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A SYSTEM THAT USES ARTIFICIAL INTELLIGENCE TO DETERMINE THE TYPES OF EPIDEMICS USING X-RAYS

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Abstract—

The COVID-19 epidemic has put many lives in jeopardy from the very start. This study models the detection of epidemic kinds using the visual geometry group network (VGGNet). One hundred twenty-six thousand chest X-ray pictures were selected from the Kaggle database and analyzed in four categories: pulmonary TB, normal lung, pneumonia, and COVID-19. Using the chest X-ray pictures, we were able to identify and categorize the aforementioned condition using the VGGNet architecture. We test characteristics like sensitivity, specificity, and accuracy to see how well these classes work. According to the metrics that were assessed, the specificity was 0.96, the accuracy was 0.97, and the sensitivity was 0.98. This method is able to distinguish between various illnesses by properly identifying variations in X-ray pictures taken from patients. The findings shown that when it comes to epidemic diagnosis, the VGG16 model may outperform VGG19. A quicker diagnosis and better prognosis for patients are both made possible by the VGG16-based method. Additionally, the results demonstrated that compared to computed tomography (CT) pictures, the suggested model using chest X-ray images is more accurate, easier to implement, and cheaper. Deep learning, chest X-ray pictures, COVID-19, image categorization I.

INTRODUCTION

Severe pneumonia caused by coronavirus 2019, or COVID-19, may vary in severity from patient to patient based on their immune system. The Chinese city of Wuhan was the first site of this pathogen's discovery in December 2019 [1, 2]. Some of the first symptoms that COVID-19 patients may experience are a high temperature, dry cough, muscle soreness, fatigue, shortness of breath, and loss of appetite. If left untreated, these symptoms might progress to ARDS, arrhythmia, and shock. A mild respiratory infection caused by COVID-19 may not always need antibiotic treatment. Conversely, the virus is more likely to infect those who already have preexisting medical conditions, such as diabetes, chronic lung disease, or cardiovascular disease [3, 4]. More and more COVID-19 patients are flooding healthcare facilities, thus researchers are searching for faster and more accurate ways to diagnose the virus and detect antibodies. X-rays and CT scans are widely accessible and reasonably priced at public health centers, emergency departments, and rural health clinics. The rapid detection of COVID-19-induced lung infections [5] is facilitated by their usage. Since it takes so long and only detects a sensitivity of 60–70%, the RT PCR approach is not ideal. It is possible to guarantee early treatment by analyzing pictures of patients' lungs to identify the detrimental effects of COVID-19. Along with RT-PRC, CT scanning may provide a more sensitive way for diagnosing COVID-19 pneumonia and other lung pathological alterations (Laya Mahmoudi, Faculty of Management and Accounting, AllamehTabataba'i University Tehran, Iran, laya.mahmoudii@gmail.com). It is common practice to wait a long period after symptoms begin before scheduling a CT scan [5]. In nations where testing kits are limited, X-rays and chest CT scans are typically utilized to detect COVID-19, hence clinicians are advised to rely solely on these findings when making decisions. Researchers have shown that a mix of laboratory data and clinical imaging features may help detect COVID-19 at an early stage [5]. By combining CT and X-ray scan pictures of the lungs with modern data mining and machine learning methods like Convolutional Neural Network (CNN),

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the condition may be detected rapidly and reliably, reducing the issue of testing kit shortage. This study recommends deep learning for COVID-19 detection in X-ray images, with a focus on transfer learning. An improvement to the VGG-16 and VGG-19 convolutional neural networks is also recommended for this task. The radiologist may find this material helpful in quickly identifying the X-ray regions of interest. The paper is organized as follows: In Section 2, we review the relevant literature; in Section 3, we detail the methodology; and in Section 4, we provide the results of the experiments, including a comparison and assessment of their performance. The study's conclusions, which will be used in future publications, are presented in the last part.

RELATED WORK

Automated categorization of digital medical pictures makes use of many machine learning techniques. Visual characteristics used for detection, diagnosis, or classification may be determined by machine learning pattern recognition. There are three common ways to categorize the methods used to train machine learning algorithms: supervised, unsupervised, and reinforcement learning. Acquiring experience with useable photos and using that information to anticipate new, unseen images (test data) is what supervised learning is all about [1, 2]. In order to identify COVID-19, researchers have suggested a deep learning method in [6, 7]. To determine whether current antivirals may help patients infected with COVID-19, Zhang et al. [8] trained the DenseNet network using COVID-19 RNA sequences. Kong et al. [9] reported that a patient with severe COVID-19 had opacities in the right place. Additionally, Yoon et al. [10, 11] discovered that, in the lower left lung area, one out of three patients had one nodular opacity. The left and right lungs showed four and five irregular opacities, respectively. The Convolutional Neural Network (CNN) is a well recognized AI approach that has gained significant attention in recent years. CNN has been successful with several medical image analysis, including magnetic resonance imaging (MRI)[12,13], x-ray [14], computed tomography (CT) scans [15], and ultrasound [16]. There are several areas where CNN has been successful, including language communication processing [17], computer vision [18], audio recognition [19], and voice recognition [20].

