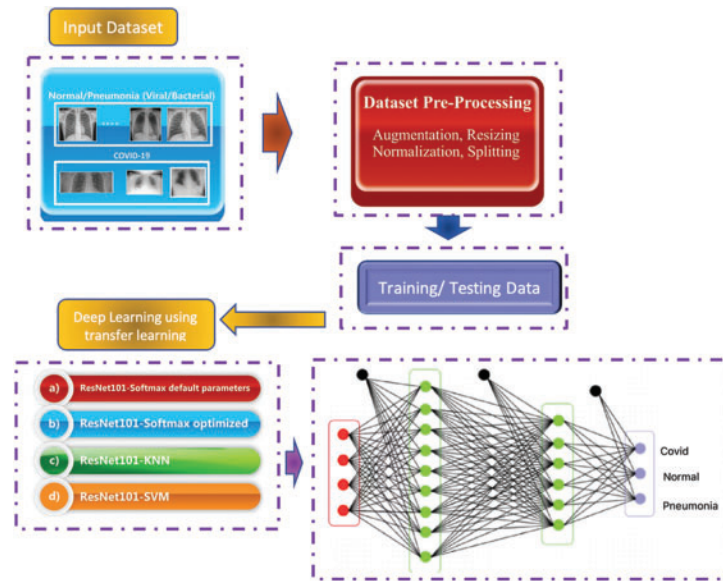


Figure 1: Schematic diagram to predict COVID-19 lung infection using deep convolutional neural network (CNN) ResNet101 by optimizing parameters and with deep features

2 Methodology

This section presents the dataset used and methods utilized.

2.1 Dataset

Standard datasets, such as the Italian Society of Medical and Interventional Radiology (SIRM), The Cancer Imaging Archive (TCIA), Radiopaedia and the Radiological Society of North America (RSNA), contain collections of familiar pneumonia X-ray images were utilized to differentiate COVID-19 from normal pneumonia. The COVID-19 ($N = 1525$) was taken from GitHub collected by Cohen et al. [50], Radiopaedia and TCIA. The pneumonia ($N = 3863$) and chest x-ray healthy ($N = 1525$) were collected from the Kaggle repository and National Institutes of Health (NIH) dataset [39]. Fig. 1. shows the workflow of our model.

2.2 Convolutions Neural Network

The CNN model has a significant role in extracting dynamic features, rather than manual features elimination. The features extracted from the activation map are also fed back to machine learning (ML) algorithms [51]. This has made the CNN models very useful compared to prior machine learning algorithms. To train the CNN models, two approaches are used: (1) train with no prior training, (2) train using transfer learning. Following the first approach, training the CNN model requires many samples for training from scratch. With limited data, as in our case, this training can prove inadequate. However, the second option addresses this issue, as the CNN models can be retrained by using a process known as transfer learning. This approach is the most effective method to adopt the knowledge [52]. In common transfer learning (TL) approach, convolutional layers (CL) are used as fixed feature extractors, and only fully connected layers (FL) are set for a new specific task [53]. The CNN comprised of convolution layer, fully connected layer and a pooling layer. In this study, we

used multiclass (COVID-19, pneumonia, and normal). Thus, new fully connected layer has only three neurons.

2.3 Transfer Learning Approach

We applied the transfer learning approach; this means the networks such as ResNet101 of Convolution Neural Network were pre-trained on a large dataset. The network ResNet101 consisted of inception layers, convolution layers and fully connected layers. In this case, the ImageNet dataset consisting of 14 million images was used to pre-train the network. This initial training helps the first layer to find extremely generatable features from a more extensive datasets; later layers of the network take on specifics of smaller dataset for the adaptive model. We used ResNet101 in our study, described in the below section:

The convolutional neural networks require high computational resources as very high operations are performed for performing convolution and pooling operations for computing low-level, mid-level and high-level features, weight filters, and weight channels. For example, if we have pooling with filter 512, then memory and parameters are computed as depicted below:

