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Detection of Covid-19 Using CAD System Depending on Chest X-Ray and Machine Learning Techniques

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Abstract
SARS-COV-2 (severe acute respiratory syndrome coronavirus-2) has caused widespread mortality. Infected individuals had specific radiographic visual features and fever, dry cough, lethargy, dyspnea, and other symptoms. According to the study, the chest X-ray (CXR) is one of the essential non-invasive clinical adjuncts for detecting such visual reactions associated with SARS-COV-2. Manual diagnosis is hindered by a lack of radiologists' availability to interpret CXR images and by the faint appearance of illness radiographic responses. The paper describes an automatic COVID detection based on the deep learning-based system that applied transfer learning techniques to extract features from CXR images to distinguish. The system has three main components. The first part is extracting CXR features with MobileNetV2. The second part used the extracted features and applied Dimensionality reduction using LDA. The final part is a Classifier, which employed XGBoost to classify dataset images into Normal, Pneumonia, and Covid-19. The proposed system achieved both immediate and high results with an overall accuracy of 0.96%, precision of 0.95%, recall of 0.94%, and F1 score of 0.94%.

KEYWORDS: SARS-COV-2, Chest X-ray, Deep Learning, Transfer Learning, Dimensionality Reduction.

I. Introduction

Millions of individuals have been infected with the new coronavirus illness (COVID-19), which has claimed many lives throughout the world [1]. This outbreak has been declared a worldwide health emergency by the World Health Organization (WHO)[2, 3]. COVID-19 is caused by the severe acute respiratory syndrome coronavirus-2 (SARS-COV-2) virus, which is highly contagious and can be transmitted even from asymptotic patients throughout the incubation period[4-7].

According to the researchers, the virus mostly affects the human respiratory system, resulting in severe bronchopneumonia, which includes symptoms such as fever, dyspnea, dry cough, tiredness, and respiratory failure[8]. Furthermore, Because of the scarcity of test kits and specialists in hospitals and the rapid rise in the number of patients infected, an automatic screening system can act as a second opinion for expert physicians to quickly identify infected patients who require immediate isolation and further clinical confirmation needed.

The chest X-ray (CXR) is one of the most significant non-invasive diagnostic supplements that play an important role in the preliminary assessment of various pulmonary disorders[9].

Chest X-ray can be utilized as an alternative technique for screening and identifying COVID-19 or other corresponding diseases; this process is done with the help of expert radiologists who interpret CXR images for infectious lesions associated with COVID-19. Manual interpretation of these minor visual features on CXR images are complex and requires domain expertise. Additionally, when the number of infected patients grows exponentially, it becomes increasingly difficult for the radiologist to finish the diagnosis promptly, resulting in significant morbidity and death[10].

Recent Deep Learning (DL) technology may be used to construct an automated computer-Aided Diagnostic System to combat the Covid-19 epidemic (CAD). Breast cancer [11], melanoma[12], lung cancer[13], and skin cancer[14] are some of the illnesses and anomalies that can be detected using this technique. Similarly, building a fast and efficient CAD system that can detect Covid-19 and pneumonia using chest X-ray images is crucial to preventing the health system from failing and limiting the number of infections among healthcare workers[15, 16].

This study's contribution may be summarized in the following points:

1-The suggested system classifies chest X-ray images into normal, pneumonia and Covid-19 cases using Transfer learning techniques (MobilNetV2) for feature extraction and XGBoost as a classifier.

2- The proposed approach is a framework that removes the need of hand-crafted feature extraction techniques which required time and efforts that require significant substantial processing.
3- Because the suggested model is speedy and lightweight, it could be performed on minimal power consumption devices, which can then be employed in health facilities to reduce the strain on the health system caused by the rising incidence of infections.

