Deep learning features for COVID-19 screening using Computed Tomography (CT) scans

By

Hugo Morvan

B.S., University of South Dakota, 2023

A Thesis Submitted in Partial Fulfillment

Of the Requirements for the

University Honors Program

Department of Computer Science

The University of South Dakota

May 2023

The members of the Honors Thesis Committee appointed

to examine the thesis of Hugo Morvan

find it satisfactory and recommend that it be accepted.

KC Santosh, PhD

Chair, Computer Science

Director of the Committee

Zachary Tschetter

Instructor, Computer Science

Kathleen McElhinney

Librarian/Associate Librarian

Abstract

Artificial intelligence (AI) is increasingly being used to extract distinctive features from lung abnormalities in CT scans, facilitating accurate analysis of COVID-19 evidence. Moreover, CT scans are considered to be a more cost-effective diagnostic tool than other imaging modalities, such as magnetic resonance imaging (MRI) or positron emission tomography (PET). With the aid of AI-guided tools, the analysis of CT scans for evidence of COVID-19 can be conducted even in resource-constrained regions, where other diagnostic modalities may not be available. In this study, the performances of three convolutional neural network were evaluated to detect COVID-19 on full CT-scans. The model was trained on a publicly available dataset of 2000 CT scans, and utilized the USD's Lawrence Supercomputing Machine for training. The specific node used in this study consisted of a dual 12-core SkyLake 5000 series CPU, NVIDIA Tesla V100 32GB CPU, and 192GM RAM. The better deep learning model showed promising results, achieving an accuracy of 65.44% on a validation dataset with the lowest possible loss of 0.642 when the training was limited to 20 epochs. However, further validation and refinement of the model is necessary to improve its accuracy and reliability for clinical use. Overall, the proposed 3D deep learning model has the potential to be a valuable diagnostic tool for COVID-19, particularly in resource-constrained settings.

Contents

List of Figures

List of Tables

1 Acknowledgements

I would like to express my heartfelt gratitude to several individuals who contributed to the success of this research project. First and foremost, I would like to extend my sincerest appreciation to Dr. KC Santosh for his invaluable guidance, unwavering support, and exceptional mentorship throughout this research journey. I am also grateful to Kathleen McElhinney for her assistance with the literature review and the writting of this thesis, Zachary Tschetter for his technical expertise and support, and Bill Cone for his assistance with the Lawrence Supercomputer. I would also like to extend my gratitude to my friends Derek Zomer and Josh Henderson for their unwavering support and encouragement throughout this project. Furthermore, I would like to thank the UDiscover program for allowing me to conduct my research in the best conditions. Lastly, I would like to express my gratitude to my family for their love, support, and encouragement. Without their support, this research would not have been possible. Thank you all for your contributions to this project.

2 Introduction

The novel coronavirus disease SARS-CoV-2 (COVID-19) has spread rapidly and widely since the end of 2019. No country and no community has been spared the direct and indirect impacts of the pandemic [2]. It is assumed that when COVID-19 becomes endemic there will be low-level circulation of virus, which underscores the continues importance of public health and social measures even in those countries where vaccination programs are well underway [2][3]. The risk of emergence of further variants of concern increases with every instance of transmission. The best way to reduce the risk of further virus mutation is to reduce transmission [2], hence the importance of developing reliable and fast means of detecting the presence of the virus. Currently, diagnostic techniques based on viral RNA amplification, specifically qRT-PCR (quantitative real-time polymerase chain reaction), are the gold standard diagnostic methods for COVID-19 [4]. However, the RT-PCR test for SARS-CoV-2 virus does have some pitfalls that necessitate improvements in the way the method is used. As with immunodiagnostic tests, the RT-PCR test can have difficulties in distinguishing between true positive and true negative COVID-19 infected individuals, therefore it is a wise precaution not to rely on PCR test results alone, and to consider other clinical and molecular evidence [4]. Chest Computed Tomography (CT) scans can be used as a complementary mean for COVID-19 screening. Almost all hospitals have CT image screening, thus using them could provide a more reliable, useful, and quicker technology for the classification and assesment of COVID-19 [5]. This could also allow patient to avoid the discomfort of an intrusive RT-PCR test, as well as keeping medical personel from coming in close contacts with potentially contagious patients. In a comparative study, [6] showed that CT-scans may have a higher sensitivity than RT-PCR, proving even further the potential of CT-scan based screening tools. Artificial Intelligence (AI) has promoted countless contributions in the field of medical imaging [7], and deep learning is the most efficient technique that can be used in medical Science. It is a fast and efficient method for the diagnosis and prognosis of various illnesses with a good accuracy rate [5].

