Published by :
http://www.ijert.org

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 12 Issue 11, November-2023

An Enhanced VGG16 Model for CT Imaging-Based COVID-19 Diagnosis

Triawan Nugroho, Muhammad Bilal, Muhammad Shehzad Hanif

Department of Electrical and Computer Engineering,
Faculty of Engineering, King Abdulaziz University,
Jeddah 21589, Saudi Arabia

***Abstract*— COVID-19 is a contagious disease distinguished by its elevated transmissibility and notable fatality rate, posing a considerable threat to the general welfare of the global populace. Accurately and efficiently detecting COVID-19 is paramount to effectively executing preventive measures and treatment methods. Medical imaging modalities, particularly computed tomography (CT) scans, have become known as a feasible alternative for diagnosing COVID-19. This study introduces and assesses an improved diagnostic model for COVID-19 utilizing Convolutional Neural Networks (CNN). The VGG16 architecture, a pre-trained CNN model, was altered via transfer learning techniques, including fine-tuning and feature extraction, to tailor it to our specific objective. Furthermore, we have included a callback system that played a pivotal role in refining the training process. The improved VGG16 model was assessed using a dataset obtained from a hospital in Sao Paulo. This dataset had a total of 2482 CT scans, with 1252 instances classified as COVID-19 positive and 1230 cases classified as negative. The findings of the study indicate that the adapted VGG16 model exhibited an exceptional level of performance, as shown by an accuracy rate of 98.12%, a recall rate of 99.46%, a precision rate of 96.90%, and an F1-score of 98.16%.**

***Keywords*—**Covid-19, CT scans, Convolutional Neural Networks, deep learning, performance, VGG16

I. INTRODUCTION

An outbreak of COVID-19, which emerged from the SARS-CoV-2 virus, had its genesis in China towards the end of 2019 and quickly spread worldwide, presenting a significant risk to global public health [1]. On January 30, 2020, the World Health Organisation (WHO) declared the COVID-19 outbreak a Public Health Emergency of International Concern (PHEIC). This statement highlights the substantial threat that the virus presents, particularly to nations with healthcare systems that are susceptible or ill-equipped [2]. As of October 17, 2023, the cumulative count of verified COVID-19 cases has surpassed 600 million, accompanied by a significant fatality rate of roughly 6,926,687[1]. Consequently, COVID-19 has emerged as one of the most devastating illnesses in the annals of human history [3]. Besides its direct health impacts, the pandemic has affected various aspects of society in multiple ways. The health sector faced additional challenges due to the physical symptoms of the virus and the increased mental health issues caused by prolonged isolation, fear, and socio-economic pressures.

Determining the infection early is crucial in controlling COVID-19's severity and spread. Early disease detection is crucial for managing the disease in its initial phases [4]. Several diagnostic methods have been proposed, including PCR (RT-PCR), rapid antigen assays, and antibody tests. The reverse transcription-polymerase chain reaction (RT-PCR) test is one of the most widely used testing methods for COVID-19 [5]. Nonetheless, the RT-PCR's sensitivity is relatively low as the results range from 28% to 85%, and the procedure is known to be manual, complex, laborious, and time-consuming [6]. Moreover, false negative results are frequently produced by this test within the initial week of infection. This may transpire in the event that the sample is obtained beyond the period of viral replication or in the absence of viral genome detection [7].

Hence, enhanced diagnostic techniques for COVID-19 that are precise, expeditious, and uncomplicated are imperative. One potential viable substitute for the RT-PCR test is automated analysis techniques applied to medical imaging modalities, such as computed tomography (CT) scans and chest X-rays (CXR). These methodologies provide the evaluation of the impact of COVID-19 on various organs at different phases of the disease, aiding healthcare practitioners in their identification. For instance, CT scans can detect ground-glass opacities, consolidation, and crazy-paving patterns in the lungs of COVID-19 patients, indicative of viral pneumonia [8]. In contrast, CXR can show bilateral patchy shadows or opacities in the lungs, which are less specific but more common in COVID-19 patients [9]. Given that respiratory symptoms often manifest as the first indicators of COVID-19, the aforementioned techniques primarily focus on the thoracic area and the pulmonary system. This methodology has the benefit of decreased testing length and improved dependability [10].