Suggested Approach

In this study, a convolutional neural network (CNN) is trained using the transfer learning technique. In this research, a pre-trained convolutional neural network (CNN) with maintained weights was imported into the ImageNet database and trained using the transfer learning technique on the dataset. Since the vanishing gradient issue makes it difficult to train the network's first layers, using the transfer learning approach to train the CNN has the benefit of previously having taught them. Alternatively, the network has mastered fundamentals like form detection and picture edge detection, among others. Therefore, the pre-trained model makes use of the pictures in the current database's fundamental learning characteristics. In figure 1 are the stages that make up the suggested approach.

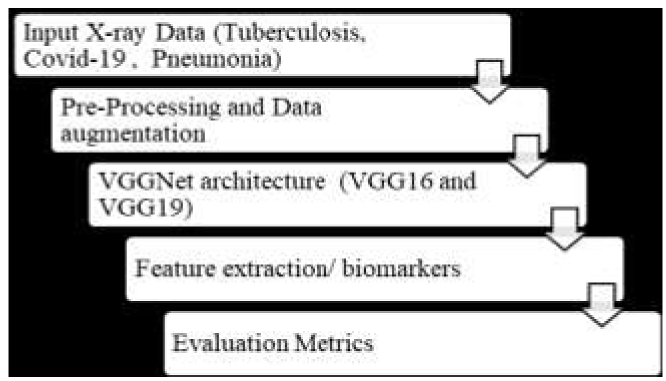

Fig 1. Show the steps of the proposed method

Computer time is reduced using his coaching approach [1,2,4,6,10,11] as just the last levels of the network need to be taught. The whole flow diagram showing the phases of the proposed technique is shown in Figure 1. The exploitable architecture that we tailored to our requirements is shown in Figure 2. To verify that the proposed models are generalizable, we enhance the data by rotating the random picture fifteen degrees in each direction.

Using a model that was trained on one issue to predict labels for another problem is known as transfer learning [22]. Shortening the time it takes to train a neural network model is the biggest benefit of using transfer learning. Additionally, it might lead to a decrease in mistakes made while generalizing. Connecting the primary and secondary issues is essential. To address the issue of lung sickness diagnosis in this case, we use the knowledge of a

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model trained for general image recognition. Sixteen convolution layers, three fully linked layers, five MaxPool layers, and one SoftMax layer might make up a VGG model with nineteen members, denoted as VGG19. We also have VGG11 and VGG16, which are other variants of VGG. There are 19.6 billion FLOPs in VGG19. It's possible that VGG-19 is a deep convolutional neural network with 19 layers. From the ImageNet database, you will get a pre-trained network version that has been trained on more than 1,000,000 pictures [12, 13, 23]. Transfer learning is implemented by fine-tuning. We removed the fully connected layer head and instantiated the VGG19 network with pre-trained weights on ImageNet to prepare the VGGNet model for fine-tuning. Next, we use the following layers to construct a new fully-connected layer head for class prediction: Starting with AveragePooling2D, moving on to Flatten, Dense, Dropout, and finally Dense activated with the "softmax" function. On top of VGG19, it is layered. After that, we train just the fully connected layer head and freeze the convolutional weights of VGG19. This completes our fine-tuning setup. In figure 2 is shown the structure of the suggested approach.

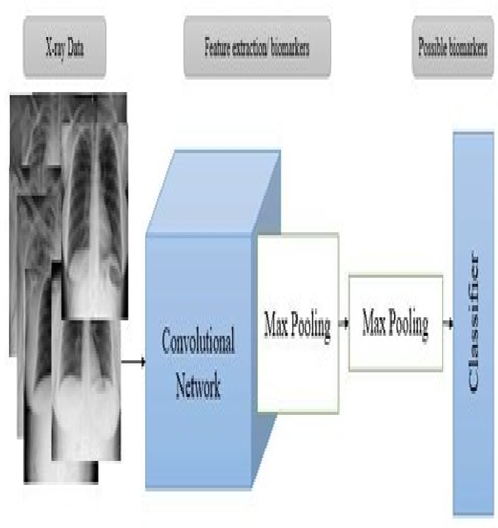

Fig.2. Structure of proposed method

Initial preparation One common procedure in computer vision is pre-processing. The picture component is prioritized by preprocessing approaches, which may aid recognition or even deep learning training. The following steps were taken before the DICOM pictures were processed:

Image pixel value normalization.

