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Prediction and Monitoring of COVID-19 using CNN & FPN for Classification Challenges

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ABSTRACT

This research proposes a fast and accurate approach to identify COVID-19 from a patient's chest CT scan. We have used a dataset with 48,260 CT scan pictures from 282 healthy people and 15,589 images from 95 COVID-19 patients. In the first stage, our suggested image processing method evaluates the lung view to eliminate CT pictures that do not accurately show the lung interior. This reduces processing time and false alarms. Next, we provide a unique architecture for enhancing neural network classification accuracy on pictures with tiny key items. Our model uses a unique feature pyramid network built for classification challenges to study multiple picture resolutions without losing data from tiny objects. Because COVID-19 infections come in diverse sizes, our technique greatly improves classification performance. After these two steps, the system assesses the patient's state using a threshold. We are the first to assess our model and our system on Xception. Our model classified over 7996 photos correctly in the single image classification step. It properly recognized about 234 of 245 patients during the patient condition identification phase.

KEYWORDS: Covid-19, Convolution Neural network, Artificial Intelligence, Deep Learning, CT-Scan algorithm.

1. INTRODUCTION

The World Health Organization (WHO) declared an outbreak of a novel viral disease as an international public health concern on January 30, 2020, and on February 11, 2020, the WHO designated the disease caused by the new coronavirus COVID-19 [1]. In Wuhan, China, the first COVID-19 cases were discovered. These patients were linked to the local wild animal market, which suggests that the virus might be transmitted from animals to humans [2].

New coronavirus outbreaks in China and other countries quickly spread across the country. Many political, economic, and sporting events were thrown off course, and the virus had a profound impact on the lives of millions of people
around the world.

The potential of the novel coronavirus to propagate quickly and widely is by far its most crucial attribute. There are two ways in which the virus spreads: directly from an infected person to others, and indirectly through the surfaces and air that they come into contact with. Since the disease can be prevented by appropriately

identifying and quarantining those who are infected, this is an important part of the process. As a result of viral pneumonia in the lungs, severe acute respiratory syndrome occurs. People who are infected with the novel coronavirus experience a wide range of symptoms. Fever, dry cough, and exhaustion are the most common new coronavirus symptoms [1]. There is no onesize-fits-all treatment for this condition. Other signs and symptoms, such as a sore throat, headache, and a loss of taste and smell, can develop in COVID-19-related symptoms such as shortness of breath, chest pain, and loss of mobility or speech are present in some patients, but they are usually severe [1]. This disease can be diagnosed by RT-PCR, Isothermal nucleic amplification test, Antibody test, Serology tests, and medical imaging [3].

COVID-19 and many viral illnesses can be diagnosedwith RT-PCR. However, some experiments can only be performed using this method due to a lack of experience and experimentation. The tests in [4]. The paucity of diagnostic tools in most contaminated places around the world is prompting researchers to develop new and more convenient methods of detecting the disease. For the detection of COVID-19, researchers use CT scans and X-rays, which may be easily obtained at almost any treatment facility. New coronaviruses can be detected in the lungs of most patients with COVID-19 infections and used to identify the condition. The novel coronavirus induced pneumonia in patients with COVID-19, according to an analysis of CT scans [2]. The capacity to identify COVID-19 using CT scans and X-rays has been approved by radiologists, and a number of approaches have been presented to utilize these images. A novel coronavirus has been found to be present in the lungs of most individuals who show symptoms of COVID-19 at least four days after they should have [4]. Medical imaging can be employed for early COVID-19 identification despite the fact that it is not indicated for final diagnosis [5].

On CT scans, some patients with early-onset COVID-19 symptoms had fresh coronavirus infections. In the meantime, their RT-PCR test results were also negative, but the CT scan's diagnostic results were confirmed when both tests were redone several days later. The major diagnostic tool for the COVID-19 can be used to confine the Suspicious individual and prevent the virus from being transmitted to other people in the early stages of the disease, while medical imaging is not indicated for the conclusive diagnosis ofCOVID-19. Medical imaging has the advantage of being able to detect viral infections through machine vision. Deep learning is one of the greatest methods for machine vision [6] and a subfield of Artificial Intelligence (AI). A wide range of industries, from medical to agriculture to economics, have benefited from the use of machine vision and deep learning.