Moreover, when comparing CT scans and chest X-rays, as illustrated in Figure 2, it is widely acknowledged that CT scans exhibit a higher level of sensitivity in detecting indications that are diagnostic of a COVID-19 infection. A significant advantages of CT scans is their ability to provide precise and distinct visual representations of underlying anatomical

---

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 12 Issue 11, November-2023

structures, hence avoiding the issue of overlapping objects such as soft tissues [11][12]. Due to its inherent three-dimensional characteristics and superior image resolution, medical professionals often exhibit a preference for CT scans in comparison to chest X-rays[13]. Nevertheless, tackling this issue presents a significant challenge due to the scarcity of radiologists in comparison to the increasing influx of new residents, as well as the considerable number of repeat examinations requested by sick patients who are eager to track the advancement of their condition [14]. However, these techniques also have some limitations, such as the risk of radiation exposure, the need for expert interpretation, and the possibility of false positives or negatives due to other lung diseases or infections.

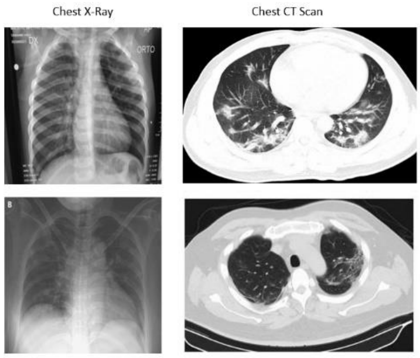

Figure 1 Chest X-rays VS Chest CT Scan

To overcome these limitations, this study proposes using Convolutional Neural Networks (CNN) on CT images to provide accurate metrics for identifying patients with COVID-19. CNN shown outstanding ability in several computer vision tasks, encompassing scene comprehension, object identification, recognition of faces, and semantic segmentation, among others [15]–[20]. CNN has emerged as a prominent deep-learning methodology for classifying medical images, primarily because of its capacity for self-learning [21], [22]. Many researchers have explored the use of CNN to diagnose COVID-19 by applying the capabilities of Deep Learning (DL). However, the accuracy of the DL-based models for diagnosing COVID-19, as well as the criteria for assessing the performance, still need improvement. Comparing its performance to existing methods, this study aims to tailor and assess an improved CNN-based COVID-19 model diagnosis utilizing CT images.

In the swiftly advancing sector of medical imaging, with a particular focus on identifying COVID-19, numerous innovative deep learning strategies have been introduced, each demonstrating significant potential and effectiveness. In their research, Gifani et al.[23] developed a framework for deep transfer learning that integrates an ensemble method in their research. They used various pretrained convolutional neural network (CNN) architectures, such as Efficient Nets (B0-B5), ResNet-50, Inception-V3, and DenseNet-121, in their framework. They tested their framework on a publicly available dataset of 746 CT scans, which they split into 349 COVID-19 positive and 397 negative cases. They obtained accuracy, precision, and recall of 85%, 85.7%, and 85.4% respectively.

Expanding upon this, Wang et al. [24] incorporated a transfer learning approach with their modified Inception model, named M-Inception. This model was enhanced by integrating a squeeze-and-excitation block and a global average pooling layer. They conducted their study on a specialized dataset of 600 CT scans, balanced between COVID-19 and viral pneumonia cases, attaining an accuracy, precision, and recall of 82%, 81.8%, and 82.3% respectively.

Butt et al. [25] focused on creating a predictive model using deep learning methods for distinguishing COVID-19 induced pneumonia from Influenza-A virus infections, as well as from healthy individuals, using lung CT images. They utilized the four renowned pretrained CNN models, such as ResNet-50, DenseNet-121, Inception-V3, and Xception, which were fine-tuned on the dataset comprising 521 CT images. Their results showed an accuracy of 86.7%, a precision of 87.1%, and a recall of 86.7%.

Hernández Santa Cruz [26] utilized a dual-stage algorithm and an advanced ensemble deep learning architecture in their research, with the objective of diagnosing COVID-19 through the analysis of CT images. The widely recognized VGG-16 Convolutional Neural Network (CNN) was employed to perform feature extraction on a dataset consisting of 746 CT scans. Following this, a set of three classifiers, namely Logistic Regression, Support Vector Machine, and Random Forest, were employed to perform classification. The results yielded an accuracy rate, an F1 score, and an Area Under the curve (AUC) of 86.70%, 85.86% and 90.82% respectively.

Özkaya et al. [27] introduced an alternative methodology that involves the utilization of Convolutional Support Vector Machines (CSVM) for the purpose of distinguishing COVID-19 instances based on CT scans. The process of feature extraction was carried out by employing a CNN architecture consisting of four convolutional layers and two fully connected layers. Subsequently, a linear Support Vector Machine (SVM) was employed, with a Radial Basis Function (RBF) kernel, to perform classification. This approach yielded an accuracy rate of 94.03%, precision of 93.98%, and recall of 94.01%.

