COVID-19 Diagnosis from CXR images through pre-trained Deep Visual Embeddings

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Abstract
COVID-19 is an acute respiratory syndrome that affects the host's breathing and respiratory system. The novel disease's first case was reported in 2019 and has created a state of emergency in the whole world and declared a global pandemic within months after the first case. The disease created elements of socio-economic crisis globally. The emergency has made it imperative for professionals to take the necessary measures to make early diagnoses of the disease. The conventional diagnosis for COVID-19 is through Polymerase Chain Reaction (PCR) testing. However, in a lot of rural societies, these tests are not available or take a lot of time to provide results. Hence, we propose a COVID-19 classification system by means of machine learning and transfer learning models. The proposed approach identifies individuals with COVID-19 and distinguishes them from those who are healthy with the help of Deep Visual Embeddings (DVE). Five state-of-the-art models: VGG-19, ResNet50, Inceptionv3, MobileNetv3, and EfficientNetB7, were used in this study along with five different pooling schemes to perform deep feature extraction. In addition, the features are normalized using standard scaling, and 4-fold cross-validation is used to validate the performance over multiple versions of the validation data. The best results of 88.86% UAR, 88.27% Specificity, 89.44% Sensitivity, 88.62% Accuracy, 89.06% Precision, and 87.52% F1-score were obtained using ResNet-50 with Average Pooling and Logistic regression with class weight as the classifier.
Keywords:
COVID-19, Deep Visual Features, Transfer Learning, Classification, Logistic Regression.

1. Introduction

The novel coronavirus disease or COVID-19 has had a hazardous impact on human life and put great world powers in a state of crisis within months. The novel disease has been a major burden on the healthcare system all over the world. Coronavirus is a large family of zoonotic viruses (Diseases transmitted from animals) that can affect humans in diseases from the common cold to acute respiratory syndrome, or even pneumonia in severe cases [1]. The Traditional method of COVID-19 diagnosis, specific to Pakistan, is through polymerase chain reaction (PCR) tests, which take at least 24-72 hours in a primary medical facility and can take up to 3-7 days in rural areas. Since PCR tests are 90% effective within the first 4 days [2], it is too late to take the necessary measures. According to World Health Organization (WHO) official reporting, as of April 2022, there are more than 5 Billion confirmed cases [3]. And certainly, there will be more cases that were either misdiagnosed or could not even get a PCR screening due to the unavailability of resources in rural or tertiary medical facilities. Evolutions in Artificial intelligence (AI) suggest that one can train Machine Learning (ML) models to identify chest X-ray(CXR) images from individuals who have COVID-19 or use transfer learning-based Convolutional Neural Network (CNN) or ConvNets, for our COVID-19 classification task. According to Blažić, chest imaging is one of the main tools for screening individuals with COVID-19 used in hospitals [4]. It is also found to be faster than PCR testing and it provides us with an opportunity to automate the process of COVID-19 diagnosis and test the efficacy of ML models for Computer-Aided Diagnosis(CAD).

In this study, we aim to propose a machine learning model which leverages the benefits of transfer learning-based deep neural networks and feature-engineered ML models. The objectives of this research include training ML models using Deep Visual Embeddings(DVE) as image features and exploring which DVE, along with pooling schemes, performs efficiently under our X-ray classification setting.

This research paper is organized into the following sections. The introduction is included in Section I. Section II discusses the Literature survey and related works. Section III explains the methods and experimentations. It covers the portion, where we have discussed our approach to the problem and the datasets used in our work. Section IV includes the results and discussions. Section V highlights the conclusion and possible limitations of our work.