One of the greatest ways to diagnose tumour and infections caused by various diseases is through the use of machine vision and deep learning. Many medical images have been segmented using this method. These include lesions in the brain and skin, applications to breast lesions and lung modules [6, 6], sperm identification, and tracking [7].Radiologists, on the other hand, are notoriously inaccurate in their diagnosis of disease. According to [8], the procedure utilize is roughly 90% accurate, whereas radiologists' diagnosis is about 70% accurate. COVID-19 has been diagnosed using machine vision and deep learning because of their usefulness in medical imaging, particularly CT and X-ray pictures.

Deep learning and computer vision have been greatly improved by convolutional neural networks. Some models, such as ResNet [6], DenseNet [9], EfficientNet [10] and Xception [11], have been introduced since the emergence of conventional layers and have shown reliable results.

Detecting COVID-19 patients from the images (output files) generated by the lung HRCT scanner is the focus of this paper. No medical specialist is needed to configure this system, which takes all CT images of a patient and determines the presence or absence of COVID-19 in that patient. COVID CTset comprises 15,589 scans of COVID-19 from 95 patients and 48,260 images of normal people from 282 people. When we begin our research, we use an image processing technique to identify CT Scan images that show probable lung infections. In this way, the network does not have to examine all of the photos, which speeds up the process. By only supplying the network with appropriate images, we raise diagnostic precision. Finally, we will train and test three deep convolution neural networks to classify the photos we've selected. Improved classification accuracy has been a major goal of our suggested augmented convolution model. We use two alternative methods to assess our model at the very end. One method uses singleimage categorization, while the other uses a completely

automated diagnosis system that has been tested on more than 245 patients and 41,892 photos to make a determination. By utilizing a feature visualization method to segment the infections in the COVID-19 categorized images, we look into the infected areas as well. On a total of 11,302 photos, they were able to identify normal patients, pneumonia, and COVID-19 using Xception and Resnet50v2 networks concatenated together, with an overall accuracy of 99.5. Around 3322 CT scans were chosen from a pool of 3506 CT scans in [12] for the purpose of developing and testing the proposed network, COVNet. COVID-19 was found in half of the patients in a study of 120 CT scans (2482 CT scans), and the best accurate network classification was 97.38 percent [13]. The 287 CT images were taken from patients with COVID-19 or CAP, as well as healthy people;
the data was then classified using an algorithm called CovidCTNet, which had a 90% success rate. In [14], reports on the learning and evaluation of an Innovative Deep Learning Network based on the CT scans of 5372 patients from multiple Chinese hospitals has been presented. Using CT images, the novel coronavirus has been segmented in [15]. These articles [24,25,5,2,29] also used machine learning and deep convolution models to categorize CT Scan and X-ray pictures. To sum up, here's how the document is structured: Detailed descriptions of the dataset, neural networks, and methods will be provided in Section 2. Section 3 presents the experimental results, while Section 4 discusses the study. In this section, we summarise our findings and provide a link to the public codes and dataset.