In their investigation, Panwar et al. [28] used the Grad-CAM method to enhance the interpretability of their deep learning model, which was based on a pre-trained VGG-19 CNN. They processed a dataset of 5,856 chest X-rays, utilizing a softmax classifier for categorization, resulting in an accuracy, precision, and recall of 96.08%, 96.06%, and 96.08% respectively. They also employed Grad-CAM for generating heatmaps that visually identified critical areas in the X-rays for diagnosis.

Pathak et al. [29] introduced a novel methodology combining Deep Bidirectional Long Short-Term Memory (DBLSTM) and Mixture Density Networks (MDN) to diagnose COVID-19 from chest X-ray images. Their approach, involving feature extraction from a dataset of 5,856 chest X-rays and optimization using Maximum Likelihood Estimation and Memetic Adaptive Differential Evolution, resulted in a binary classification accuracy of 98.37% and a three-class accuracy of 96.29%.

Finally, Ruano et al. [30] integrated deep learning with conventional classification methods for the detection and categorization of COVID-19 in CT images and chest X-rays. They extracted features from two datasets comprising 746 CT scans and 5,856 chest X-rays, subsequently classifying them

Published by :
http://www.ijert.org

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 12 Issue 11, November-2023

using random forests, support vector machines, and logistic regression. This approach yielded mean accuracies of 92.33% for CT scans and 96.99% for chest X-rays.

This research introduces a deep learning (DL)-based framework for identifying COVID-19 through CT scans. It utilizes a dataset of CT scans from SARS-CoV-2 patients, which is publicly available [27]. The study makes several contributions to existing scholarly literature, summarized as follows:

- First, a deep learning (DL) method was developed with the objective of identifying COVID-19 throug the use of CT-Scans. This was achieved by using the VGG16 convolutional neural network (CNN) architecture, accompanied by the application of data augmentation methods. The present technique effectively addresses the limitations associated with RT-PCR testing, offering a heightened level of dependability and sensitivity in the early detection of the illness.
- Second, we innovatively customized the VGG16 CNN architecture to suit the specific characteristics of COVID-19 image data. This novel approach enhances the effectiveness and efficiency of the model.
- Third, we applied advanced data preparation and augmentation strategies using comprehensive image processing techniques to improve the model's ability to generalize. In order to maximize the effectiveness of the model, we also optimized the training process by using an adaptive learning rate and early stopping.
- Fourth, we performed a comprehensive experimental analysis, measuring the performance of the VGG16 model on various metrics, such as accuracy, precision, and recall. This rigorous evaluation ensures the practical applicability and robustness of the model.
- Fifth, we demonstrated enhanced capability of our model in accurately predicting COVID-19 from real-time CT imaging data. This advancement can significantly aid healthcare professionals in making prompt and precise decisions, particularly vital in urgent and critical scenarios.

II. MATERIAL AND METHOD

A. Dataset

The present research used a CNN based on the VGG16 architecture for the purpose of detecting COVID-19. The dataset used in this study consisted of actual patient images obtained from a hospital located in Sao Paulo, Brazil. The information in question was made publicly available by Soares and Angelov [31] with the intention of fostering more study and facilitating the advancement of knowledge in the field. The dataset included a total of 2482 computed tomography (CT) scans, with 1252 indicating positive cases of COVID-19 and 1230 indicating negative cases of COVID-19 but presenting other pulmonary illnesses. The photos were categorized into two distinct categories, namely COVID and non-COVID. Figure 2 presents a collection of representative CT scans derived from the dataset, showcasing individuals both afflicted and unaffected by COVID-19.

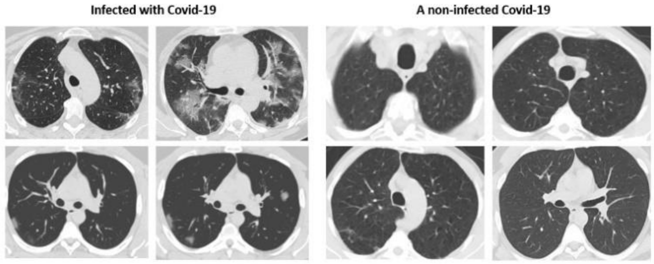

Figure 2 Covid-19 and non-Covid-19 example images

B. Methods

The framework delineated in this research, shown in Figure 1, gives a systematic methodology for the analysis of chest CT images. The approach used in our study consists of three defined phases: preprocessing, image augmentation, transfer learning as showed in Figure 3.