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Table 1 Literature Survey

Source	Models	Cross Validation	Dataset Samples		Acc. (%)	Recall (%)	Spec. (%)	Sens. (%)	F1-Score (%)
			COVID	Healthy					
[6]	Fine-tuned VGG-19	5-fold	473	1845	99.5	98.8	-	99.5	99.2
[7]	End-to-end CNN with SVM classifier	5-fold	219	1341	98.9	-	99.7	89.3	96.7
[8]	Comparative analysis of Transfer learning models	No	4274	1583	84.0	82.0	-	84.0	80.0
[9]	XCovNet	No	392	392	98.4	97.4	-	98.4	97.9
[10]	Deep CNN	No	215	500	83.6	-	-	90.3	-
[11]	Transfer learning on AlexNet, GoogleNet and Squeezenet	No	438	721	95.4	96.7	96.2	92.1	94.3
[12]	DarkCovidNet	5-fold	200	200	87.0	89.9	92.1	85.3	87.3
[13]	Deep CNN (DeTraC)	No	105	80	93.1	-	85.1	100	-
[14]	CoroNet	No	89	7966	93.5	93.5	93.6	-	93.5
[15]	Fine- tuned ResNet-101	No	325	5318	98.0	-	98.0	97.0	-
[16]	Fine-tuned VGG-16	No	206	206	97.0	95.0	96.0	-	-
[17]	Fine-tuned DenseNet201	No	644	4000	92.0	-	99.0	94.0	90.0
[18]	Modified AlexNet	No	176	85	94.0	-	96.0	100	-

2. Literature review

Ever since Alexnet [5], Deep Learning and ConvNets have revolutionized the paradigms of AI and ML. Many transfer learning applications play a significant role in assisting with state-of-the-art deep ConvNet models. A number of researchers have made significant contributions by leveraging transfer learning. This section discusses in detail the contributions of other Authors to X-ray diagnosis systems using Deep Learning and Artificial Intelligence applications. Table 1 gives a complete summary of contributions by other Authors.

In [6], Faisal et. al fine-tuned CNN Based architecture VGG-19 [19], NASNet [20], and MobilenetV2 [21]. In [7], Majid et al. proposed a deep ConvNet model trained from scratch. Along with a Bayesian optimization algorithm, a support vector machine (SVM) classifier was used to classify between extracted deep features. In [8], Xing et al. used transfer learning on models: ResNet50 [22], Xception [23], InceptionResNetV2 [24], and VGG16 to formulate a COVID-19 classification approach, from a collection of CT-scans and CXR images, using SVM (Support Vector Machine) as the benchmark classifier. In [9], Madaan et al. explored the training of DNNs from scratch and investigated the influence of different design choices such as pooling size and strides of 2D CNNs. In [10], Nishio et al. proposed a system that utilized pre-trained VGG16 architecture and several data augmentation schemes on a 3-class classification system. In [11], Tuan D. Pham fine-tuned three pre-trained deep learning models without data augmentation to train 2-class and 3-class classification systems. In [12], Ozturk et al. proposed a binary and multi-class model for COVID-19 and pneumonia detection namely DarkNet. In addition to creating the model from scratch, In this study, The you-only-look-once (YOLO) real-time object detection system was used by the DarkNet model as a classifier. In [13], Abbas et al. have extracted features from high-resolution CXR images with the help of models pre-trained on ImageNet and trained them using other Transfer learning models. In [14], Agarwal et al. proposed a 3-class CoroNet, deep learning architecture. Where they have used an AutoEncoder as a feature extractor and then transfer learning for multi-label classification. In [15], Kusakunniran et al. used a fine-tuned ResNet-101 as the foundation model, but, trained it from scratch. In [16], Cuong Do et al. used a VGG-16 model, pre-trained on ImageNet, and fine-tune it's final layers to improve classification accuracy. In [17], Manokaran et al. also proposed a fine-tuned DenseNet201 [25] and performed end-to-end training, and compared their results with other transfer learning-based models. In [18], Maghdid et al. have used a modified AlexNet for multi-class classification. They have also employed fine-tuning of hyper-parameters to improve the model's overall performance.

Many authors have approached this issue in unique and admirable ways. However, most of these approaches still have certain limitations. For instance, Authors [6], [7], [10], [12]–[14], [18] , have used very small datasets.

Whereas, in an image classification-based deep learning setting a dataset of mere hundreds puts a question on the model's overall performance and confidence. In some cases, for instance, in [9], Deep Neural Network parameters are optimized directly onto the test partition, which is a bad practice and is likely to produce over-optimistic results. Authors [6]–[8], [11], [14], [15] have not performed cross-validation to further validate the trained model's mean accuracy and other performance metrics. While authors[10], [11], [13]–[15], [17], [18] have evaluated their model with accuracy metric on an imbalanced dataset.