2. DATASET AND METHOD

A. Dataset COVID-CTset1 [16] is the dataset we've used in our project. From March 5th to April 23rd, 2020, Negin radiology in Sari, Iran, collected the data. Patients' lung HRCT images are captured with a SOMATOM Scope model and the syngo CT VC30-easyIQ software version at this medical centre. Radiology images were saved in DICOM format with 512x512 pixel resolution in 16-bit grayscale. Because the DICOM files contained the patient's private information, we changed them to TIFF format instead. TIFF files still contain the same 16-bit grayscale data, but they do not reveal any personal information about the patients. The standard libraries that come with most programming languages can be more easily integrated into this format. It is one of our new innovations to use a 16-bit data format instead of 8-bit data, which improves classification results. When there are only a few infections in the image that are difficult to detect even by clinical professionals, converting DICOM files to 8bit data may result in data loss. When a computer processes a 16-bit CT scan image, it may be able to discern information that the human eye cannot see. The photos have pixel values ranging from 0 to 5000, with significant variation in the highest possible pixel values. To avoid these issues, it's best to scale the images using a constant value or scaling each image based on its maximum pixel value. COVID-CTset images are all 16-bit grayscale images in TIFF format. A radiology specialist, authors, and clinical experts worked together to segregate photos in which COVID-19 infections are clearly visible. By dividing each image's pixel value by the image's maximum pixel value, we were able to make these images viewable on normal monitors. Images with 32-bit float type pixels were able to be displayed on regular displays, and the quality of the images was sufficient for study. It is shown in Fig. 1 some of the photographs from our dataset.

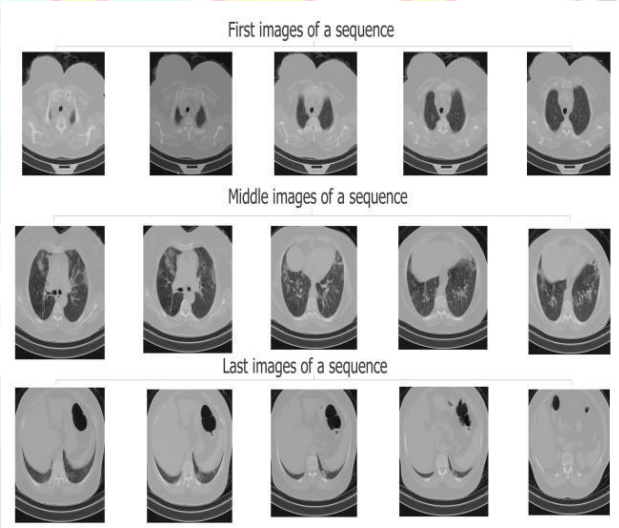

Fig. 1 depicted the first, middle, and final images of a patient's CT scan. There are sequence 15,589 photos from 95 patients infected with COVID-19 and 48,260 images from 282 healthy individualism the COVID-CTset (Table 1). Each patient has three folders, each containing a different thickness of CT scans taken by the CT imaging system.

TABLE I. DATASET DISTRIBUTION

Image Type	COVID-19 patients	Normal patients	COVID-19 images	Normal images
Number	95	282	15589	48,260