Input	Memory	Parameters
Pool 3×3 Conv, 512	memory: $14 * 14 * 512 = 100 \text{ K}$	params: $(3 * 3 * 512) * 512 = 2,359,296$
FC 1000	memory: 1000	params: $4096 * 1000 = 4,096,000$

2.3.1 Resnet 101

He et al., proposed the ResNet model [54] in 2016, an abbreviation of the residual network. This method is used in diverse applications, medical imaging, pattern recognition, computer vision etc. The CNN is comprised of multiple layers connected to each other in a specific manner and trained for performing various tasks [55]. There are 104 convolutional layers (CL) with 33 filters one filter for each layer, respectively. In the residual connection, 9 out of 33 layers use the previous layer output directly. The residual connections have used an operand for summation operations. The four remaining layers receive the output of the previous block as input and apply it to the convolutional layer (CL) with a filter size of 1×1 and a stride of 1, followed by a group of normalization layers.

2.4 Training/Testing Data Formulation

The standard 10-fold cross-validation (CV) method was utilized for testing and training data validation as detailed in [56–59].

3 Results

In this study, ResNet101-softmax with default and optimized parameters, ResNet101-KNN, and ResNet101-SVM were applied for multiclass COVID-19 detection. The hyperparameters of the ResNet101 model were optimized with the following parameters reflected in Table 1.

The performance was computed in terms standard performance evaluation parameters. Table 2 presents multiclass class classification (COVID, Normal, Pneumonia; Bacterial, COVID, Normal; Bacterial, Viral, Normal) results using Deep Learning ResNet101. The highest performance with default hyperparameters using ResNet101 yielded with multiclass (COVID-19, normal, pneumonia)

in detecting pneumonia (99.29% accuracy, 0.99 AUC) followed by COVID-19 (98.08% accuracy, 0.98 AUC). The multiclass (Bacterial, COVID-19, normal) yield the highest accuracy to detect bacteria (98.20% accuracy, 0.98 AUC) followed by normal (97.91% accuracy, 0.98 AUC), COVID-19 (96.11% accuracy, 0.96 AUC). The multiclass (COVID-19, viral, normal) yield the highest accuracy to detect viral (99.62% accuracy, 1.00 AUC) followed by normal (96.21% accuracy, 0.96 AUC), COVID-19 (95.83% accuracy, 0.96 AUC).

Table 1: Experimental optimized hyperparameter settings for ResNet101 model

Hyperparameter	Value
Optimizer	Adam
Momentum	0.90
Initial learning rate	0.0001
L2 regularization	0.00004
Max epochs	10
Minibatch size	12

Table 2: Multiclass classification (COVID, normal, pneumonia; bacterial, COVID, normal; bacterial, viral, normal) with transfer learning approach using deep learning ResNet101

Sensitivity	Specificity	PPV	NPV	FPR	Accuracy	AUC	Type
ResNet101 with transfer learning (ResNet101-softmax)							
97.82%	98.14%	93.75%	99.34%	0.018	98.08%	0.98	COVID-19
94.56%	98.76%	95.50%	98.46%	0.04	97.84%	0.97	Normal
99.70%	100%	100%	99.40%	0.002	99.29%	0.99	Pneumonia
ResNet101 with transfer learning (ResNet101-softmax)							
96.68%	99.45%	99.14%	97.34%	0.005	98.20%	0.98	Bacterial
94.56%	96.70%	91.58%	97.92%	0.032	96.11%	0.96	COVID
96.73%	98.35%	95.70%	98.76%	0.016	97.91%	0.98	Normal
ResNet101 with transfer learning (ResNet101-softmax)							
92.39%	97.67%	95.55%	96.00%	0.023	95.83%	0.95	COVID
95.65%	96.51%	93.62%	97.64%	0.034	96.21%	0.96	Normal
100%	99.45%	98.76%	100%	0.005	99.62%	1.00	Viral

Fig. 2. reflects the confusion matrix of multiclass to predict COVID-19 using ResNet101 with 10-fold class validation.