In this paper, we explore the effectiveness of three deep learning models to detect COVID-19 from CT scans whole volumes. The model is trained on a dataset of 2000 CT scans, publicly available [8]. The model is trained on the USD's Lawrence Supercomputing Machine on a GPU node consisting of a dual 12-core SkyLake 5000 series CPU, and NVIDIA Tesla V100 32GB CPU and 192GM RAM.

3 Related Work

3.1 Dataset availability

Among the publicly available dataset containing CT-scans labeled for COVID-19 classification, 2 categories of datasets emerge: 2D and 3D datasets. 2D datasets are generally images extracted from CT-scans using random slicing, or manual slicing for significant regions, realised by a physician or a doctor. 3D datasets contains full CT-scans and come in .mha or .dicom file format, as produced by CT-scans machines. In addition to the image data, there is sometimes additional metadata such as age, sex, or other biological data. The labeling of datasets are realised by physicians and/or utilising one or several RT-PCR tests. An issue with 2D datasets is that either a physician needs to manually select the relevant slices, or an algorithm needs to be used for slicing, which may carry the risk of overlooking the area of interest. Additionally, selecting 2D images from 3D CT-scans results in having numerous images from a single patient and can lead to performance overestimation of models, as appointed by [9]. One of the difficulties of using 3D datasets is that they tend to be larger in size, which can significantly increase the amount of time required to process and train machine learning models. This can pose a challenge in cases where deep learning algorithms are used to detect COVID-19 through CT-images, as these algorithms require substantial amounts of annotated training data to learn useful computational models. As a result, the size of qualitative datasets can rapidly expand, leading to further computational complexities and potentially longer processing times [9]. Therefore, it is crucial to find ways to optimize the use of 3D datasets in machine learning algorithms while balancing the trade-offs between data size and model accuracy.

In the litterature, two datasets are commonly used for COVID-19 detection on CT-scans. The first one is called SARS-COV-2 images [10] and contains images from 60 patients identified with COVID-19 for a total of 1252 CT images of patients with COVID-19 and 60 patients not identified with COVID-19 for a total of 1230 CT images of patients without COVID-19. The data was collected from hospitals of Sao Paulo, Brazil [10]. The second commonly used dataset is called COVID-19 CT-Scan Dataset [11] and contains 275 CT-scans of patients with COVID-19 and 195 CT-scans of patients without COVID-19. Both datasets are 2D datasets, and the images are extracted from 3D CT-scans using random slicing. The images are in .png format and are 512x512 pixels. The datasets are labelled by physicians and/or utilising one or several RT-PCR tests. According to Zhao, the author of [11], the size of the dataset is relatively small for deep learning purposes. This leads the author to experiment with transfer learning and data augmentation to palliate to the small size datasets of CT-scans [11]. These two datasets will be cited throughout the paper as [10] and [11] respectively.

3.2 2-Dimensional Approach

As mentionned above, the literature on COVID-19 detection using chest CT-scans can be divided into 2 categories: the papers where 2-dimensional data is used to train a neural network, and the papers where 3-dimensional data is used to train a neural network. The major challenge of using CT-scans modality for deep learning purposes is that it is a 3-dimensional object, thus it contains a lot of data (compared to other image modalities) which can cause to rapidly reach the computing capabilities of a computer / the limits of GPU memory. One strategy to remediated to this problem is to reduce the dimension of the dataset by going from a full (3D) CT-scan to a set of several (2D) CT-scan images using slicing techniques.

In [12], Turkoglu started with a dataset of 746 CT images then used data augmentation techniques (reflection, rotation) to expand this dataset to 3730 images. Using transfer-learning techniques, the author used a Multiple Kernels-ELM-based Deep Neural Networks (MKs-ELM-DNN) method and obtained an accuracy score of 98.36% [12].