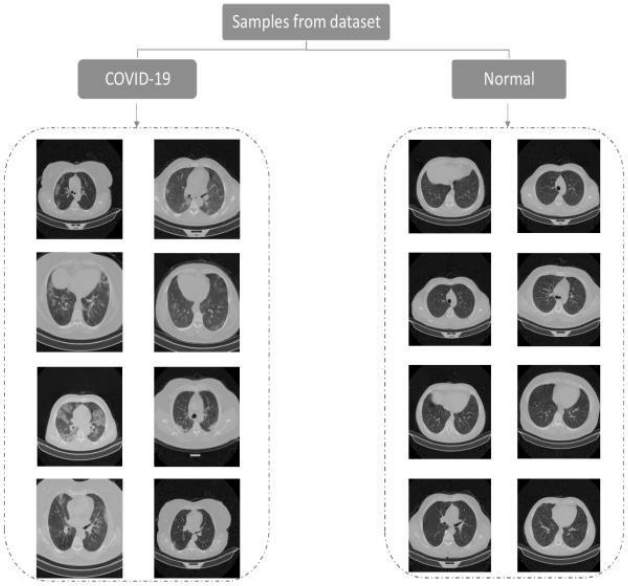

Fig. 2 Samples of Dataset

B. CT SCANS SELECTION ALGORITHM

If the patient is infected with COVID-19, the lung HRCT scanner obtains a series of consecutive images (we can call it a video or consecutive frames) from his chest. The infection spots may be visible in some photographs but not in others of a picture sequence. These photos are analyzed by a clinical professional to determine whether or not the patient has been infected. An image from each patient's lung HRCT was used for training and validation in many earlier approaches. In this case, we opted to automate the patient lung evaluation. If we use a neural network trained to identify CVOID-19 cases based on specific data from within the lung, then we have a leg up on the rest of the field in this regard. Testing that network on every image in a patient's imaging sequence could cause it to fail. Fig. 2 depicts a closed lung at the beginning and end of each CT scan picture sequence. A lack of exposure to real-world scenarios during training means the network may make mistakes in detection and hence perform poorly. For this, we can divide the data into three categories: infection-visible, infection-free, and lung-closed. Despite the fact that this solves the issue, separating the dataset into threeclasses incurs additional costs, such as the need to spend time creating new labels and altering the evaluation method used in the network. It also takes longer to process CT scans because the network will have access to all of the patient's images. However, we've come up with a few more ways to get rid of the images that aren't apparent in the lungs. Because the networks no longer have to see all of the images as in the previous method, this cuts down on the amount of time it takes to execute significantly. Fig. 3 clearly shows that the open lung image has lower pixel values (almost black) in the centre of the lung than the closed lung image. The pixel values in the photos were first analyzed in a location in the centre of the photographs. When comparing open-lung and closed-lung photos, it's important to note the variations in this area. Because the dataset's images were not all of the same scale and because the lung position varied among the patients, we used the images' 512*512-pixel resolution to set the region to range from 120 to 370 pixels on the x axis and 240 to 340 pixels on the y axis as a starting point for our experiments ([120,240] to [370,340]). Images of the middle of the lung should be included in this region to support the inclusion of information. In our collection, we have photos that are 16-bit grayscale. Almost all photographs have a pixel value of 5000 or more in common. This maximum value varies greatly from image to image. At this point, we seek to measure the pixels in the indicated region of each image that have a value of less than 300, which we refer to as "dark pixels," in order to eliminate certain photographs and choose therest for further analysis. Based on the results of our research, we've settled on this particular value. There are no more or less than 300 pixels in a chosen area for each image of a sequence (dark pixels). After that, we'll multiply the difference between the highest and lowest numbers we could find by 1.5 to arrive at the final answer. Our cutoff point is set at this computed value. For example, if the highest number of dark pixels in a CT scan image sequence is 3000, and the lowest number of dark pixels is 30 pixels, the threshold is 2000. The lung is almost completely closed in the image with the fewest dark pixels in the region above the threshold, whereas the lung is visible inside the image with the darkest pixels above the threshold. Because the images in a sequence (CT scans of a patient) have the same imaging scale, we determined this threshold in this manner. However, the results may differ from one CT scan to the next (of

different patients). Those photos with less counted dark pixels than the threshold, are discarded after thatin the centre of the image

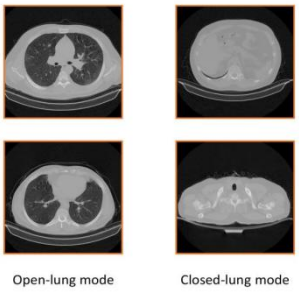

Fig. 3 depicted that closed-lung has higher pixel than open-lung values

C. Enhanced deep convolution neural network for classification

Many fields, including agriculture, biomedical engineering, industry, and more, have benefited greatly from the use of machine vision. The use of convolution layers in deep neural networks, in particular, has resulted in exceptionally accurate performance in machine vision. The selected CT scan pictures exported from the CT scan selection method were classified into normal or COVID-19 using deep convolution networks in this study. Learning and detecting items of various sizes in an image becomes easier with the help of Feature Pyramid Network (FPN) [17]. Earlier techniques relied on feeding the network a picture pyramid (consisting of several scales of the input image) as input. A feature extraction technique can be improved, but the time and resources required to do so are inefficient. By establishing a bottom-up and top-down feature hierarchy with lateral connections from the network's generated features, FPN overcomes this challenge. Using FPN improves detection accuracy when images contain objects of
varying scales without affecting detection speed since it helps the network create more semantic information.

