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# Enhancing COVID-19 Diagnosis through AI-Driven Analysis of Chest CT Images

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*Abstract*—The COVID-19 pandemic has necessitated innovative approaches to expedite and enhance diagnostic capabilities. Chest computed tomography (CT) imaging has emerged as a valuable tool for identifying characteristic pulmonary manifestations of COVID-19. In recent years, artificial intelligence (AI) techniques, particularly deep learning algorithms, have been increasingly employed to aid in the analysis and interpretation of chest CT images for COVID-19 diagnosis. This abstract presents a focused review of the role of AI in enhancing COVID-19 diagnosis through the analysis of chest CT images. We highlight recent advancements in AI-driven methodologies, including convolutional neural networks (CNNs), for automated detection and characterization of COVID-19-related lung abnormalities. Moreover, we discuss the potential impact of AI on improving diagnostic accuracy, reducing interpretation time, and supporting healthcare professionals in decision-making. Challenges and future directions for integrating AI-driven analysis into clinical workflows are also addressed, underscoring the transformative potential of AI in combating the COVID-19 pandemic.

Keywords: Artificial intelligence, deep learning, COVID-19 diagnosis, chest CT images, medical imaging, convolutional neural networks (CNNs).

## 1. INTRODUCTION

In January 2020, due to the global spread of the coronavirus illness 2019 (COVID-19), the World Health Organisation declared a public health emergency of international concern (PHEIC). The order Nidovirales, family Coronaviridae, subfamily Coronaviri- nae is where human coronaviruses (CoV) are classified [1]. The viruses in the subfamily Coronavirinae can be categorised into four types: α, β, γ, and δ. CoVs (α, β, γ, and δ) primarily affect the respiratory and gastrointestinal systems of a diverse array of animal species, encompassing birds and mammals. A new family of β-coronavirus, known as SARS-CoV-2 (COVID-19), emerged in the end of 2019. Acute respiratory distress or multiple organ failure can occur in severe cases of COVID-19, which is a highly contagious virus [2]. Worldwide, the number of positive cases is rising at an exponential rate, and over 5 million people have been infected with the virus to date. Because of the rapid increase of infected cases, numerous countries' health systems are on the verge of collapse [3]. These days, diagnostic kits and ventilators are in low supply in most nations. Due to the restricted diagnostic tools available, many countries can only use limited COVID-19 testing, which makes the medical situation problematic [4]. Therefore, the search for a quick, affordable tool that can accurately identify and diagnose COVID-19 is urgently needed. Attempts have been conducted to find an adequate and fast way to detect infected patients at early stage. Usually, the disorder is verified by a reverse transcription polymerase chain reaction (RT-PCR). It's possible that the RT-PCR sensitivity is insufficient to identify and diagnose questionable patients in a timely manner [5]. This explains why the death rate is so high globally. CT scans, on the other hand, are non-invasive imaging methods that can detect these distinctive lung symptoms [6]. Consequently, CT scans may be utilised to detect COVID-19 and other types of pneumonia early on. To emphasise the distinction, Fig. 1 shows representative chest CT images of normal and COVID-19 positive individuals together with their clinical diagnoses. The CT scan of the chest in COVID-19 cases reveals a homogenous opacity of the infected lungs, primarily pneumonic opacity, and bilateral lung infiltration (areas highlighted in green). However, in many computer vision domains, the use of Artificial Intelligence (AI) based solutions has grown significantly [7]. Artificial intelligence (AI)-based methods can process enormous volumes of data at unthinkable speeds, surpassing human accuracy. This is explained by AI's ability to examine and deduce hidden patterns and traits with essentially no assistance from humans [8]. In addition, the task of gathering, evaluating, and applying a vast amount of knowledge required to resolve intricate clinical issues confronts modern medicine. AI's ability to find meaningful relationships in data can be useful in this circumstance as it can help with diagnosis, treatment, and result prediction in a variety of clinical scenarios [9]. Consequently, a large portion of AI solutions have been applied to medical practices and healthcare systems [10]. Drug development and design [11], patient monitoring [12], enhancing physicians' diagnostic skills [13], and medical image analysis [14] are a few examples of medical uses. Currently, research efforts are being done to create novel AI-based COVID-19 diagnostic techniques [15]. Specifically, employing Convolutional Neural Networks (CNN), which revolutionised a number of scientific domains [7] by offering unconventional and effective answers to numerous image-related issues that had long been unresolved or only partially addressed [16].