In [13], Sen et al. used a bi-stage hybrid model to detect COVID-19 from CT images of two different datasets ([10] and [11]). The first stage of this approach is to use a CNN architecture to extract features from the CT images. The second stage is a bi-stage feature selection approach that selects which features to be used for the classification using the Support Vector Machine (SVM) classifier. This method yield a prediction rate of 98.39% on [10], and a 90.0% prediction rate on [11].

In [14], Ghassemi et al. used pre-trained deep neural networks and a cyclic generative adversarial net (CycleGAN) model for data augmentation. This method reached an accuracy of 99.60% on a dataset of 189 patients (Iranian hospital).

In [15], Aria et al. used transfer learning techniques to overcome the problems raised by using small-sized datasets. Their paper proposes an adversarial deep domain adaptation-based approach for diagnosing COVID-19 from lung CT-images, termed ADA-COVID. They achieved an accuracy of 99.96% on [10].

In [16], Carvalho et al. used a combination of hyperparameters optimization, feature selection and a multi-layer perceptron classifier to classify images from [10] and [11]. The proposed methodology achieved an accuracy of 99.7% and 98.7% on the respective datasets.

In [17], a DenseNet201 based deep transfer learning (DTL) method is proposed by Jaiswal et al. to classify CT images from [10]. The proposed model is utilized to extract features by using its own learned weights on the ImageNet dataset along with a convolutional neural structure to achieve an accuracy of 97%.

In [18], Arora et al. used transfer learning from existing pre-trained models and a super-residual dense neural network to classify CT images from [10] and [11]. Their method claimed to have achieved a precision of 100% and 94.12% respectively.

In [19], Singh and Yow propose an iterpretable deep learning model Ps-

ProtoPNet to detect COVID-19 from CT-scan images from [20]. The highest accuracy that their model achived was 99.29%.

In [21], Rahimzadeh et al. used an image processing algorithm to discard the CT images where the lung is not properly visible in order to reduce processing time and false detection. They used a ResNet50V2 deep neural network on a dataset that they introduced consisting of 48260 CT scan images from 282 normal persons and 15589 images from 95 patients with COVID-19 infections. The proposed method achieved an accuracy of 98.49% in the single image classification stage, and an accuracy of 95.51% at the patient identification stage.

In [22], Yang et al. propose three deep learning architectures, feature-ensemble deep neural network (F-EDNC), fully connected-ensemble deep neural network (FC-EDNC), and output-ensemble deep neural network (O-EDNC) to classify CT images from [10]. The results suggest that the F-EDNC architecture is the best performing architecture with an accuracy of 97.75%, followed by FC-EDNC and O-EDNC with 97.55% and 96.12% accuracy respectively. [Explain what an esemble neural network is later ?]

In [23], Loey et al. used data augmentation techniques along with Conditional Generative Adversarial Networks (CGAN) to generate new images from the dataset of [11]. They used five different deep learning architectures to classify the generated images and achieved best results with the ResNet50 architecture. The authors obtained an accuracy of 82.91%, a sensitivity of 77.66% and a specificity of 87.62%.

In [24], Alshazly et al. experimented with twelve different convolutional neural network architectures to classify CT images from the dataset of [10] and [11]. The proposed model achieved average accuracies of 99.4% and 92.9%, and sensitivity scores of 99.8% and 93.7% on [10] and [11] respectively. The authors also proposed a method to visualize the decision made by the models by using the Grad-CAM technique.

In [5], Shah et al. compared the performances of a self-developed model named CTnet-10 to the performances of several pre-existing CNN architectures in classifying the CT images from [11]. The VGG-19 architecture showed the best results with an accuracy of 94.52%.

In [25], Heidari et al. proposed a privacy-aware method for COVID-19 detection in chest CT scans using a lightweight deep neural network, transfer learning, and blockchain technology. The proposed method achived an accuracy of 99.76% on a combination of 5 different datasets from hospitals in Iran.

3.3 3-Dimensional Approach

In this section is presented a list of papers that used 3-dimensional approaches to detect COVID-19 from CT scans. Contrary to the papers in the previous section, these papers do not use 2-dimensional slices of the CT scans, but the whole 3-dimensional volume of the CT scan. This approach is more accurate than the 2-dimensional approach, but it is also more computationally expensive, hence the lesser number of papers that use this approach.