We suggest a new model that makes use of FPN for picture classification, despite the fact that it was originally designed for object detection networks as shown in fig 4. Because several scales of COVID-19 diseases exist, FPN can be used to extract a variety of semantic elements from the image input. Because our model learns better about the infection spots, it is able to detect COVID infections even when they are very small, and more significantly, it detects COVID false positives less frequently.

D. Training phase

Two components make up our dataset. Every person listed in Section II (A) has an own raw data section. Training, validation, and testing data are included in the second portion. We used the TIFF format to convert the photos to 32-bit float types so that they could be viewed on regular monitors. We divided the dataset into five folds for training, validation, and testing in order to provide more actual and accurate results. Nearly a quarter of the patients with COVID19 were given the option of being tested in all three folds. While training, some of the testing data was used to verify the network, and the rest was used for training. It was nearly impossible for us to choose a number of normal photographs to equal the number of COVID-19 images because there were so many more normal patients and images than there were infected ones.

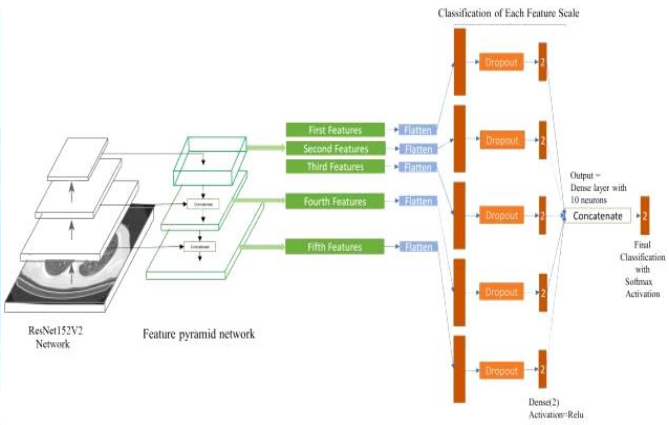

Fig. 4 depicted our model with integration of ResNet152V2 and FPS

Normal photos were considered more frequently for networking testing than the training images because of this. Table 2 summarizes the results of the training and testing process.

TABLE II. TRINING AND TESTING OF DATASET

Fold	Training Set / Testing Set				
	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
COVID-19 patients	77/18	72/23	77/18	81/24	73/22
COVID-19 images	1820/465	1812/462	1824/466	1841/467	1817/464
Normal patients	42/237	35/225	41/244	39/231	43/240
Normal images	1961/7860	1854/7854	1751/7784	1974/7896	1814/7851

Normal photos were considered more frequently for

networking testing than the training images because of this. Table 2 summarises the results of the training and testing process. The number of normal people in the training set is less than the number of COVID-19 patients, which may raise the question of why this is the case. Because some of the patients with COVID-19 had visible infections in their picture sequences for training and testing purposes. A COVID-19 patient's number of pictures is less than that of a normal person. As a result of our selection process, the number of normal photographs is nearly as high as the total number of Class 19 (COVID-19) images. This quantity was sufficient for the network to learn how to accurately categorize the photos, and the results were excellent. We chose a big number of normal photographs for testing since we still had a large number of normal images to deal with. With Xception [11], Resnet50V2 [13], and our model using ResNet152V2 [19] network as a backbone, we ran through 50 epochs of training our dataset. Using pre-trained weights from ImageNet [18] as a source of transfer learning, we were able to speed up the convergence of the networks during training. We used the Nadam optimizer and the Categorical Cross-entropy loss function to get the optimal solution. Additionally, we used data augmentation techniques to speed up the learning process and prevent the network from becoming overfitted by the data.