Removing the white space around the photos by cropping them. Because there is some inconsistency in the data set and in the sizes of the by-ray pictures, we normalized all of the images to 224 by 224 pixels. In the end, 224 224 3 images were entered into the suggested model after RGB reordering. We used a 20-degree rotation range for the information augmentation due to the constrained nature of the data source. By flipping the X-ray pictures horizontally and vertically, a lot more information may be extracted. Using the same data sets, this database may provide feedback on new concepts. Using a dataset of 12,068 chest X-rays, our AI system is now undergoing testing and evaluation. The model was trained using 75% of the database photos, with 15% being used for testing and 10% for assessment. They don't mess with the patients and there are different sets for testing and training. C. Enhancement of data Data augmentation is a method that significantly expands the quantity of data at your disposal. The distribution of X-ray photographs in each of the four classifications—normal/healthy, viral/bacterial pneumonia, and COVID-19 infection—as obtained from the two databases is shown in Figure 3. Consequently, in order to avoid overfitting, augmentation approaches increase the quantity of pictures belonging to COVID-19 and other classes. Rotation and Gaussian blur were used as methods for enhancing the data in this investigation [1, 2].

Suggested Approach Improvement In this study, a convolutional neural network (CNN) is trained using the transfer learning technique. In order to do this, this research presents a deep learning-based enhanced convolutional neural network using VGG-16 and VGG-19. Here is the approach that has been suggested for screening epidemics using x-rays. We trained the models using X-ray pictures from patients with pneumonia, SARS-CoV-2, and healthy controls, modifying the VGGNet architecture. The x-ray images undergo the pre-processing procedures detailed below after being extracted from the datasets discussed above. If chest x-rays reveal no abnormalities or indications of lung disease, the suggested approach may help diagnose the problem. The first model and the second model are built using a deep learning network that is based on the Visual Geometry Group (VGG) models [2] and transfer learning. When compared to standard convolutional neural networks, the in-network depth is much better. By switching between many convolutions and nonlinear activation layers, it achieves a superior structure compared to one. The layer structure

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improves feature extraction, uses Maxpooling for low-sample applications, and activates with the linear unit (ReLU). The site's pooled value is determined by picking the most significant value in the picture region. The three datasets that were taken into account in this study are detailed in this section. To the best of our knowledge, these are the three largest publicly available datasets. A database of chest X-rays for tuberculosis (TB) A database of chest X-ray pictures including both normal and tuberculosis (TB) positive patients has been developed by a group of researchers from the Universities of Dhaka in Bangladesh and Qatar University in Doha, Qatar. This paper's database includes 3047 pictures, including 3047 representative images and 3047 photos. This tuberculosis database was built from the following URL: https://www.kaggle.com/tawsifurrahman/tuberculosiss-tb-chest-xray-dataset. Chest X-ray Database for COVID-19 COVID-19 Radiography Database (Recipient of the COVID-19 Dataset Award from the Kaggle Community) Using a combination of medical professionals, colleagues from Pakistan and Malaysia, and researchers from Bangladesh's University of Dhaka and Qatar University's Doha, Qatar, a database of COVID-19 positive patients and normal and viral infection photos has been created. This paper's database was generated using 3006 Covid-19 photographs. Gathered from https://www.kaggle.com/tawsifurrahman/covid19 is the database description. pneumonia radiography database Database of Chest X-rays This lung infection was identified using a dataset consisting of 30,60 verified chest x-ray pictures from the pneumonia database. The data for this database came from the following source: https://www.kaggle.com/paultimothymooney/chest-xray pneumonia. Best wishes In Table I, we can see a summary of the data set and the problems that were found. The correlation between picture count and patient count for each category is seen below.

TABLE I. Datasets distribution.

Classes	DR condition	NO. of image
0	Normal	3047
1	Covid-19	3006
2	Pneumonia	3060
3	Tuberculosis	3047

Assessment Criteria Deep learning systems trained to identify and categorize lung nodes are evaluated using a variety of standards. We determined the accuracy, sensitivity, and specificity of our suggested CNN model to evaluate its performance.