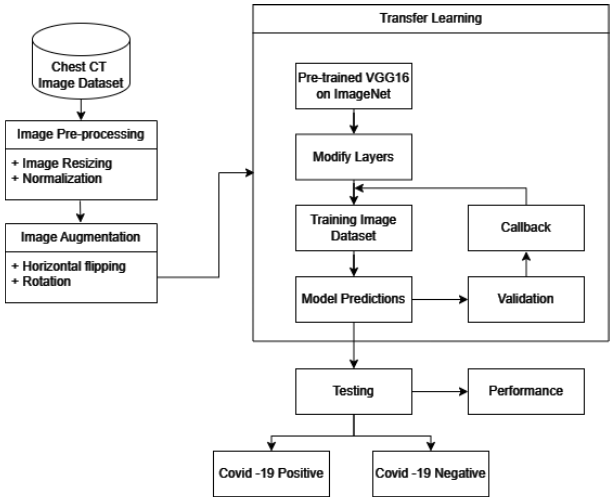

Figure 3 Workflow diagram of Deep Learning for Detecting COVID-19

1) Image preprocessing phase

To prepare the model, image preprocessing procedures were executed, including resizing and normalization. The process ensures that every image has a uniform dimension of 224x224 pixels, thereby achieving dataset uniformity. Inconsistency in the model's image processing is critical, as fluctuations in image dimensions may result in training-related inefficiencies and errors. Normalization, an additional critical stage, involves the adjustment of pixel intensity values. Scaling pixel values to a range of 0 to 1 is frequently more efficient for deep learning network models, whereas the typical range is from 0 to 255. This adjustment is well-suited for the development of models as it aids in the reduction of computational burden throughout the training phase of the model. In order to standardize the images, Equation (1) was employed.

$$\text{Normalized value} = \frac{\text{Pixel value}}{255} \quad (1)$$

Published by :
http://www.ijert.org

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 12 Issue 11, November-2023

2. Data augmentation phase

Data augmentation methods were applied to effectively increase the number of training samples without collecting new images [32]. This technique enhances the model's generalization ability by introducing variability in the dataset. One of the data augmentation methods used in this study was horizontal flipping, which reverses the images horizontally. This method diversifies the training dataset, helping the model generalize better and prevent overfitting.

2) Transfer learning

In this study, we use VGG16, a deep neural network architecture that has already been trained on the ImageNet dataset. The VGG16 model is a sophisticated Convolutional Neural Network (CNN) with many standard building blocks, including convolution layers, pooling layers (including max pooling), and fully connected (FC) layers. For our specific task of detecting COVID-19 from chest CT images, we further customize the model by adding additional layers, as shown in Figure 4.

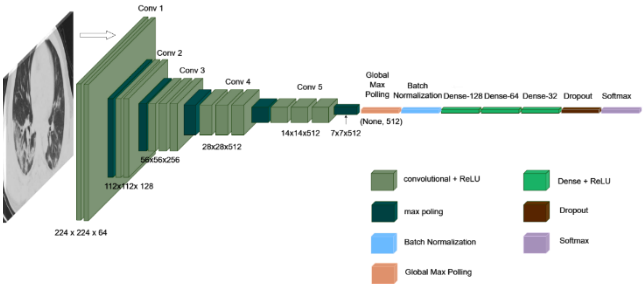

Figure 4 Our Customized VGG16 Neural Network Architecture

These modifications include Batch Normalization, several Dense layers, dropout and output layers. The neural network uses the Adamax optimizer with an initial learning rate of 0.0001. The model trains for 150 epochs, using a mini-batch size of 50. Furthermore, we use a callback to improve the neural network model's training. This callback controls the training process by adjusting the learning rate based on the model's performance, monitoring training and validation metrics, and implementing early stopping to prevent overfitting.

a) Batch Normalization: Batch Normalization is a crucial component within the neural network framework used in our research, which focuses on the analysis of chest CT images for the purpose of COVID-19 identification. The purpose of this layer is to standardize the inputs for each succeeding layer, so guaranteeing that the activations adhere to a uniform distribution. This is of utmost importance in order to facilitate the efficient training of the neural network. The normalization procedure adheres to a prescribed formula:

$$BN\ (X) = \gamma \left(\frac{X - \mu}{\sigma^2 + \epsilon}\right) + \beta \quad (2)$$

Where X is the input, μ is the mini-batch mean, σ^2 is the mini-batch variance, γ is a scale parameter, β is a shift parameter, and ∈ is a small constant for numerical stability. By applying this formula, batch Normalization effectively modifies the input data of every layer in order to get a mean value of zero and a standard deviation of one. This is very important in our study, where we use a deep learning model to analyze complex chest CT images. It helps to avoid the internal covariate shift, which is a problem in deep learning where the input distributions of each layer change during training, making it difficult for layers to adapt and learn effectively [33].