3. RESULT AND DISCUSSION

As a result, we've divided the information in this section into two parts. Images from the test set were used to train the trained networks, which are then used to classify the images
in this section. The automated system for determining whethera person is normal or COVID-19 is reported in the Patient condition identification section. We used Google Colaboratory Notebooks, which provided us with a Tesla P100 GPU, a 2.00 GHz Intel Xeon CPU, and 12 GB of RAM on Linux to run our algorithms and networks. Keras library
[19] was used to construct and execute the deep networks using Tensorflow backend [20]. Each network was trained using the parameters outlined in Section II (D). To select the
best-converged training network, we employed the accuracy measure to keep track of the network validation results after each epoch. Four criteria for each class and the aggregate accuracy of all classes were used to evaluate our trained
networks [16].

Accuracy (for each class) = TP + TN / (TP + FP + TN + TP) (1)

Specificity = TN / (TN + FP) (2)

Sensitivity = TP / (TP + FN) (3)

ResNet152V2 and FPSPrecision= TP / (TP + FP) (4)

Accuracy (for all classes) = No. of correctclassified images / No. of all images (5)

TP (True Positive) represents the number of correctly classified images, FP (False Positive) represents the number of incorrectly classified images, FN (False Negative) represents thenumber of images that were detected as belonging to the incorrect class, and TN (True Negative) represents the number of images that do not belong to any other class and have not been classified as such. Training and validation accuracy is shown in Fig. 5 and Fig. 6 during the course of 20 iterations of the training process respectively. Improved precision can be achieved more quickly using our model. Our model has the potential to augment the basic model in this way.

Fig. 5: Training Accuracy

We summarise our findings. In contrast to X-ray scans, which can be analysed by examining asingle image, CT scan data cannot be reviewed in this way. To make a medical diagnosis using CT scans, the system or an expert must examine more than one image at a time. Because of this, when developing an autonomous diagnostic system, the researchers must assess their system in a way that is distinct from single picture categorization. As far as we know, this is the first time a model has been evaluated in this manner. The pictures

from the patient's CT scans must be sent into the system if we want it to screen for COVID-19 infection in our planned fully-automated approach. In the next step, the suggested CT scan selection method is used to pick the CT images that show the lung. COVID-19 or normal photos will be sent into the deep neural network for classification.We must establish a threshold to indicate the health of a patient. As long as there are more COVID-19-positive CT scan pictures than the threshold, that patient is considered infected; otherwise, he or she is healthy. As the model's accuracy improves, so does the cut-off value. As long as at least one CT scan of a patient is recognised as COVID-19 (in between the filtered CT scans by the selection method) in a trained model with high accuracy, that patientwould be regarded to have been infected. A surprising finding may be seen in Table III. One tenth of filtered CT scan pictures are used as a reference point for threshold 1. After the selection algorithm has filtered the CT scan pictures, the patient will be marked as infected if at least one of the filtered images is detected as COVID in threshold1. An infection with COVID-19 is diagnosed if at least one-tenth of the filtered CT scan pictures are found to be contaminated. Table III indicates that our model works very well at threshold 1, which demonstrates the network's strong performance. Although our model performs well in threshold 1, other networks fail to do so, indicating that these networks are less accurate than our model. Due to the feature pyramid network, which delivers a high capacity to accurately detect infections while not detecting incorrect points as infections, this extraordinary result has been achieved. Based on the accuracy of the model, users can choose this threshold. Here, we provide the whole findings by using a second criterion (equivalent to one-tenth of one percent). However, for models like ours, we advocate adopting the first threshold.It is clear from Table III that our model is better at identifying patient conditions than other networks when the COVID threshold is quite low. This suggests that our model
has a considerably lower rate of false positives for COVID infections than simpler models.