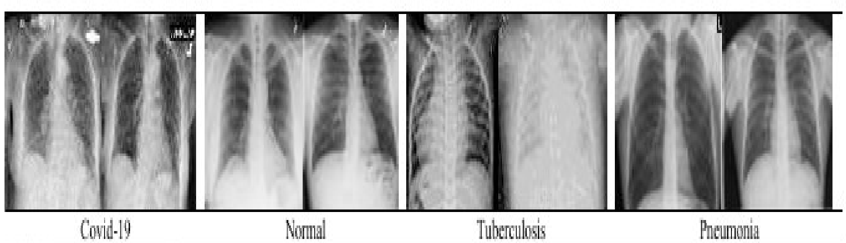

Fig.3. Examples of images used

Precision: Show the proportion of "correct predictions made" to total "total predictions made" for that class [24–27, 33–35].

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

A tiny fraction of cases, as estimated below, will have a positive model result if the person's result is

positive. This is known as the sensitivity, real positive rate.

$$Sensitivity = \frac{TP}{TP+FN} \quad (2)$$

TABLE II. Confusion Matrix.

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Confusion Matrix		Classified As:	
		Negative	Posi
Actual Class	Negative	TN	F
	Positive	FN	T

The Confusion Matrix, as its name suggests, provides a matrix as an output and details the model's overall performance.

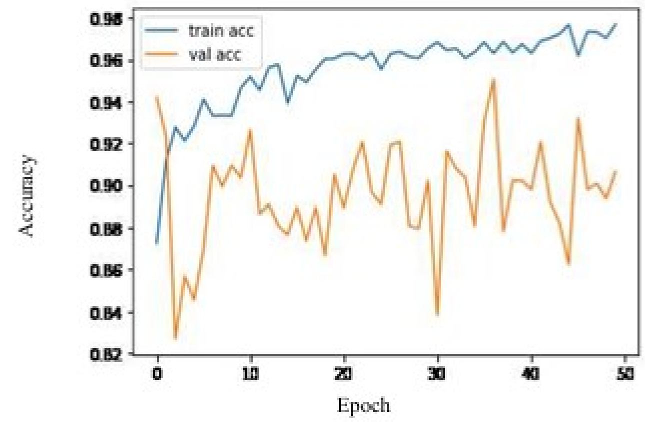
TABLE III. SOFTWARE REQUIREMENTS.

Distribution	Anaconda Navigator and Google Colab
API	Keras
Library	Tensor Flow, OpenCV
Packages	Matplotlib, NumPyNumPy, pandas, sci-kit learn
Language	Python 3.7
IDE	Jupyter Notebook
GPU Architecture	Google Colab
Applications	labeling, TensorBoard

Research Based on Experiment This work shows that the three most popular medical imaging modalities—X-ray, ultrasound, and CT scan—are used to diagnose COVID-19 using transfer learning from deep learning models. The concept is to use intelligent, deep learning image categorization algorithms to serve as an additional pair of eyes for overworked medical personnel. Here we go over the procedures we used in our experiment to see how well the different methods worked in terms of: How to tell the difference between a regular chest X-ray and one that might indicate lung disease. Diagnosing COVID-19 from a chest X-ray associated with pneumonia.

TABLE IV. VGGNET architecture results in different parameters.

	Optimizer	Batch size	Epochs
VGG19	Adam	32	20
	Adam	32	5
	Adam	16	10
	RMS prop	32	20
VGG16	RMS prop	64	15
	Adam	32	50



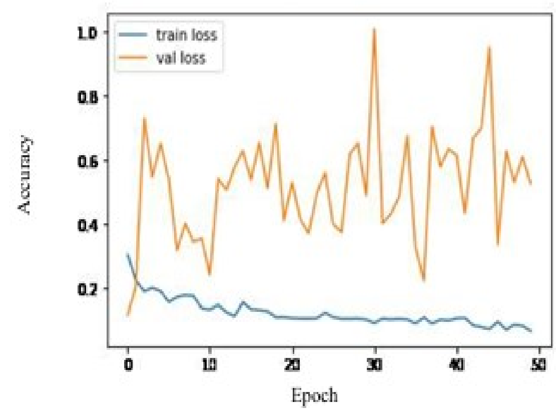


Fig.4. Result of VGG16 During the training of the CNN model,

Figure 4 displays the loss curves and classification accuracy in both the train and validation sets. Performance indicators, including convergence graphs of loss functions for several transfer learning techniques, are summarized in Table IV of the experiment. Denoted by "train" and "Val," respectively, are the training and validation loss convergence curves. Figure 5 displays the output of the VGG16 algorithm's classification process fed the covid-19 X-ray picture. D. Radiologist's Findings: In order to inform future investigations, the study team contrasted AI results with those of human radiologists. Radiologists prepared and used a large amount of actual data to do this. This method outperformed master radiologists and specialists, with the latter two performing somewhat worse. Doctors' workloads are reduced by this system. Artificial intelligence can scan a CT picture in 2.73 seconds, compared to the 6.5 minutes it takes radiologists, according to studies. Compared to radiologists, AI performed somewhat worse when it came to detecting pneumonia, as shown in this paper. The current model's accuracy in comparison to the real