3. Methods

The fundamental aim of this research is to provide CAD-based automated recognition of COVID-19 and to propose a machine learning model which leverages the advantages of deep neural networks and feature engineered machine learning models. Certain limitations by other authors, discussed in the previous section, undermine overall confidence in such a model. Deep learning tasks require large datasets and perform complex image classification tasks such as Medical Image diagnosis. The datasets need to be cross-validated on larger datasets to justify the confidence of such a model. The project methodology is illustrated in Fig1. This study is distributed into the following objectives, Performed in the order,

1. Collecting Datasets for COVID-19 and Healthy CXR images from various publically available sources. The details of the collected Datasets are elaborated in Table 2.
2. To train ML models using Deep Visual Embeddings as image features extracted from state-of-the-art transfer learning models.
3. Perform a comparative analysis of popular Transfer learning models, along with different pooling schemes, to evaluate which model provides better results.

3.1 Datasets

As discussed in the literature survey section, the most common limitation of other authors was the size of datasets deployed in their respective models. Lacking in training samples may not provide robust results in terms of model deployment and performance. The datasets used in this project are collected from various public sources. Table 2 gives the information on the total contents of the datasets. The total number of COVID-19 images was 4,494 and the number of healthy images was 10,545 after all samples were combined and duplicates were deleted. All the images used here are chest PA-view. The complete dataset was used for DVE evaluation from different pre-trained ConvNets, which is discussed in the later section.