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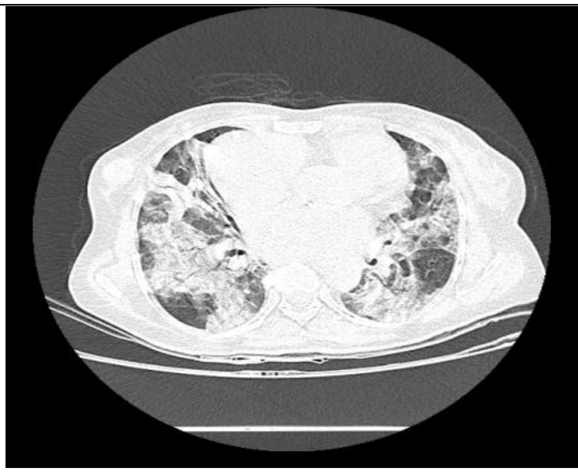
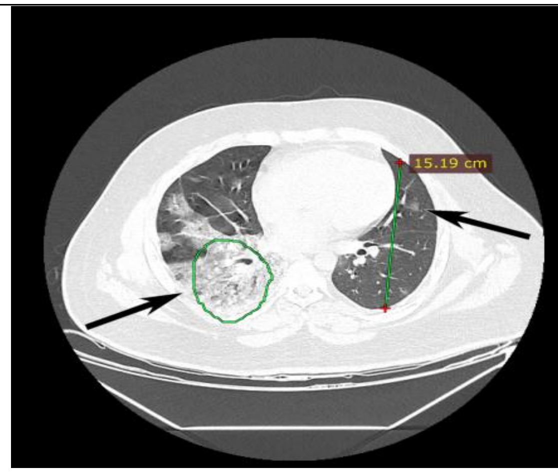
|  |   |
| Normal Lung image | Infection Lung Image Normal Lung image |

Fig. 1: Samples of normal scans chest CT s versus ones diagnosed with COVID-19.

Improve and create a reliable method for COVID-19 detection using chest CT scans. The latest advancements in pattern recognition technology, based on deep learning, will be employed to do this. Ultimately, the findings of this study offer a low-cost and reliable foundation for the fight against COVID-19. This is really helpful, particularly when physicians have a lot of cases to review quickly. This is how the remainder of the paper is structured. In Section II, the proposed CNN model is presented. The experimental results and comments are presented in Section III. Section IV serves as the paper's conclusion.

## 2. PROPOSED METHOD

A popular artificial neural network for image and video processing is CNN, or feed-forward CNN [16]. Comparing these CNNs to other feature extraction and classification methods, they require comparatively less pre-processing. This implies that in unsupervised learning, the network is solely in charge of creating its own filters. Other conventional algorithms that rely on certain pre-processed hand-crafted features do not operate in this manner. One of CNNs main advantages is that they may be started without requiring human intervention or initial parameterization. Convolutional procedures for input picture processing and layer stacking are at the heart of deep learning research. This is how the convolution operation is defined:

$$(X * K)(i, j)= \sum\sum K(m, n)X(i - m, j - n)\ldots\ldots\ldots\ldots(1)$$

where K is a 2D convolution matrix, X is the input picture With the stride parameter, the K matrix moves across the input matrix. The steps in the framework algorithm and the general comprehensive deep learning architecture for COVID-19 identification are as follows:



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INPUT:

IMG = Chest CT image to be diagnosed;

DS = Dataset of COVID-19 labelled chest CT images;

OPERATION:

- PREPARE DS Using Data Augmentation Steps;
- Initialize Tensor Flow CNN Network Parameters;
- SPLIT DS to 70% Training and 30% Testing;
- BEGIN Training
- Iterate Through DS with Full Training Epochs;
- Evaluate Accuracy At Each Epoch Till Convergence;
- END Training

OUTPUT: Diagnosis (IMG);

COVID-19 identification In Table I, CNN is shown. The performance of the suggested network, as well as any CNN network in general, is essentially controlled by two main elements. The convolution filter size, chosen to be (5×5), is the first. Despite being marginally bigger than the standard CNN filter size [18], this filter size enables the detection of lung anomalies in broader regions than typical image classification issues. The activation function at the final completely connected layer is the second factor. Since it limits the $\Phi(x)$ value from a broad scale to within the range [0: 1], the sigmoid function Eq. (2) is chosen. The covid chest CT multiclass classification problem is well-suited for this since the cases shown have nine diagnoses.

$$\Phi(x)= (1 + 1 \quad -1)\ldots\ldots\ldots\ldots..(2)$$

TABLE I: The suggested CNN architecture for COVID-19 detection, with complete layer implementation details.

| Sl. No | Layer Type | Output shape |
|---|---|---|
| 1 | 2D Convolution | [19496×64] |
| 2 | Average Pooling | [65×65×64] |
| 3 | 2D Convolution | [61×61×32] |
| 4 | Average Pooling | [20×20×32] |
| 5 | 2D Convolution | [16×16×8] |
| 6 | Flatten | [2048] |
| 7 | Fully Connected | [128] |



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| | | |
|---|---|---|
| 8 | Fully Connected | [61 |
| 9 | Dropout | [62 |
| 10 | Fully Connected | [34 |
| 11 | Fully Connected | [16 |

## 3. EXPERIMENTS AND RESULTS

The effectiveness of the suggested CNN model for COVID-19 detection is examined in this section. It describes the details of the network training phase and the COVID chest CT dataset that was used in the experiments. Then, it presents the experimental outcomes and a discussion of them.

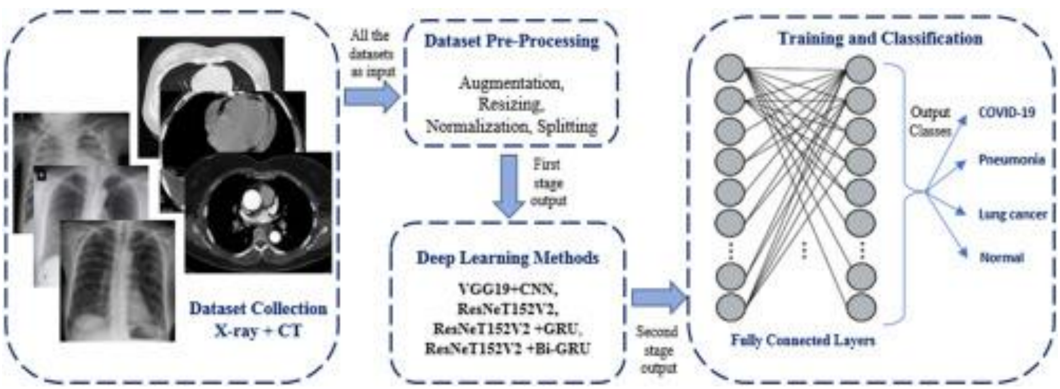


Fig. 2: Block schematic of the suggested deep-chest multi classification model.

### A. Chest-CT dataset

This work makes use of a publicly available dataset of chest CT patients of pneumonia [17]. The collection includes some normal CT pictures along with nine different kinds of pneumonia (e.g., COVID-19, MERS, SARS, and ARDS). The dataset's nine distinct cases of pneumonia significantly aid in mitigating the proposed model's under fitting, since the machine must learn multiple variants from the nine cases. Fig. 2 displays some photos from the dataset for illustrative purposes. Pictures are added to the dataset on a regular basis from different open access sources. The dataset has amassed 316 CT scans of the chest thus far.