b) Dense Layers: Three Dense layers were employed after the pre-trained VGG16 model to enhance the feature extraction process. The first Dense layer, consisting of 128 neurons, received the normalized output from the previous layers. This layer was fully connected, with each neuron receiving inputs from all 512 units of the VGG16's output. This layer utilized the ReLU (Rectified Linear Unit) activation function, which introduced non-linearity to the network, enabling the extraction of complex features and relationships that were essential for the classification task. The number of 128 neurons balanced the model's complexity and generalization, allowing for effective learning without overfitting. The subsequent Dense layers, with 64 and 32 neurons respectively, continue this process of feature integration and abstraction. They also used the ReLU activation function to preserve the non-linearity at each level of abstraction. They further reduced the number of neurons systematically, which helped to focus the model on the most relevant features for the task. By consolidating the information step by step, the ReLU-activated Dense layers prepared the data for the final classification layer. This layer determined the predictive output based on the processed features.

c) Dropout: We use the Dropout layer with Dropout (rate=0.45, seed=123) in our study. This layer helps to prevent overfitting in neural networks by creating a diverse range of sub-structures during the training process [34]. Figure 3 shows how Dropout changes a standard neural network. On the left, we see a normal neural network where all the neurons are active and connected. On the right, we see the same network after using Dropout: some neurons (crossed out) have been temporarily "turned off" or deactivated during a specific phase of training. This means that they do not affect the activation of the next layer's neurons, and they do not take part in the forward pass or the backward pass of the learning process.

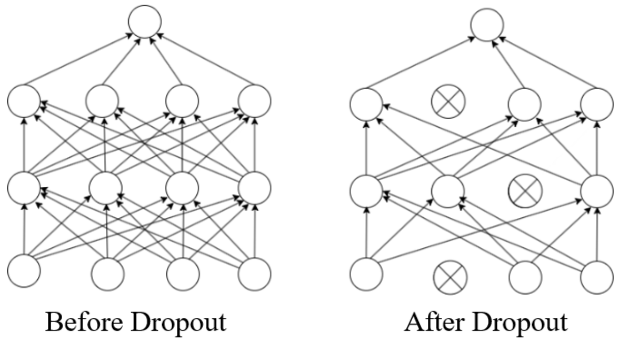

Figure 5 Neural network before and after the implementation of dropout

In our study, we set the rate=0.45 for the Dropout layer. This means that there is a 45% probability that any neuron will be temporarily dropped during the training pass. The seed=123 in the Dropout layer makes the randomness the same every time we train the model. If we use the same seed and the same initial conditions, the same neurons will be dropped in each training epoch. This is important for debugging and consistent model evaluation.

d) Classification (Output Layer): The output layer of the neural network architecture plays a crucial role in the classification of chest CT images, especially to identifying

Published by :
http://www.ijert.org

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 12 Issue 11, November-2023

COVID-19. This layer uses the softmax activation function, which is essential in transforming the accumulated feature representations into a probabilistic format across the specified categories. The formula defining the softmax function is as follows:

$$Softmax\ (Z_i) = \frac{e^{Z_i}}{\sum_{j=1}^{K} Z_i} \qquad (3)$$

In this formula, Z_i represents the raw output (also known as the logit) of the i^{th} neuron in the output layer, which is the calculated score for class i before normalization. The term K denotes the number of classes, which is 2 in our study, corresponding to the binary classification of COVID-19 positive or negative. The constant e is the base of the natural logarithm, it used for exponentiating each logit. The softmax function normalizes these exponentiated values, ensuring that they sum to one and thus form a valid probability distribution. This transformation is essential for interpreting the network's output as probabilities, providing a clear and quantitative assessment of whether a given CT image indicates the presence of COVID-19.

III. RESULT

Using python programming and TensorFlow's keras platform, we implement and evaluate the performance of the architectures described above based on the accuracy, Recall, precision, and F1-score metrics obtained from a test dataset. To train, validate and test the methods developed in this application, we use a laptop computer with AMD Ryzen 7 5800H, NVIDIA GeForce RTX 3060 6 GB, 16 GB RAM. We first use 70% and 15% of the COVID-19 dataset to train and validate the VGG16 structure in Figure 4, and we obtain the training and validation graph successfully as shown in Figure 6. Then, we test the performance of VGG16 with the remaining 15% of the dataset.