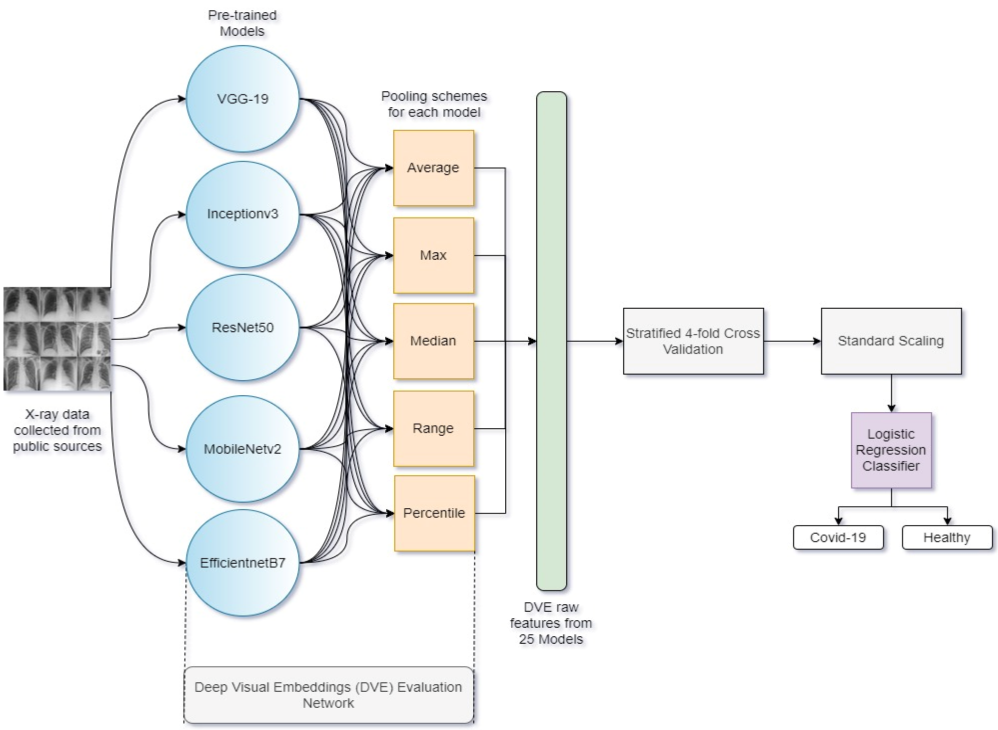

Figure 1 Process flow diagram of proposed system

Table 2 Publicly Collected Datasets from various sources

Serial no.	Dataset Name	CXR samples	
		COVID-19	Healthy
1	COVID-19 Radiology Database [29]	3616	10192
2	Chest X-ray Images with 3 Class: Covid-19 , Normal and Pneumonia[30]	221	234
3	COVID-19 X-ray Dataset with COVID-19 CNN Pneumonia Detector[31]	94	94
4	COVID-19 Chest X-ray Image Dataset[32]	69	25
5	Covid_w/wo_Pneumonia Chest X-ray[33]	531	-
6	COVID-19 chest x-ray image data collection[34]	305	-
7	Chest X-ray for covid-19 detection[35]	174	174

3.2 Deep Visual Embeddings Evaluation

Deep Visual Embedding (DVE) are image features extracted from our dataset, CXR images, with the assistance of pre-trained Deep-CNN models. In this stage of experimentation, we use the collected datasets from Table 2, to evaluate DVEs on the complete dataset using deep ConvNets initially trained on the ImageNet. It is observed from the literature survey that researchers prefer transfer learning models over deep-CNNs designed from scratch. We have performed CNN-based feature extraction on five transfer learning models: EfficientnetB7 [36], Inceptionv3 [37], ResNet50, VGG-19 and MobileNetv2, and, without their classification layers. The models pre-trained on ImageNet take less training time and will provide better results in classifications. At this point, we understand that Deep Neural Networks out-perform any hand-crafted feature engineering when it comes to feature identification. However, their performance is limited when it comes to small data, we intend to leverage the feature identification from ConvNets and use Machine Learning based traditional classifier. The DVEs evaluated from these models are then pooled with five pooling schemes. The pooling schemes include average pooling, max pooling, median pooling, range pooling, and percentile pooling. The feature extraction was performed using the cloud-based ‘Google Colab’ platform, without GPU or TPU usage.

3.3 Machine Learning

The mentioned models along with 5 pooling schemes generate a sum of 25 DVEs from the raw dataset of CXR images. All the raw features are then normalized using standard scaling and stratified nested 4-fold cross-validation, to avoid overfitting constraints. Authors in [9] have their model validated on the same dataset as training, which can provide over-optimistic results. To overcome this limitation, a 4 fold cross-validation is employed to have minimal bias and to validate the model performance such that it does not provide misleading results in practice.

3.4 Logistic Regression Classifier

For the classification, of our radiological CAD system, we have chosen logistic regression classifier. It performs very well under binary limited data conditions and similar observations have been made by Author[38] as well. Logistic Regression classifier also provides Class weight, which is proven to improve results in Applied Machine Learning problems with class imbalance. It works on the concept, that both the majority and minority classes, which are Healthy and COVID CXR images respectively, are given initially added weights based on the ratio of class imbalance ratio. In this case, the minority class i-e COVID is given more weight than the majority class of Healthy samples, such as modifying the log loss function to avoid higher bias or any misclassification. The list of results is attached in Table 3. Our benchmark metric to evaluate the model is UAR (Unweighted Average Recall). Since Accuracy is defined as the ratio of total correct predictions over total predictions, the Accuracy parameter might provide erroneous results in this case, as classes are imbalanced. Other metrics such as F1-score, Recall, and precision have been used, but the Unweighted Average Recall is a better metric to optimize when the available sample classes are imbalanced, and it is closely related to the accuracy. In this phase of experimentation, we have used logistic regression classifier with class weight on the 25 DVE obtained from the previous phase. The results are shown in Table 2.