### B. Network training phase

To lessen the impacts of over fitting, the suggested CNN model makes use of data augmentation [19]. All dataset images are preprocessed by randomly reflecting and translating in the [-30, 30] range before a sample image is sent to the network. In order to prevent positional bias in the data, the random translation step is required. Label-preserving transformations are used to apply these preparation operations uniformly to all photos in order to artificially increase the size of the dataset [20]. Stochastic gradient descent with a batch size of ten examples, a momentum of

0.9, and a weight decay of 0.001 was used to train the model. An Intel Core i5 running at 2.9 GHz with 8GB of RAM was used for the training and results.

## 4. Results and discussion

The process for establishing tests to assess the suggested network model and recording the findings is covered in this section. Using the standard experimental design, 70% of the photos in the dataset were allocated to training and 30% to validation at random. Since there isn't a test-set split for the chest CT image dataset, the split in this instance has no bearing on the outcomes.

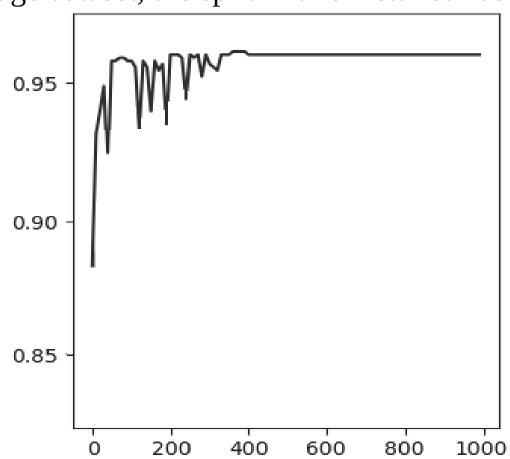


Fig. 3: The proposed CNN model accuracy performance in the first 1000 epochs.

For this section, the graph shows performance stability after the first 500 epochs with 96% accuracy [22]. The dataset is used to assess the suggested deep learning method's performance. Metrics as listed below are used in performance evaluation as shown in Fig 3. The accuracy of the approaches is tested using the following performance metrics: area under the receiver operating characteristic (ROC) curve (AUC), accuracy (ACC), sensitivity (SE), and specificity (SP).



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$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Sensetivity} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

where TP, TN, FP, and FN stand for true positive, positive, true negative, and false negative, respectively. False Negative is FN, whereas False Positive is FN. An additional metric for assessing the model's effectiveness is the validation loss, which shows how effectively the model generalises to new data. The loss function is shown in equations. Where λ is the individual loss function or log-loss in the suggested model, and yˆi is the network prediction with the ground truth values yi. As shown in Fig. 4, the suggested network obtained 96% accuracy on the chest CT dataset with 0.2 log-losses. Taking into account the small size of the dataset, this is an excellent outcome. Table II lists the limited published research that has been done on the COVID-19 in the literature. The research community's limited access to test results and the fact that COVID-19 symptoms differ between nations and may cross over with other types of pneumonia (like SARS) are blamed for this. Nonetheless, there have been some limited study efforts on the COVID-19 pandemic, which can be summed up as follows: A few methods were created using the transfer learning [25]–[27] framework. Nonetheless, this might be very helpful in general picture classification issues, as it could transfer learned features such as colour blobs and edges to other image classification assignments. Despite the fact that the COVID-19 scenario is a global