II. Related Work

Researchers have used DL-based methods to solve a variety of difficult medical problems, including skin cancer [14], brain disease [17], breast cancer [11], pneumonia detection, and lung tumor segmentation [18].Additionally, Numerous clinical and radiological investigations presenting various radio imaging findings and epidemiology of COVID-19 [6, 8, 19]. In [20], the authors used hybrid chest radiography (Chest X-ray) image model using a DL-based decision tree (DT) classifier to identify COVID-19. This classifier was tested on a set of three built binary DTs. Use the Torch library by comparison. For the third DT, the Decision tree accurately categorizes X-ray images as Healthy or unhealthy with 95% accuracy. In [21], the authors have developed and effectively verified the DeTraC system, a deep CNN for identifying COVID-19 patients from their chest X-ray scans. 11 SARs, 105 COVID-19, and 80 healthy individuals are included in the dataset for chest X-rays. They proposed a decomposition strategy for inspecting the dataset for anomalies by finding class borders and used that knowledge to acquire a high accuracy of 93%. In[22],The performance of state-of-the-art convolutional neural network architectures developed earlier for medical image classification was evaluated using a collection of CXR images from patients with pneumonia, proven COVID-19 disease, and normal occurrences. According to the findings, transfer learning can be used to extract important aspects associated to the COVID-19 condition. Brunese [23] showed how to detect COVID-19 from X-rays using a deep learning method. The strategy was broken down into three steps. CXR was initially used to look for symptoms of pneumonia.. Secondly, COVID-19 was recognized from pneumonia. Finally, COVID-19 location in chest X-ray was detected. The results was with a detection time of about 2.5 seconds and an overall accuracy of 97%. In [24], the authors suggested a DL model which was trimmed iteratively. COVID-19- symptoms were tested using X-ray images. In this approach , COVID-19's unique features representations were learned utilizing a customized CNN and an ImageNet-trained model. Using the newly gained knowledge, patients were classified as COVID-19-viral abnormalities, normal, or bacterial pneumonia cases. In experiments, the proposed model works well, with an accuracy of 99.01% and an AUC of 0.9972%.

III. Materials and Methods

The proposed system for detecting and classifying patients as a COVID-19, Pneumonia, and Normal are illustrated in Figure 1. The train and testing set are utilized throughout training and testing process. The proposed model consists of Three main parts: Feature Extraction, Dimensionality reduction and Classification.

The MobilNet V2 architecture extracts features and followed by a classifier. After extracted these features from images, the Linear Discriminant Analysis (LDA) reduce these features to make it suitable as an input to the classification process which XGBOOST classifier are employed to classify X-ray images.

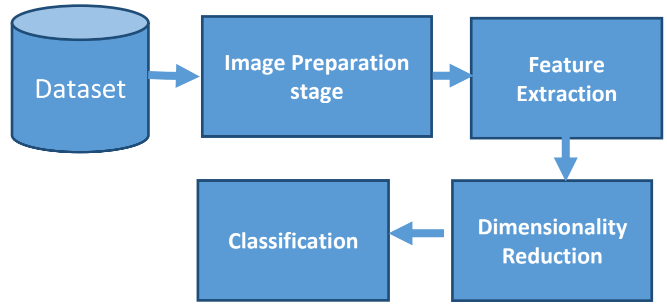

Fig. 1: Block diagram of the proposed system.