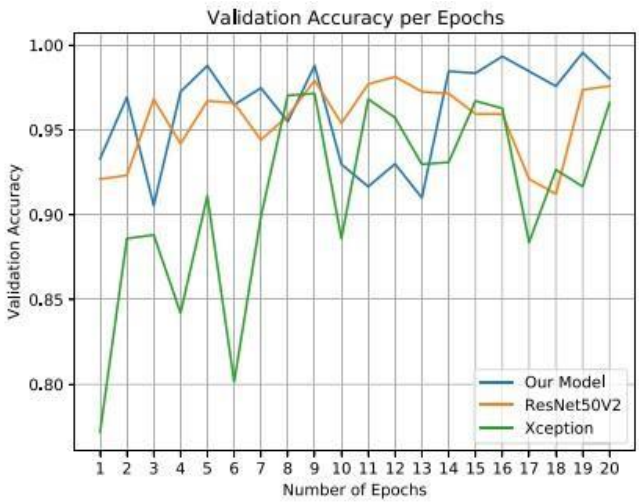

Fig. 6: Validation Accuracy

The average findings between five-folds reveal that our model obtained 98.49% overall accuracy and 94.96% sensitivity for the COVID-19 class during the single picture evaluation phase. Evaluation findings for Xception demonstrate 96.55 percent overall accuracy and 98.02 percent COVID-19 sensitivity, respectively. Our research shows that our model is more accurate at detecting infection spots than other models, such as Xception and ResNet50V2. This is because our model is more accurate at detecting infection points than other models, such as ResNet50V2. We tested our model on about 245 patients and 41,892 pictures of varying thicknesses throughout the period of completely automated patient condition detection.

Table III shows that our model produced the best results and accurately identifies 234 people out of 245 people, which is a good enough number. Because COVID's class precision isn't extremely high like accuracy or sensitivity due to an uneven test dataset, it's worth noting. For the network performance testing, we used about 450 COVID-19 photos and 7800 regular images. However, because the number of COVID-19 photos in the test-set is significantly fewer than regular test images, our model's COVID-19 accuracy amounted to 81 percent, which is a decent result.This does not indicate that the network is underperforming because of this degree of accuracy.

TABLE III. PATIENT CONDITION IDENTIFICATION THRESHOLDS FOR THE TRAINED NETWORKS

	Threshold 1 (equal to 0)			Threshold 2 (equal to 0.1)		
	Our Model	ResNet 50V2	Xception	Our Model	ResNet 50V2	Xception
Covid Correct Detected	17	16	16	17	16	15
Wrong Detected as Normal	1	1	1	1	2	2
Normal Correct Detected	231	230	230	232	230	231
Wrong Detected as Covid	6	7	7	5	7	6

What makes this work trustworthy is that it was developed and tested in real-world scenarios like analysing video or picture sequences rather than single images, and that it was assessed on a large dataset with high accuracy and minimal false positives, as well as good inference speed. We believe that our publicdataset and code will help other researchers enhance AI models and apply them for better medical diagnostics [21-23].

4. CONCLUSION

The identification of COVID-19 in lung HRCT images may now be done totally automatically, thanks to the technique we describe in this study. A fresh dataset with 15,589 photos of healthy people and 48,260 photographs of COVID-19 patients was also introduced. An imageprocessing technique was presented at the outset that would filter CT scans for just those pictures that reveal the lung's interior clearly. The accuracy and speed of thenetwork can be improved by using this approach. A new deep convolution neural network was then implemented to enhance categorization. Many classification issues can benefit from the usage of this network, especially those involving photos with little but essential objects. The CT

scan pictures were classified either COVID-19 or normal using three distinct deep convolution networks. The best results were attained by our model, which makes use of ResNet50V2 and a modified feature pyramid network. In order to execute COVID-19's completely automated identification system, we employed the trained networks. More than 7796 photos and about 245 patients and 41,892 different thicknesses were used to test our technique in two distinct methods. Our model was able to correctly classify 98.49% of images in the first assessment method. More than 234 patients were accurately recognized by our model in the second evaluation step (patient condition identification)

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

REFERENCES

[1] WHO, Q&A on Coronaviruses (Covid-19), 2020https://www.who.int/emergencies/diseases/novel-coronaviruses-2019/question-and-answers-hub/q-a-detail/q-a-coronaviruses (accessed 31. 05.20).

[2] R.R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh and D. Batra, "Grad-cam:visual explanations from deep networks via gradient-based localization," Int. J. Comput. Vis., vol. 128, pp. 336–359, 2019.