In [26], Zhao et al. proposed a new segmentation method, which integrates a 3-dimensional V-Net with a shape deformation module implemented using a spatial transform network (STN). The proposed method achieved an area under the curve (AUC) of 94.70%, a sensitivity of 96.70% and a specificity of 92.70% on a dataset consisting of 112 CT scans, including 58 COVID-19 positive cases and 54 COVID-19 negative cases. Due to the limited size of the dataset, the authors applied data augmentation techniques to increase the size of the dataset, including random flipping, random cropping and random rotation. Rescaling and resampling strategies were also applied to CT scans to overcome the GPU memory limit abd to reduce the computational cost.

In [8], the authors did not use artificial intelligence techniques to detect COVID-19 from CT scans. Instead, they compared the accuracy of junior and senior radiologists to detect the visual manifestations of COID-19 on 10,735 CT scans. The results showed that the radiologists had an overall accuracy of 80.0%. The author also created a dataset of 2000 CT scans, which is publicly available on AWS Registry of Open Data [8], and is the dataset that is used in this paper.

4 Methods

4.1 Data Description

For this paper, we consider the STOIC2021 Training dataset. The STOIC project collected Computed Tomography (CT) images of 10,735 individuals suspected of being infected with SARS-COV-2 during the first wave of the pandemic in France, from March to April 2020. For each patient in the training set, the dataset contains binary labels for COVID-19 presence, based on RT-PCR test results, and COVID-19 severity, defined as intubation or death within one month from the acquisition of the CT scan [27]. The part of this dataset which is used for the experiments presented in this paper is publicly available on AWS Registry of Open Data [8] and consists CT images from 2000 individuals. Each CT-scan is in the dimension of 512*512*(143 - 866) for width*height*depth. The depth value varies from 143 to 866 as each CT-scan has a different amount of layers corresponding to the height of the patient, the mean amount of layers being 433. Among the 2000 individuals, 1205 (60.25%) are COVID-19 positive and 795 (39.75%) are COVID-19 negative. The dataset is split into a training set of 1600 individuals (59.81% COVID+), and a validation set of 400 individuals (62.00% COVID+). The training set is used to train the deep neural network, the validation set is used to tune the hyperparameters of the deep neural network.

4.2 Pre-processing Methods

Pre-processing the dataset before training the deep neural network is necessary as each CT-scan has a different shape. The goal of the pre-processing is therefore to convert each CT-scan into a standardised shape, that is readable by the neural network. First, each CT-scan volume is converted from its original ".mha" file type into a number tensor using the python library Numpy by converting each pixel value into a number of corresponding intensity. This allows for the subsequent pre-processing operations to be effectuated. The volume is then normalized to contain values between 0 and 1, 0 being the lowest density in the scan (dark pixels), and 1 being the highest (white pixels). Finally, the volume is resized on all three axis to fit the desired dimensions for the input of the neural network using a zoom function from the SciPy python library and a scaling factor. The scaling factor is calculated as follow :

$$ScalingFactor = \frac{DesiredDimension}{CurrentDimension} \tag{1}$$

The input shaped choosen for the experimentation is 128*128*64 as it reduces the size of the dataset to 8Gb, which is small enough to be fitted on a computer GPU. Larger input shapes were attempted but the GPU memory was not sufficient to train the models. The input shape of 128*128*64 is also large enough to capture the main features of the CT scans..

4.3 Deep Neural Networks

In this section, the different deep neural networks used for the experimentation are presented. The first model is a simple 5 layers convolutional neural network, the second model is inspired by the ResNet34 architecture, and the third model is inspired by the VGG-16 architecture. The models are implemented using the Tensorflow python library.

4.3.1 Convolutional Neural Network

Convolutional Neural Networks (CNNs) are a type of multilayer neural networks that are used for image recognition. They are composed of convolutional layers, pooling layers, fully connected layers and activation layers. CNNs are used to recognize visual patterns direclty from pixel images [28] thus the interest for this technology in this research.

4.3.2 Simple Model

The first architecture used for the experimentation is a simple three-dimentional, 5 layers convolutional neural network. The model is composed of 5 layers, 4 layers composed of a 3D convolutional layer, a 3D max pooling layer, and a batch normalization layer. The layer is composed of a global average pooling layer, a dense layer of 512 neurons and a dropout layer of 0.3. The activation function used for the convolutional layers and the fully connected layer is ReLU. The output layer is composed of a dense layer of 1 neuron and a sigmoid activation function. The model is implemented using the Keras sequential python library. The architecture of the model is visualized in Figure 1 using the open-source VisualKeras tool created by [1].