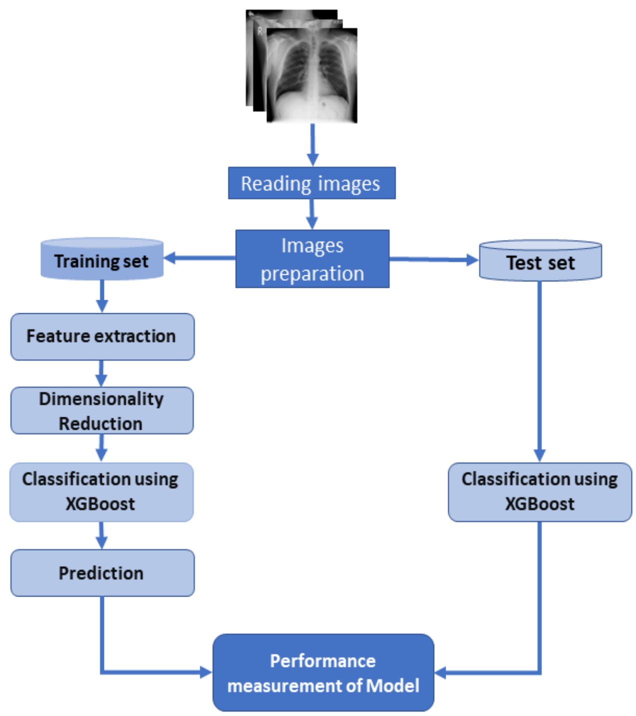

Fig. 2: Flowchart of the proposed system.

A. Datasets acquisition

In this paper, a dataset which was taken from a public repository have been employed. The dataset produced by a team of researchers from the University of Qatar, Dhaka University in Bangladesh, and its Malaysian and Pakistani collaborators. The dataset can be found in the Kaggle repository website as "Covid-19 radiography dataset"[25]. This dataset includes 3,616 X-ray images of Covid-19 patients, 1,345 of viral pneumonia cases, and 10,192 images of normal X-rays.

TABLE I
DATASET DESCRIPTION

Dataset	Num. Classes	Normal	COVID-19	Pneumonia
Covid-19 radiography dataset	3	10,192	3,616	1,345

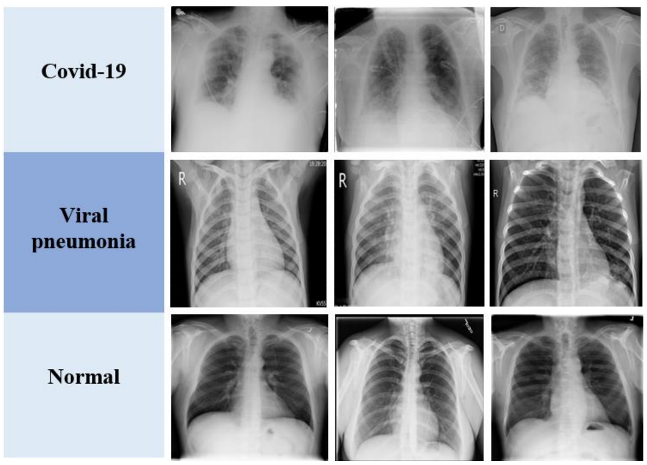

Fig. 3: Chest X-ray images of patients with COVID-19, viral pneumonia, and normal individuals.

B. Image Preparation Stage

Pre-processing aims to make the images more suitable for further processing. The preparation approaches will consider several features of the dataset's set of images.

The first method is to convert all images in the dataset to 128X128 pixels and take only files PNG extension. The primary purpose of this reduction of images is to speed up the training process and achieve accurate testing results. The final step in the image preparation is accomplished by using the Label Encoding method.

This process is concerned with converting categorical labels into a numeric format so that Machine Learning algorithms can understand them. The LabelEncoder() function in the sickit-learn library handles this.

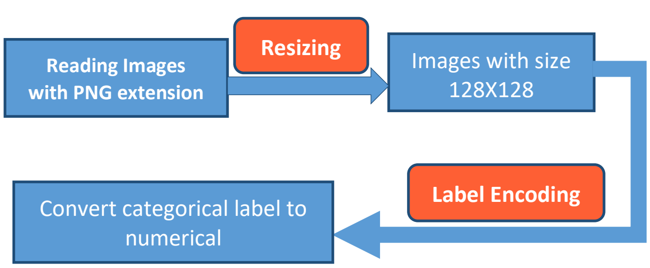

Fig. 4: Image preparation stage.