Table 3 shows the results of the multiclass classification with optimized hyperparameters using transfer learning approach. A highest detection performance with optimized hyperparameters using ResNet101 yielded with multiclass (COVID-19, normal, pneumonia) to detect pneumonia (98.80% accuracy, 0.99 AUC) followed by COVID-19 (98.32% accuracy, 0.98 AUC). The multiclass (Bacterial,

COVID-19, normal) yield the highest accuracy to detect bacteria (98.51% accuracy, 0.99 AUC) followed by normal (96.61% accuracy, 0.97 AUC), COVID-19 (96.71% accuracy, 0.95 AUC). The multiclass (COVID-19, normal, viral) yield the highest accuracy to detect viral (99.62% accuracy, 0.99 AUC) followed by normal (96.97% accuracy, 0.97 AUC), COVID-19 (96.59% accuracy, 0.96 AUC).

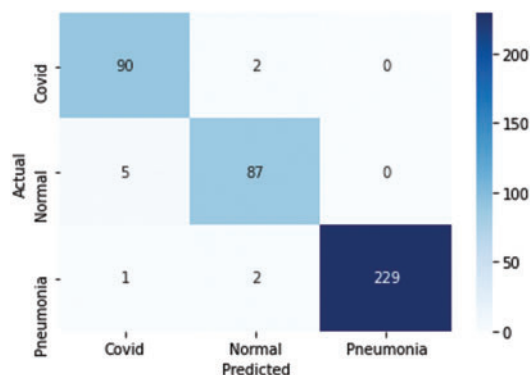


Figure 2: Confusion matrix to detect multiclass (COVID-19, normal, pneumonia) on test data using deep learning ResNet101

Table 3: Multiclass classification (COVID, normal, pneumonia; bacterial, COVID, normal; bacterial, viral, normal) with transfer learning (TL) approach using deep learning ResNet101 with optimized hyperparameters

Sensitivity	Specificity	PPV	NPV	FPR	Accuracy	AUC	Type
ResNet101 with transfer learning (ResNet101-softmax)							
95.65%	99.07%	96.70%	98.77%	0.009	98.32%	0.98	COVID-19
97.82%	98.15%	93.75%	99.74%	0.018	98.07%	0.97	Normal
98.27%	99.45%	99.56%	97.86%	0.005	98.80%	0.99	Pneumonia
ResNet101 with transfer learning (ResNet101-softmax)							
98.68%	98.37%	98.02%	98.70%	0.016	98.51%	0.99	Bacterial
92.39%	98.35%	95.50%	97.15%	0.0164	96.71%	0.95	COVID
96.74%	97.94%	94.68%	98.76%	0.020	97.61%	0.97	Normal
ResNet101 with transfer learning (ResNet101-softmax)							
93.47%	98.26%	96.62%	96.57%	0.017	96.59%	0.96	COVID
97.82%	96.51%	93.75%	98.80%	0.034	96.97%	0.97	Normal
98.75%	100%	100%	99.46%	0.0021	99.62%	0.99	Viral

Fig. 3. reflects the accuracy and loss graph of training and validation data using ResNet101 for multiclass classification. The accuracy of training and validation data is reflected in the upper portion of the graph. At the 150th epoch, the performance was yielding (100% accuracy, 0.0004 error) and (99.03% validation accuracy, 0.0764 error).