[3] Wikipedia, Covid-19 Testing – Wikipedia, 2020 https://en.wikipedia

[4] Geneticeducation, Reverse Transcription PCR: Principle, Procedure, Application, Advantages and Disadvantages, 2020 https://geneticeducation.co.in/reverse-transcription-pcr-principleprocedure-applications-advantages-and-isadvantages/#Disadvantages (accessed 31.05.20).

[5] ACR, ACR Recommendations for the Use of Chest Radiography and Computed Tomography (CT) for Suspected Covid-19 Infection | American College of Radiology, 2020. https://www.acr.org/Advocacy-and-Economics/ACR-PositionStatements/Recommendations-for-Chest-Radiography-and-CT-for-SuspectedCOVID19-Infection(accessed on 31.05.20).

[6] K. He, X. Zhang, S. Ren and J. Sun, "Deep residual learning for image recognition," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 770–778, 2016.

[7] M. R. Mohammadi, M. Rahimzadeh, and A. Attar, "Sperm Detection and Tracking in Phase-Contrast Microscopy Image Sequences Using Deep Learning and Modified csr-dcf," 2020 (arXiv preprint), arXiv:2002.04034

[8] T. Javaheri et al.., "Covidctnet: An OpenSource Deep Learning Approach to Identify Covid-19 Using CT Image," 2020 (arXiv preprint), arXiv:2005.03059

[9] G. Huang, Z. Liu, L. van der Maaten and K.Q. Weinberger, "Densely Connected Convolutional Networks," arXiv, 2016.

[10] M. Tan and Q.V. Le, "Efficientnet: Rethinking Model Scaling for Convolutional Neural Networks," 2020.

[11] F. Chollet, "Xception: deep learning with depthwise separable convolutions," in proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 1251–1258, 2017.

[12] L. Li et al., "Artificial intelligence distinguishes covid-19 from community acquired pneumonia on chest ct", Radiology, pp 200905, 2020.

[13] K. He, X. Zhang, S. Ren and J. Sun, "Identity mappings in deep residual networks," Lect. Notes Computer. Sci., pp. 630–645, 2016.

[14] S. Wang et al., "A fully automatic deep learning system for covid-19 diagnostic and prognostic analysis", Eur. Respir. J. 2020.

[15] A. Voulodimos et al., "Deep learning models for Covid-19 infected area segmentation in CT images," medRxiv, 2020.

[16] M. Rahimzadeh, A. Attar, and S. M. Sakhaei, "A fully automated deep learning-based network for detecting COVID-19 from a new

and large lung CT scan dataset," Biomed. Signal Process. Control, vol. 68, p. 102588, 2021.

[17] T. Y. Lin et al., "Belongie, Feature pyramid networks for object detection," in proceedings of the IEEE Conference on Computer vision and Pattern Recognition, pp. 2117–2125, 2017.

[18] J. Deng et al., "Imagenet: a large-scale hierarchical image database," in IEEE Conference on Computer Vision and Pattern Recognition, IEEE, pp. 248–255, 2009.

[19] F. Chollet et al., keras, 2015.

[20] M. Abadi et al., "TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems," Software available from tensorflow.org, 2015.

[21] H. Rohmetra, N. Raghunath, P. Narang, V. Chamola, M. Guizani, and N. R. Lakkaniga, "AI-enabled remote monitoring of vital signs for COVID-19: methods, prospects and challenges," Computing, vol. 2019, 2021, doi: 10.1007/s00607-021-00937-7.

[22] A. H. Shamman, A. A. Hadi, A. R. Ramul, M. M. Abdul Zahra, and H. M. Gheni, "The artificial intelligence (AI) role for tackling against COVID-19 pandemic," Mater. Today Proc., no. xxxx, 2021, doi: 0.1016/j.matpr.2021.07.357.

[23] W. Zhao, W. Jiang, and X. Qiu, "Deep learning for COVID-19 detection based on CT images," Sci. Rep., vol. 11, no. 1, pp. 1–12, 2021, doi: 10.1038/s41598-021-93832-2.