4. Results & Discussion

From the experimentations, we have two major outcomes to present. At first, Table 3 shows the 25 DVEs, evaluated from an average of 4-fold cross-validation and standard scaling normalization. These DVEs show which embeddings perform better in comparison to other transfer learning models for our X-ray classification task. For instance, compared to other models, the EfficientNetB7 is the most recently published and it is the scaled-up variant of MobileNet and ResNet Architecture [36]. But, from our empirical testing, it is found that the ResNet-50 model with average pooling gives more promising results with a UAR of 88.86%, whereas the EfficientNetB7 has the second-highest UAR of 88.43%. However, with a Sensitivity of 93.07%, which is greater than other performance metrics, there is a strong possibility that the EfficientNetB7 will generate a lot more false-positives than other models. Secondly, it is also observed that the

Average pooling outperforms other pooling schemes, with prominent results in all the models followed by percentile pooling. We also signify the importance of using 4-fold cross-validation, which is found better than train/test split and helps in reducing the bias of the overall model. The performance metrics of our final model are 88.86% UAR, 88.62% Accuracy,89.06% precision, 89.44% Sensitivity, 88.27% Specificity and 87.52% F1Score.

Table 3: Results of Logistic Regression on DVEs

Model Name	**Pooling**	**UAR**	**Spec.**	**Sens.**	**Acc.**	**Prec.**	**F1**
EfficientNetB7	Average	88.43	83.79	**93.07**	86.55	89.27	85.98
	Percentile	88.03	84.14	91.93	86.45	88.68	85.79
	Median	88.02	84.65	91.39	86.65	88.47	85.9
	Range	86.08	82.55	89.62	84.65	86.85	83.65
	Max	86.07	82.54	89.6	84.63	86.82	83.64
InceptionV3	Average	85.55	84.41	86.69	85.09	85.15	83.65
	Percentile	85.29	84.36	86.22	84.91	85.17	83.49
	Median	83.41	82.29	84.53	82.95	83.03	81.35
	Range	83.39	82.41	84.38	82.99	83.25	81.42
	Max	83.37	82.33	84.42	82.95	83.06	81.34
MobileNetV2	Average	85.44	83.69	87.18	84.73	85.38	83.4
	Percentile	84.82	85.61	84.04	85.14	84	83.32
	Median	84.74	82.51	86.98	83.83	84.46	82.48
	Range	84.71	83.11	86.31	84.06	84.52	82.61
	Max	84.69	82.52	86.87	83.81	84.45	82.46
ResNet50	Average	**88.86**	88.27	89.44	88.62	89.06	87.52
	Percentile	88.23	**88.31**	88.14	88.26	88.18	86.96
	Median	87.21	84.35	90.07	86.05	87.73	85.1
	Range	87.18	84.33	90.03	86.02	87.69	85.07
	Max	81.58	80.75	82.41	81.24	82.04	79.47
VGG19	Average	87.48	86.67	88.3	87.15	86.05	85.72
	Percentile	86.17	83.97	88.37	85.27	84.54	83.89
	Median	86.14	83.87	88.41	85.22	84.51	83.84
	Range	84.95	82.32	87.58	83.88	83.73	82.49
	Max	74.92	72.8	77.05	74.06	72.63	71.86

5. Conclusion

In this research, we have investigated the efficacy of different design choices for the diagnosis of COVID-19, using Machine Learning models, from X-ray images. Five Deep Neural Networks with as many pooling schemes were used to evaluate Deep Visual Embeddings and tested using stratified 4-fold cross-validation and logistic regression with class weight as the classifier. The foremost results were achieved from the ResNet50 model with an average pooling scheme, the model gives a UAR of 88.86%. The Coronaviruses are zoonotic in nature, which implies they are transferred from animals to humans. Detailed investigations by professionals have made observations that SARS-CoV was transmitted from a variant of cats to humans and MERS-CoV from camels to humans[39]. Research has also shown that several known coronaviruses are circulating in animals that have not yet infected humans[40]. This research can be used as another stepping stone for our leap in the paradigms of AI and Machine Learning. It can also be used in the future when a different novel disease is encountered by society. Or, the proposed model can be deployed into medical practice to observe the human-AI interaction in practice. Two-thirds of the global population lacks access to radiology diagnostics, according to a report by World Health Organization[41]. Thus it is believed that computer-aided diagnosis holds the key to overcoming this particular obstacle.

5.1 Limitations

The datasets for this research were collected from publicly available resources and then reviewed thoroughly. The tests and experimentations were based on the premise that these datasets were examined by experts in the first place.

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