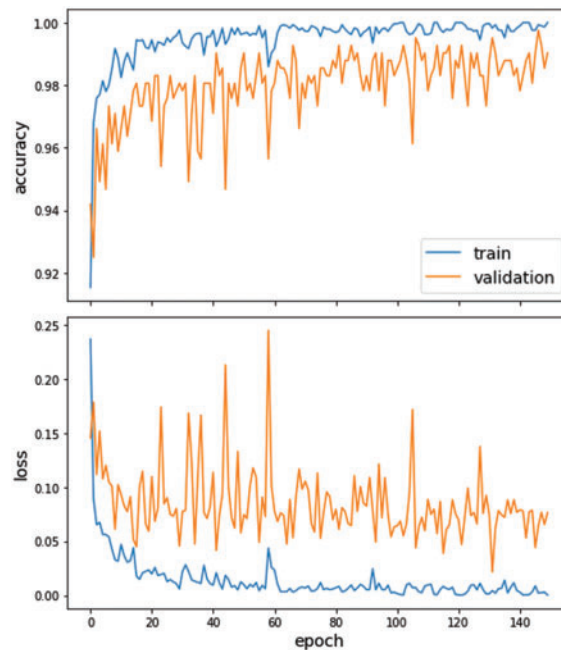


Figure 3: Accuracy and loss plot to classify COVID-19, pneumonia and normal by reflecting validation, training accuracy and corresponding error utilizing ResNet101 with transfer learning

The Multiclass (Covid-19, normal, viral) classification using ResNet-KNN is reflected in [Table 4](#).

Table 4: Multiclass (COVID-19, normal, viral) classification ResNet-KNN

	Precision	Recall	F1-score	Support
COVID	99.0%	88.0%	93.0%	428
Normal	91.0%	99.0%	95.0%	471
Viral	99.0%	100%	99.0%	419
Accuracy			96.0%	1318
Macro avg	96.0%	96.0%	96.0%	1318
Weighted avg	96.0%	96.0%	96.0%	1318

The Multiclass (Covid-19, normal, viral) classification using ResNet-SVM is presented in [Table 5](#).

Table 5: Multiclass (viral, COVID-19, normal) classification ResNet-SVM

	Precision	Recall	F1-score	Support
COVID	100%	98.0%	99.0%	428
Normal	99.0%	100%	99.0%	471
Viral	100%	100%	100%	419
Accuracy			99.0%	1318
Macro avg	99.0%	99.0%	99.0%	1318
Weighted avg	99.0%	99.0%	99.0%	1318

Table 6 reflects the results of the multiclass (COVID-19, viral and normal) classification by extracting deep features from ResNet101 the average pooling layer and fed to machine learning algorithms such as SVM linear and KNN. The ResNet101-SVM yielded 99.84% performance to detect viral, 98.56% in detecting COVID-19, whereas the ResNet101-KNN yielded 99.46% accuracy in predicting viral.

Table 6: Multiclass (COVID-19, normal, viral) classification with deep features extracted from deep learning i.e., ResNet101-SVM and ResNet101-KNN

Sensitivity	Specificity	PPV	NPV	FPR	Accuracy	AUC	Type
SVM linear							
96.02%	99.77%	99.52%	98.12%	0.002	98.56%	0.98	COVID-19
99.57%	99.29%	98.74%	99.76%	0.012	99.39%	0.99	Normal
100%	99.77%	99.52%	100%	0.00	99.84%	1.00	Viral
KNN							
86.92%	99.43%	98.67%	94.04%	0.005	95.37%	0.93	COVID-19
99.15%	94.68%	91.21%	99.50%	0.053	96.28%	0.97	Normal
99.76%	99.33%	98.58%	99.88%	0.006	99.46%	1.00	Viral

Fig. 4. depicts the multiclass classification using deep learning ResNet101-SVM yielded AUC (0.98) to detect COVID, AUC (0.99) to detect normal, and AUC (1.00) to detect viral.