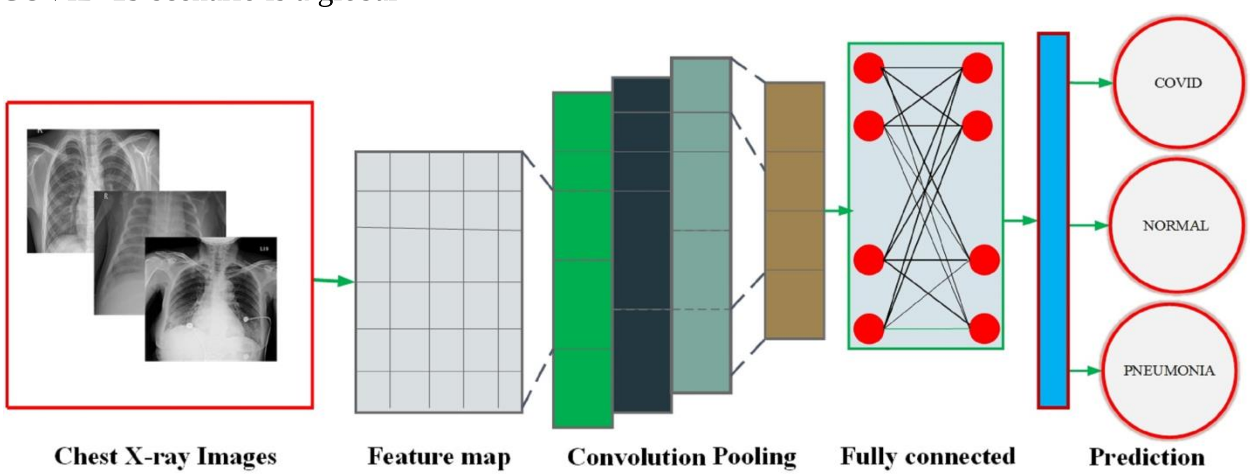


Fig. 4: The suggested CNN COVID-19 detection model's performance.

The quantity of positive samples has a major impact on the effectiveness of deep learning-based techniques. To validate the high accuracy that was obtained, most published approaches employed an average of 50 COVID-19 positive cases, which is a rather small number.

TABLE II: The calculated F1-score and geometric mean and accuracy of the ANN and DNN classifiers.

| Classifier | Class | F1-score | Geometric mean | Accuracy |
|---|---|---|---|---|
| ANN | COVID-19 | 93.68 | – | – |
| | Healthy | 94.47 | – | – |
| | Average | 94.08 | 94.06 | 94.06 |
| DNN | COVID-19 | 95.52 | – | – |
| | Healthy | 96.13 | – | – |
| | Average | 95.83 | 95.76 | 95.77 |

The performance of the suggested network model is contrasted with three benchmark baselines, which reflect the most current advancements in deep learning-based COVID-19 detection research. The comparison, which shows 5.8±3.5%, highlights the strong performance of the suggested COVID-19 detection CNN model, which beat all other baselines. Additionally, the results were verified by a team of medical experts using Equation 3, which is the same accuracy metric, to assess this part performance. After the proposed network properly categorised each CT picture, radiologists were given the opportunity to manually reclassify each one. The 99% medical-based accuracy that was attained validates the efficacy component. For the reasons noted above, most of the literature work is still in its infancy when it comes to offering practical AI solutions that can aid in the early detection of COVID-19 from chest CT scans. Additionally, CNN-based methods are strong and appropriate for the task since they integrate feature extraction and classification into a complete end-to-end model that takes the initial raw input data and generates the final classification outcomes. In conclusion, there is still a great deal of work to be done in order to help combat these pandemics and offer workable solutions that could aid humanity in the fight against viruses. In each experiment, we have manually fine-tuned a DNN by adjusting the number of learning steps, learning rate, momentum, activation function, and hidden layers as well as the number of nodes that make up each hidden layer. For the back propagation algorithm, we used a SCG optimisation technique and set the batch size to 100, momentum to 0.3, and learning rate to 0.7. Using 10-fold cross-validation for each manual formation to find the remaining DNN hyperparameters, we have computed the classification accuracy. For varying hidden layer representation sizes, same search process is repeated. Following this laborious manual approach, a DNN with three hidden layers—each with 270, 150, and 50 nodes—achieves the best classification performance. A similar procedure is used in the ANN implementation, and a hidden layer of 250 neurons yields the best results. In this work, the scaled conjugate gradient is chosen as an optimizer. The function chosen for activation is the tangent sigmoid. Moreover, the model depicted in Fig. 5 uses batch normalisation.