C. Feature Extraction stage

After the pre-processing stage, features are extracted to characterize the diseased area. The most important aspects of the images are retrieved for further use in the classification process. This study's feature extraction aims to identify the number of features in the X-ray image dataset to be prepared for the next stage. Accurate feature extraction is one of the essential processes in machine learning, which allows its algorithm to learn from raw input data and produce reliable results.
Deep Learning algorithms are one of the most powerful strategies for detecting and extracting characteristics. Deep learning is a technique for extracting information from images. Deep Learning techniques are one of the most powerful strategies for detecting and extracting features. Deep learning is a technique for extracting information from images. Transfer learning is utilized in this study to retrieve data from pre-trained CNN models (MobileNetV2).

D. MobileNet V2

A MobileNetV2 algorithm was used as a feature extractor in our proposed system. The algorithm performs magnificently in segmentation, classification, and object recognition, allowing it to be used as a backbone for image feature extraction. And because of the speed, lightness, and decrease in network complexity of this method. It delivers good performance quickly, which makes it used in a variety of real-time applications[26, 27]. The following figure 3 show the structure of MobilNet V2 structure.

ReLU6 is also employed as an activation function, because of its resilience when performing low-precision operations. Equation 1 show the formula of RelU6.

$$ReLU6(x) = \min(max(x, 0), 6) \quad (1)$$

MobileNetV2 employs (depth-wise separable convolutions), a modified version of traditional convolution. The expansion layer will act as a decompressor on the inputs and restore them to their original form. The projection layer then compresses the data to make it more undersized before applying depth-wise. As a result, the block's internal operations use high-dimensional data, but its input and output use low-dimensional data.

E. Dimensionality reduction stage

LDA is a supervised machine learning algorithm. It computes the direction of the "linear discriminant" that indicates the axis that maximizes the separation between multiple classes[28].

Following the feature extraction stage, the features extracted from images may be excessively massive especially if the dataset contains a significant quantity of data (11364, 20480) extracted feature. This set of features requiring a large computer hardware and a long time to process. The LDA approach was utilized in this work to minimize the number of features. The main goal of LDA is to reduce processing costs by projecting many features into a smaller space with a high degree of separation. LDA results on these CXR features was from (11364, 20480) to (11364, 2).

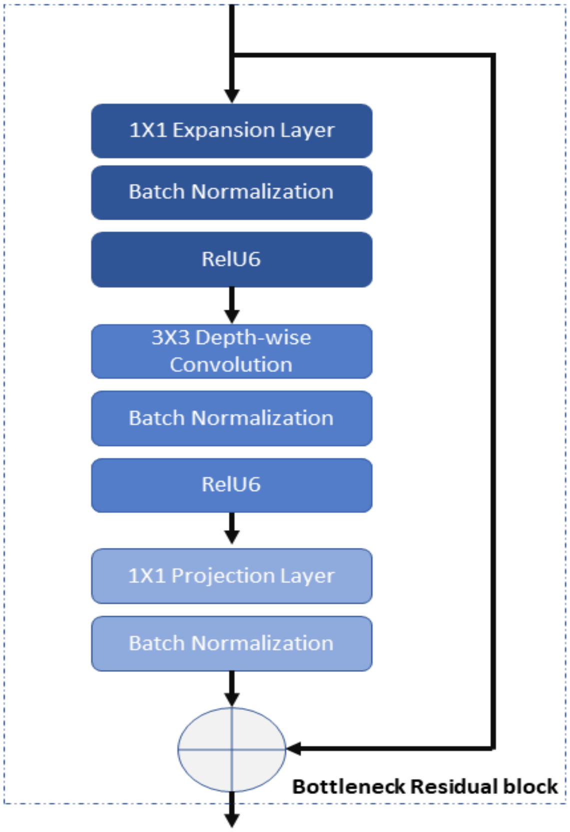

Fig. 5: Structure of MobilNetV2 algorithm[27]