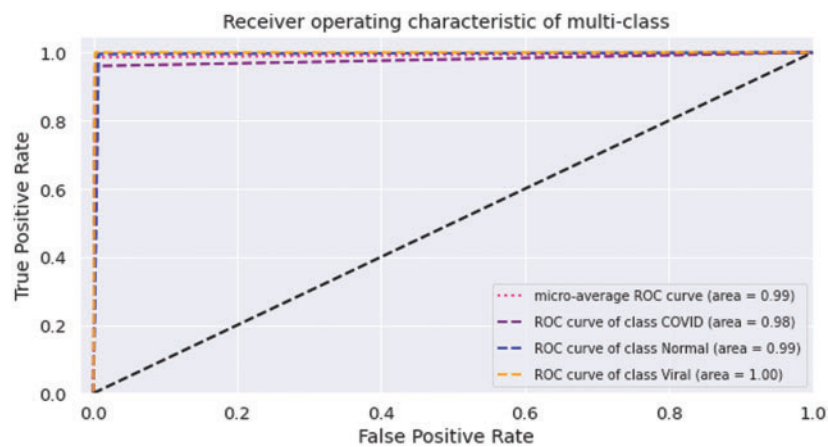


Figure 4: AUC to distinguish multiclass (normal, COVID-19, pneumonia) using deep learning ResNet101-SVM

4 Discussions and Conclusions

This study aimed to optimize and employ robust deep learning ResNet101 model to detect COVID-19 from multiclass of other community pneumonia accurately to detect COVID-19 from multiclass of other community pneumonia accurately. We computed the multiclass with and without optimizing the hyperparameters. With default hyperparameters, the overall sensitivity, specificity, accuracy, and AUC were 97.82%, 98.14%, 98.08%, and 0.98, respectively, to detect COVID-19 from

multiclass. With the optimized parameters, the performance was improved sensitivity, specificity, accuracy, and AUC were 95.65%, 96.70%, 98.32%, and 0.98, respectively to detect COVID-19. With optimized hyperparameters, overall accuracy and AUC were 98.51%, 0.99 respectively, were yielded to detect COVID-19 from multiclass (Bacterial, COVID-19, normal), whereas, accuracy and AUC of 96.59%, 0.96 were obtained to predict COVID-19 from multiclass (COVID-19, normal, viral). By extracting the deep features from ResNet101 and employing machine learning algorithms, the SVM linear yielded the highest accuracy and AUC of 100% and 1.00 to predict COVID-19 from multiclass (COVID-19, normal, bacterial) and (COVID-19, viral, normal). By applying KNN for classification using deep features, the overall accuracy of 99.73%, AUC of 0.9982 yielded to detect COVID-19 from multiclass (Normal, COVID-19, bacterial). Likewise, an accuracy of 99.46%, and AUC of 0.9966 yielded to detect COVID-19 with deep features using KNN from multiclass (COVID-19, normal, viral).

We have used a multiclass approach with 03 group combinations from COVID-19, bacterial, viral pneumonia and normal to detect COVID-19, bacterial, viral pneumonia and normal. Moreover, we used the default parameters of ResNet101. We also optimized the parameters of the Adam optimizer with (learning rate = 0.0003, beta-1, beta-2, epsilon). We also extracted in-depth features from the last pooling layer of ResNet101 and retrained the machine-learning algorithms based on these features. The SVM and KNN algorithms are used for classification.

Table 7 compares AI findings used by researchers to detect COVID-19. Most of these studies show the two-class classification using machine learning or deep learning. Ghoshal et al. [60] applied CNN and obtained an accuracy of 92.9%. Zhang et al. [61] utilized ResNet and obtained sensitivity (96.0%), specificity (79.7%) and AUC (0.952). Channa et al. [62] applied CNN and obtained an accuracy of 91.67%. Sethy et al. [63] applied ResNet50-SVM and obtained an accuracy of 95.33%. Hussain et al. [39] applied machine learning with texture features and obtained a two-class classification of 100% accuracy (COVID vs. Normal). Previous studies have conducted COVID-19 multiclass studies that have resulted in high accuracy rates. Sahinbas et al. used deep-SqueezeNet to analyze normal, pneumonia, and COVID-19 X-rays and achieved 98.26% accuracy [64]. Ucar et al. used pre-trained models VGG19, InceptionV3, ResNet, DenseNet, and VGG16. The ladder with which they achieved 80% accuracy [65]. Khan et al. utilized the CoroNet Model in a multi-study (normal, pneumonia-bacterial, pneumonia viral, COVID-19) to achieve an 89.6% performance. They analyzed 290 COVID-19 data, more than most studies mentioned above [41]. Medhi worked with deep CNN networks and achieved a 93% performance [66]. On the other hand, Zhang utilized the confidence-aware anomaly detection (CAAD) model in their binary and multiclass analysis of COVID-19 data, to reach a 95.18% accuracy level [67]. Postopus used the VGG-19 CNN model to analyze multiclass (COVID-10, bacterial, normal) X-ray images. They reached a 93.48% accuracy [68].