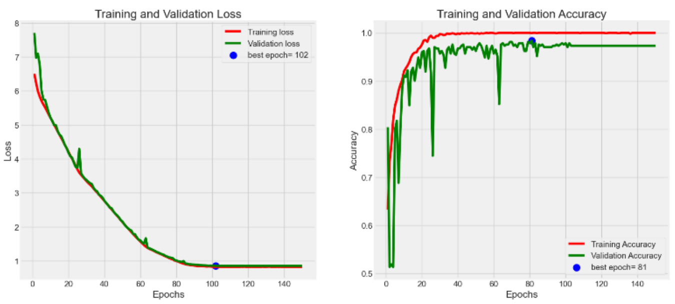

Figure 6 Training and Validation Graphs

In order to assess the robustness and unbiasedness of the classification performance achieved by the proposed technique, we use a range of performance indicators denoted by equations (4) through (7). Moreover, the results of these evaluative measures are systematically encapsulated in Table I. The table delineates the number of test images utilized, along with the true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) observed, offering a clear depiction of the model's predictive proficiency.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \qquad (4)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \qquad (5)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \qquad (6)$$

$$\text{F1} - \text{Score} = \frac{2TP}{2TP+FP+FN} \qquad (7)$$

Table 1 Experimental Results of Proposed Model

Number of Test Images	373
TP	187
TN	179
FP	6
FN	1
Accuracy	98.12%
Recall	99.46%
Precision	96.90%
F1-Score	98.16%

IV. DISCUSSION

Various diagnostic methods have been developed that employ deep learning techniques, with convolutional neural network models as the fundamental basis for these approaches. However, there are different strategies that can be applied to improve the performance of a Convolutional Neural Network (CNN) model. In our study, we employed the VGG16 architecture and introduced some enhancements to improve its performance in diagnosing COVID-19 through chest CT scan images. The results showed that our modified VGG16 model exhibits improved performance compared to other approaches reported in similar research. As shown in Table 2, which compares a number of deep learning-based methods using the same dataset, our adjusted VGG16 model surpasses the benchmarks set by previous studies.

Table 2 Comparison of results with prior studies

No	Study	Methods	Accuracy
1.	Najmul Hasan et al. [35]	DenseNet-121	92%
2.	Yang and Lima [36]	ResNet152V2 with Monte Carlo Cross-Validation	95.06%
3.	Özkaya et al [27]	Convolutional Support Vector Machines	94.03%
4.	Panwar et al. [28]	Grad-CAM	95%
5.	Pathak et al. [29]	Deep Bidirectional LSTM with Mixture Density Network	96.29%
6.	Ruano et al. [30]	Deep Learning with Random Forest and SVM	92.33%
7.	Proposed Methods	Customized VGG-16	98.12%

CONCLUSION

Our research has demonstrated the potential of leveraging a modified VGG16 convolutional neural network model for the detection of COVID-19 from chest CT scans. The custom enhancements applied to the standard VGG16 architecture, including additional convolutional and dense layers, batch normalization, and dropout, have significantly improved the model's diagnostic accuracy. Another component of our approach was the implementation of a custom callback mechanism, which is a function that is executed at certain points during the training process. This callback played a crucial role in fine-tuning the training process by dynamically adjusting the learning rate, facilitating early stopping to avert overfitting. The results of our study showed that our modified VGG16 model achieved a remarkable performance, with an accuracy of 98.12%, a recall of 99.46%, a precision of 96.90%, and an F1-score of 98.16%. These metrics indicate that our model can effectively identify COVID-19 cases from chest CT scans with high sensitivity and specificity. In future research, to improve our system's ability to distinguish COVID-19 from other respiratory conditions, we plan to incorporate additional datasets that include pneumonia and a range of other respiratory diseases. This integration aims to refine the model's diagnostic precision and effectiveness.

REFERENCES

[1] S. Chauhan, "Comprehensive review of coronavirus disease 2019 (COVID-19)," *Biomed. J.*, vol. 43, no. 4, pp. 334–340, 2020, doi: 10.1016/j.bj.2020.05.023.

[2] C. Sohrabi *et al.*, "World Health Organization declares global emergency: A review of the 2019 novel coronavirus (COVID-19)," *Int. J. Surg.*, vol. 76, no. February, pp. 71–76, 2020, doi: 10.1016/j.ijsu.2020.02.034.

[3] M. M. Hasan, M. U. Islam, M. J. Sadeq, W. K. Fung, and J. Uddin, "Review on the Evaluation and Development of Artificial Intelligence for COVID-19 Containment," *Sensors*, vol. 23, no. 1, pp. 1–35, 2023, doi: 10.3390/s23010527.