F. *Classification Stage*

In our study, and after the features reduced, the XGBoost classifier was used to classify the input chest X-ray dataset into three categories (Covid-19, Normal, and Pneumonia) due to its efficiency and scalability that allow it to be a fast execution algorithm[29]. The XGboost classifier constructed with its initialization hyperparameters. The most important mathematical equations that are used in the mathematical operations of the XGBoost model is:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), f_k \in W \quad (2)$$

Equation (2) calculate the predicted value ($\hat{y}_i$) of a trained model with K trees.

$$W = \{f(x) = \mu_{l(x)}\} \quad (3)$$

In equation (3), W is the classification and regression trees (CART) and $f(x)$ is refer to the regression tree. μ represent the leaf score, while $l(x)$ represents the leaf node.

$$\hat{y}_i^t = \hat{y}_i^{t-1} + f_t(x_i) \quad (4)$$

From equation (4) it can estimate the predicted result. (t is the number of iteration)

Hence, the purpose of choosing XGBoost as a classifier is because of its ability to process a different types of data, and have a wide range of hyperparameters that can be optimized.

IV. Performance Metrics

The accuracy, precision, F1-score, and recall are calculated using equations (5) to (8). They're utilized to assess the three categories [30].

$$\text{Acc} = \left(\frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} * 100\right) \quad (5)$$

Example: the accuracy of Covid-19 patients is calculated as following:

$$\text{Acc}_{\text{covid}} = \frac{0.9+2.7}{0.9+2.7+0.008+0.09} = 0.97$$

$$\text{P} = \frac{No.of\ true\ positive\ prediction}{\sum True = TP+FP} \quad (6)$$

$$\text{R} = \frac{No.of\ true\ positive\ prediction}{\sum Number\ of\ all\ positive\ assessment = TP+FN} \quad (7)$$

$$\text{F1} = \frac{2\ X\ precision\ X\ recall}{precision+recall} \quad (8)$$

V. Computing Environment

In this study we have trained our Model using Dell Laptop with 8 GB Ram, NVIDIA GeForce GT 2 GB display card, Windows 10 Pro 64-bit, and Python as a programming language.

VI. Experiment and Result

In this study, four main stages that detect and classify the Chest X-ray into three classes (Covid-19, Normal, and Pneumonia) X-ray images are used. Initially, the data are prepared in the image preparation stage to initiate the X-ray images and split the dataset into 75% of training data and 25% for testing the model that prepares it for the next stage.

In stage two, the MobilNet V2 is applied as a feature extractor. Next, In stage three, the Linear Discriminant Analysis (LDA) is used to reduce the number of extracted features.

Finally, The XGBoost classifier was used to classify the Chest X-ray images into (Covid-19, Normal, and Pneumonia). The Default hyperparameters of XGBoost are shown in Table II.

TABLE II
XGBoost Default Hyperparameters

Parameter	Default Value
max_depth	6
learning_rate	0.3
Booster	'gbtree'
gamma	0
subsample	1
colsample_bytree	1
colsample_bylevel	1
colsample_bynode	1
reg_lambda	1

Furthermore, Table III present a TP, TN, FP, FN values to show how performance metrics will calculated.

TABLE III
PERFORMANCE MEASUREMENT OF XGBOOST MODEL

Class	TP	TN	FP	FN
COVID-19	0.9	2.7	0.008	0.09
Normal	1	1.803	0.17	0.005
Pneumonia	0.9	1.995	0	0.083
Total	2.8	6.498	0.178	0.178

Table IV shows the performance metrics for the XGBoost model trained on test data of the “Covid-19 radiography” dataset. The ROC curve and confusion matrix is shown in Figures 6 and 7, respectively.