Table 7: Overview of studies using deep learning approaches to detect COVID-19

Authors	Modality	Subjects	Method	Performance
Ghoshal et al. [60]	X-Ray	70 COVID-19 and other conditions	CNN	92.9% (Acc.)
Zhang et al. [61]	X-Ray	70 COVID-19 and 1008 other images	ResNet	96.0% (Sens.) 70.7% (Spec.) 0.952 (AUC)

(Continued)

Table 7: Continued

Authors	Modality	Subjects	Method	Performance
Channa et al. [62]	X-Ray	259 COVID-19 and 3347 other images	CNN	91.67% (Acc.)
Sethy [63]	X-ray	25 images of COVID-19 and 25 images of Normal	ResNet50 and SVM	95.33% (Acc.)
Reference [38]		COVID-19 (1000), normal (900), pneumonia (900)		97.78% (Acc.) 97.75 (Sen.) 96.25% (Spec.)
Hussain et al. [39]	X-Ray	138 Normal, 145 COVID-19, 145 viral pneumonia and 145 Bacterial	i) COVID-19 vs. normal ii) COVID-19 vs. bacterial pneumonia iii) COVID-19 vs. viral pneumonia	100% Accuracy 97.44% Accuracy 97.56% Accuracy
This study	X-Rays	A) Transfer learning Multiclass to detect COVID-19 COVID-19 (1525), normal (1525), pneumonia (3863) Multiclass to detect a) Pneumonia (viral + bacterial) b) bacterial c) Viral B) Deep features Multiclass (COVID, bacterial,viral) to detect COVID using dataset [39]	i) ResNet101-softmax default parameters ii) ResNet101-softmax optimized parameters iii) ResNet101-SVM iv) ResNet101-KNN	i) 98.08% (Acc), 0.98 AUC ii) 98.32% (Acc), 0.98 AUC 98.80% (Acc), 0.99 AUC 98.51% (Acc), 0.99 AUC 99.62% (Acc), 0.99 AUC 99.84% (Acc), AUC 1.00 99.46% A(cc), 0.9982 AUC

The multiclass deep-learning ResNet101 was able to accurately discriminate lung infection caused by COVID-19 from non-COVID-19 bacterial and viral pneumonia. This study was multi-fold; first, the Deep learning ResNet101 with default and optimized parameters was employed for multiclass COVID-19 detection and yielded the highest accuracy of 99.62%. In the second approach, the deep features were computed from ResNet101, the average pooling layer and fed back to machine learning SVM and KNN. The detection performance was improved, yielding an accuracy of 99.84% and AUC of 1.00 utilizing ResNet101-SVM as the model was and learned twice using this approach. This approach can help clinicians and radiologists improve workflow, diagnose SAR-CoV2 infection earlier, track disease progression, and triage patients affordably and effectively.

Limitations

This current study has several specific limitations as the retrospective study was carried out with a small COVID-19 dataset. CXR, the principal imaging modality investigated in this paper, is not highly specific as PCR SAR-CoV2 diagnosis. Furthermore, sample sizes for this study were small and only investigated four classes (normal, COVID-19, bacterial pneumonia, and viral pneumonia). Future studies should test these algorithms with larger sets of data, as well as investigate new algorithms with additional types of lung infections. In future, hyperparameters optimization of deep learning

algorithms using other Bayesian optimization methods and will apply the image fusion techniques to combine the hand-crafted and dynamics features for further improving the detection performance.

Acknowledgement: The authors would like to thank the Deanship of Scientific Research. At Shaqra University for supporting.

Funding Statement: The authors received no specific funding for this study.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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