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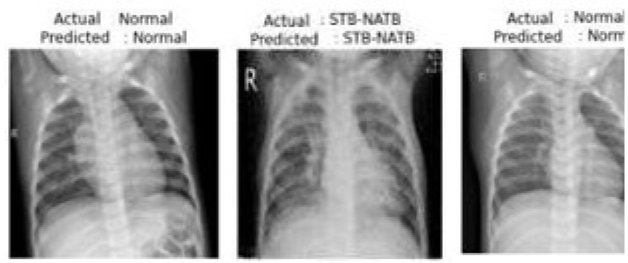
data is shown in the table below. The training of the model does not make use of this data. The current model's accuracy in comparison to the real data is shown in Table V.

	Sample	Radiologist			
		NPV	PPV	Time	NP
Normal	50	0	50	15 Min	15
Covid-19	50	7	43	15 Min	21
Pneumonia	50	8	42	15 Min	19
Tuberculosis	50	19	31	15 Min	16



Discussion

A powerful tool for medical professionals, deep learning can interpret chest X-ray pictures and feed them into the model to diagnose illnesses. Typical chest X-rays revealed pneumonia, tuberculosis, and COVID-19 bacteria. An AI-based approach that can reliably differentiate COVID-19 from pneumonia and pulmonary TB is presented in this work. The suggested method may aid doctors in identifying patients with COVID-19 in a setting where such mistakes are widespread. For medical facilities that do not have access to CT scanners, this method may prove lifesaving. More complex models, like VGG-19, lost performance because to overfitting issues and an inability to properly represent inter-category differences. We selected the top-performing VGG-16 model to study COVID-19, pneumonia, and tuberculosis viruses in the future. An alternate diagnostic technique for COVID-19 case detection may be the one described here. Last but not least, all previous studies have demonstrated promising results, therefore the present study suggests that COVID-19 should be visible using deep learning models. It seems that deep learning models are able to accurately identify objects in photographs, as seen by the high levels of accuracy reported by various methodologies. This enables deep networks to perform image classifications. It will be some time before we know if deep learning algorithm findings can be relied on for accurate diagnosis.

Study	Model	Accuracy (%)
Debabrata Dansana et al [28].	VGG-19	91%
Chiranjibi Sitaula et al [29].	VGG16	87.49
Ayan KumarDas et al. [30].	VGG-16	97.67
Ki-Sun Lee [31].	VGG-16	95.9%
Shamik Tiwari,Anurag Jain [32].	VGG-CapsNet	92%
This paper (VGG16)	VGG16	97.99%

Additionally, healthcare systems throughout the globe are under pressure because to the exponential growth of COVID-19 patients. Due to the scarcity of testing kits, conventional methods cannot be used to diagnose every patient with the illness (RT-PCR). But this isn't enough to justify the tests' poor sensitivity and lengthy execution times. Patients in high-risk quarantine who are suspected of having COVID-19 may benefit from having a chest X-ray taken while they wait for test results. The majority of healthcare systems already own X-Ray equipment, and the most up-to-date X-Ray systems have already been digitalized, so there's no need to transfer the samples. VGGNET was taught to distinguish between normal, pneumonia, TB, and COVID-19 X-ray pictures using three publically available datasets and novel methods. Chapter Six: Wrapping Up The small quantity of tagged data points was a result of the early stage of the illness. This led to a reduction in the dataset's size and amount of data points used. The possibility of overfitting exists. It is common to see better outcomes as the dataset size is raised. Two independent models, each capable of performing the aforementioned classification tasks, make up our present offering. The effective grouping of chest X-rays into the suggested classes may be possible in the future with the use of an architectural framework. We used the VGG-16 and VGG-19 models for the classification tasks. We tested several different models, and the results were all over the map (see Table IV). In conclusion, the sensitivity rate and accuracy for identifying epidemic categories have both been enhanced by 98.26% and 97.99%, respectively, in the updated network model. It is well recognized that this enhancement has a significant effect. In addition, the parameters have been significantly reduced, and the improved VGG-16 shows great potential in identifying epidemic detection categories. It also offers a positive assurance before hospital admission. In the interest of better medical diagnosis, we have built a network of highly skilled professionals. The study's limited usage of COVID-19 X-ray images is another drawback. Eventually, I'd want to see greater COVID-19 statistics made accessible by our local hospitals so that we can improve the precision of our suggested network.

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