TABLE IV
EVALUATION METRICS OF XGBOOST MODEL

Class	Accuracy	Precision	Recall	F1-score
Covid-19	0.97	0.99	0.91	0.95
Normal	0.94	0.85	0.99	0.91
Pneumonia	0.97	1	0.91	0.95
Overall	0.96	0.95	0.94	0.94

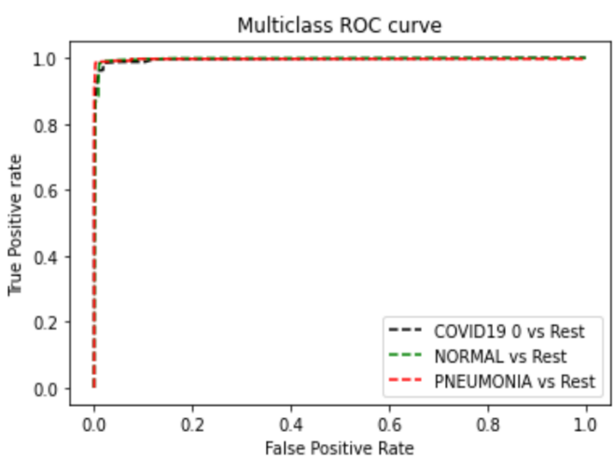

Fig. 6: ROC curve for the Classes.

TABLE V
CONFUSION MATRIX OF XGBOOST

		Predicted			Total
		A	B	C	
Actual	**A**	0.9	0.09	0	0.99
	B	0.005	1	0	1.005
	C	0.003	0.08	0.9	0.983
Total		0.908	1.17	0.9	2.978

VII. COMPARISON WITH OTHER RELATED WORKS

Diagnosing Covid-19 using chest X-ray images has many strategies that have been proposed in the literature. However, each study's approach and a number of classes differ, which should be considered when comparing results. The proposed strategy is compared to several relevant approaches in Table V.

TABLE VI
COMPARISON OF SOME OF THE RELATED LITERATURE WORK WITH THE PROPOSED METHOD

Work	Num. Classes	Method	Accuracy
[20]	3	3 Decision tree	0.95%
[21]	3	DeTrac-CNN	0.93%
[22]	3	Transfer learning-CNN	0.96%
[31]	2	Deep CNN	0.94%
[32]	2	Transfer learning	0.80%
[33]	2	residual convolutional neural network	0.95%
[34]	4	Xception	0.89%
This paper	3	XGBoost-MobilNet V2	0.96%

VIII. CONCLUSION AND DISCUSSION

According to statistics provided by [35], the COVID-19 disease has infected over 60 million people in 218 nations and territories worldwide, with more than 60 million infected cases. Everyday life, public health, and the world economy have been disrupted. Pathogenic laboratory tests such as PCR take along to give false-negative results. This study proposes a CAD system with machine learning and deep learning techniques to classify and detect COVID-19 cases in chest radiographs (X-ray).

The proposed method begins by using the MobilNetV2 which achieved significant results by extracting the features from X-ray images and then decreasing the extracted features with LDA (decrease it from 20480 to 2 feature). Eventually, the XGBoost classifier classifies the X-ray images into three categories (Covid-19, normal, and pneumonia). The proposed approach produced excellent results on the "Covid-19 radiography" dataset of X-ray images. The accuracy, precision, recall, and F1-score obtained were 0.96%, 0.95%, 0.94%, and 0.94%, respectively.

Therefore, research forecasts can also greatly assist authorities in taking timely measures and making decisions to contain the COVID-19 crisis. This research will continue to develop in future courses.

For future work, we plan to examine prediction methods with different methods or update the existing dataset to gain the most accurate and appropriate ML methods for forecasting. We recommend trying other classifiers such as AdaBoost and Gradient Tree Boosting and adding more classifications related to chest X-ray abnormalities such as pleural effusion, embolism, emphysema, and lung scarring.

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I would like to dedicate all this success that I reached at this stage of my study and what I have achieved so far, to the greatest and kindest person who helped me achieve my goals and ambitions. May God have mercy on you and make your abode heaven, grandfather.

CONFLICT OF INTEREST

The authors have no conflict of relevant interest to this article.

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