[4] S. Anjugam and P. J. Arul Leena Rose, "Study of Deep Learning Approaches for Diagnosing Covid-19 Disease using Chest CT Images," in *Proceedings - 7th International Conference on Computing Methodologies and Communication, ICCMC 2023*, Institute of Electrical and Electronics Engineers Inc., 2023, pp. 263–269. doi: 10.1109/ICCMC56507.2023.10083640.

[5] M. Kuchana, A. Srivastava, R. Das, J. Mathew, A. Mishra, and K. Khatter, "AI aiding in diagnosing, tracking recovery of COVID-19 using deep learning on Chest CT scans," *Multimed. Tools Appl.*, vol. 80, no. 6, pp. 9161–9175, 2021, doi: 10.1007/s11042-020-10010-8.

[6] V. Mehta, D. Jyoti, R. T. Guria, and C. B. Sharma, "Correlation between chest CT and RT-PCR testing in India's second COVID-19 wave: A retrospective cohort study," *BMJ Evidence-Based Med.*, 2022, doi: 10.1136/bmjebm-2021-111801.

[7] L. Benevides Lima *et al.*, "True or false: what are the factors that influence COVID-19 diagnosis by RT-qPCR?," *Expert Rev. Mol. Diagn.*, vol. 00, 2022, doi: 10.1080/14737159.2022.2037425.

[8] C. Hani, N. H. Trieu, I. Saab, S. Dangeard, S. Bennani, and G. Chassagnon, "A review of typical CT findings and differential diagnosis," no. January, 2020.

[9] L. A. Rousan, E. Elobeid, M. Karrar, and Y. Khader, "Chest x-ray findings and temporal lung changes in patients with COVID-19 pneumonia," *BMC Pulm. Med.*, vol. 20, no. 1, pp. 1–9, 2020, doi: 10.1186/s12890-020-01286-5.

[10] F. Zhang and D. A. MacRae, "Application of machine learning in CT images and X-rays of COVID-19 pneumonia," *Med. (United States)*, vol. 100, no. 36, p. E26855, 2021, doi: 10.1097/MD.0000000000026855.

[11] S. H. Khan *et al.*, "COVID-19 detection and analysis from lung CT images using novel channel boosted CNNs," *Expert Syst. Appl.*, vol. 229, no. PA, p. 120477, 2023, doi: 10.1016/j.eswa.2023.120477.

[12] A. Halder and B. Datta, "COVID-19 detection from lung CT-scan images using transfer learning approach," *Mach. Learn. Sci. Technol.*, vol. 2, no. 4, 2021, doi: 10.1088/2632-2153/abf22c.

[13] R. Mahmoudi, N. Benameur, R. Mabrouk, M. A. Mohammed, B. Garcia-Zapirain, and M. H. Bedoui, "A Deep Learning-Based Diagnosis System for COVID-19 Detection and Pneumonia Screening Using CT Imaging," *Appl. Sci.*, vol. 12, no. 10, 2022, doi: 10.3390/app12104825.

[14] M. Alazab, A. Awajan, A. Mesleh, A. Abraham, V. Jatana, and S. Alhyari, "COVID-19 prediction and detection using deep learning," *Int. J. Comput. Inf. Syst. Ind. Manag. Appl.*, vol. 12, no. April, pp. 168–181, 2020.

[15] L. Alzubaidi *et al.*, "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," *J Big Data*, vol. 8, p. 53, 2021, doi: 10.1186/s40537-021-00444-8.

[16] A. Khan, A. Sohail, U. Zahoora, · Aqsa, S. Qureshi, and A. Khan, "A survey of the recent architectures of deep convolutional neural networks," *Artif. Intell. Rev.*, vol. 53, pp. 5455–5516, 123AD, doi: 10.1007/s10462-020-09825-6.

[17] R. Sarki, K. Ahmed, H. Wang, Y. Zhang, and K. Wang, "Automated detection of COVID-19 through convolutional neural network using chest x-ray images," *PLoS One*, vol. 17, no. 1 January, pp. 1–26, 2022, doi: 10.1371/journal.pone.0262052.

[18] A. Patil and M. Rane, "Convolutional Neural Networks: An Overview and Its Applications in Pattern Recognition," *Smart Innov. Syst. Technol.*, vol. 195, pp. 21–30, 2021, doi: 10.1007/978-981-15-7078-0_3.

[19] K. Jeeveswaran, S. Kathiresan, A. Varma, O. Magdy, B. Zonooz, and E. Arani, "A Comprehensive Study of Vision Transformers on Dense Prediction Tasks," pp. 213–223, 2022, doi: 10.5220/0010917800003124.