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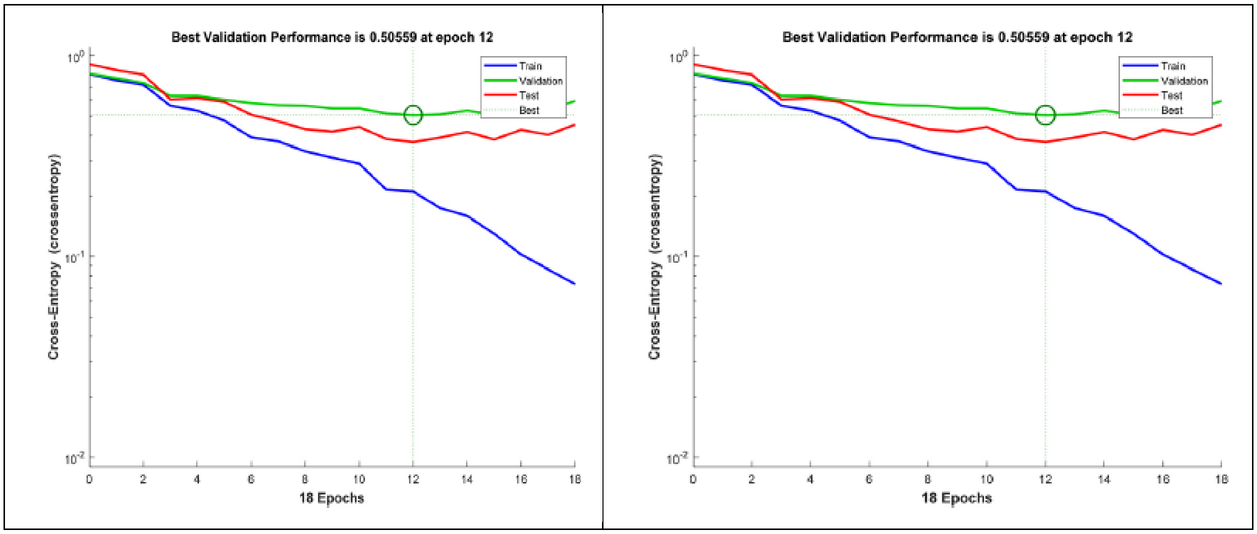


Fig.5: Training/validation curve for ANN and DNN.

## CONCLUSION

An end-to-end fully automated CNN model for COVID-19 identification from chest CT images was described in this work. The accuracy rate of the suggested CNN model was 96%. Moreover, the clinical validation of the model performance is conducted by qualified radiologists, confirming the accuracy of the findings. The findings shown in this article are encouraging, suggesting that locations lacking radiologists' support could employ the suggested technique. It can facilitate a prompt diagnosis of COVID-19 infection for radiologists and physicians, especially in situations where health services are overburdened. Nonetheless, by taking into account additional CT pictures and modifying the model for CT images, the suggested CNN model can still be improved. The limited amount of COVID-19 case data currently accessible is the primary research restriction for this study and all other COVID-19 related studies. Therefore, it is crucial to collaborate closely with nearby hospitals to increase the number of cases in order to improve performance even further. The following elements could be included in the next work: (i) enlarge the dataset and use a bigger dataset to test our suggested model. (ii) Consider using certain deep learning architectures that have been pretrained. (iii) Pretrained deep learning architectures will be used to test a few sophisticated or hybrid fusion rules. (iv) Other automated healthcare systems can incorporate our suggested approach.

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