[20] L. T. Duong, P. T. Nguyen, L. Iovino, and M. Flammini, "Automatic detection of Covid-19 from chest X-ray and lung computed tomography images using deep neural networks and transfer learning," *Appl. Soft Comput.*, vol. 132, Jan. 2023, doi: 10.1016/j.asoc.2022.109851.

[21] P. Dutta, P. Upadhyay, M. De, and P. R. G. Khalkar, "Medical Image Analysis using Deep Convolutional Neural Networks : CNN Architectures and Transfer Learning," pp. 175–180, doi: 10.1109/ICICT48043.2020.9112469.

[22] W. Li and H. Yang, "Collaborative Transformer-CNN Learning for Semi-supervised Medical Image Segmentation," *2022 IEEE Int. Conf. Bioinforma. Biomed.*, pp. 1058–1065, 2022, doi: 10.1109/BIBM55620.2022.9995501.

[23] P. gifani, A. Shalbaf, and M. Vafaeezadeh, "Automated detection of COVID-19 using ensemble of transfer learning with deep convolutional neural network based on CT scans," *Int. J. Comput. Assist. Radiol. Surg.*, vol. 16, no. 1, pp. 115–123, 2021, doi: 10.1007/s11548-020-02286-w.

[24] D. Wang, J. Mo, G. Zhou, L. Xu, and Y. Liu, "An efficient mixture of deep and machine learning models for COVID-19 diagnosis in chest X-ray images," *PLoS One*, vol. 15, no. 11 November, pp. 1–15, 2020, doi: 10.1371/journal.pone.0242535.

[25] D. et al Butt, C., Gill, J., Chun, "A Deep Learning System to Screen Novel Coronavirus Disease 2019 Pneumonia," *Engineering*, vol. 6, no. 10, pp. 1122–1129, 2020, doi: 10.1016/j.eng.2020.04.010.

[26] J. F. Hernández Santa Cruz, "An ensemble approach for multi-stage transfer learning models for COVID-19 detection from chest CT scans," *Intell. Med.*, vol. 5, no. June 2020, p. 100027, 2021, doi: 10.1016/j.ibmed.2021.100027.

[27] U. Özkaya, Ş. Öztürk, S. Budak, F. Melgani, and K. Polat, "Classification of COVID-19 in Chest CT Images using Convolutional Support Vector Machines," vol. 19, no. December 2019, pp. 1–20, 2020, [Online]. Available: http://arxiv.org/abs/2011.05746

[28] H. Panwar, P. K. Gupta, M. Khubeb, and R. Morales-menendez, "Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel

coronavirus COVID- 19 . The COVID-19 resource centre is hosted on Elsevier Connect , the company ' s public news and information ," no. January, 2020.

[29] Y. Pathak, P. K. Shukla, and K. V. Arya, "Deep Bidirectional Classification Model for COVID-19 Disease Infected Patients," *IEEE/ACM Trans. Comput. Biol. Bioinforma.*, vol. 18, no. 4, pp. 1234–1241, 2021, doi: 10.1109/TCBB.2020.3009859.

[30] J. Ruano *et al.*, "Deep learning representations to support COVID-19 diagnosis on CT-slices," *Biomedica*, vol. 42, no. 1, pp. 170–183, 2022, doi: 10.7705/biomedica.5927.

[31] E. Soares, P. Angelov, S. Biaso, M. H. Froes, and D. K. Abe, "SARS-CoV-2 CT-scan dataset: A large dataset of real patients CT scans for SARS-CoV-2 identification," *medRxiv*, p. 2020.04.24.20078584, 2020, [Online]. Available: https://www.medrxiv.org/content/10.1101/2020.04.24.20078584v3 %0Ahttps://www.medrxiv.org/content/10.1101/2020.04.24.20078584v3.abstract

[32] C. Shorten and T. M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning," *J. Big Data*, vol. 6, no. 1, 2019, doi: 10.1186/s40537-019-0197-0.

[33] S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," *32nd Int. Conf. Mach. Learn. ICML 2015*, vol. 1, pp. 448–456, 2015.

[34] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: A simple way to prevent neural networks from overfitting," *J. Mach. Learn. Res.*, vol. 15, pp. 1929–1958, 2014.

[35] N. Hasan, Y. Bao, A. Shawon, and Y. Huang, "DenseNet Convolutional Neural Networks Application for Predicting COVID-19 Using CT Image," *SN Comput. Sci.*, vol. 2, no. 5, 2021, doi: 10.1007/s42979-021-00782-7.

[36] L. Yang and D. Lima, "Covid-19 Recognition by Chest CT and Deep Learning," *EAI Endorsed Trans. e-Learning*, vol. 7, no. 23, p. 172812, 2022, doi: 10.4108/eai.7-1-2022.172812.