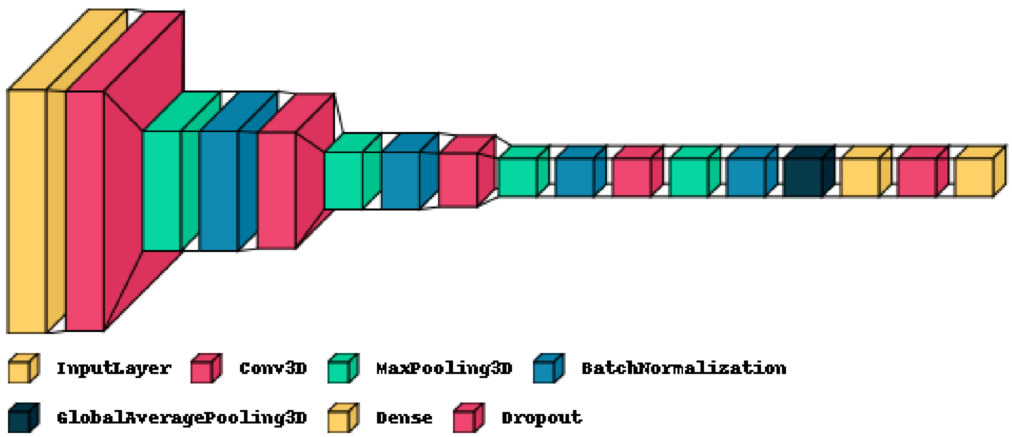

Figure 1: The architecture of the simple CNN model, visualized using VisualKeras [1]

4.3.3 ResNet34

The second architecture used for the experimentation is a deep residual network architecture (ResNet). It is a type of convolutional neural network where the input from the previous layer is added to the output of the current layer. This skip connection makes it easier for the network to learn and results in better performance. The ResNet architecture has been successful in a number of tasks, including image classification, object detection, and semantic segmentation [29]. There exist several variations of the ResNet architecture, identified by their depth. The ResNet34 architecture is a 34 layers deep residual network. The model used for in this project has been adapted to three-dimensional data, and is implemented using the Keras sequential python library. The architecture of the model is presented in Figure 2.

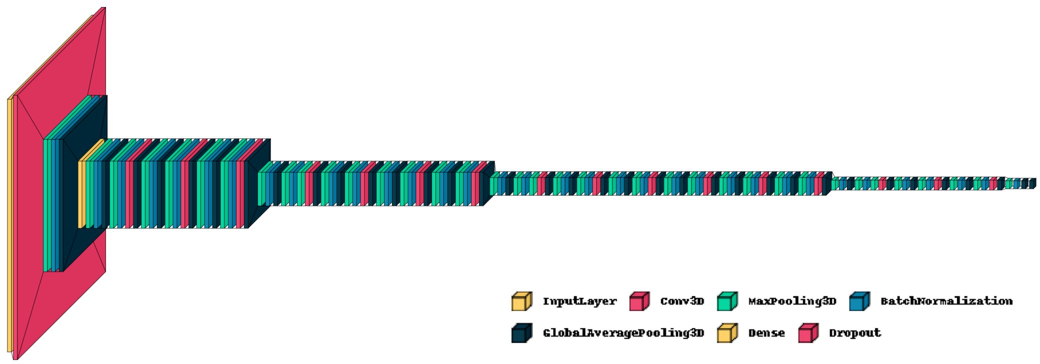

Figure 2: The architecture of the ResNet34 model, visualized using VisualKeras [1]. z-scale modified to fit the page.

4.3.4 VGG-16

The third architecture used for the experimentation is a Visual Geometry Group (VGG) architecture. It is a type of convolutional neural network with a series of 16 convolutional layers followed by fully connected layers [30]. The VGG architecture has been successful in a number of tasks, outperforming other architectures at the time of its creation [30]. The model used for in this project is has been adapted to three-dimensional data, and is implemented using the Keras sequential python library. The architecture of the model is presented in Figure 3.

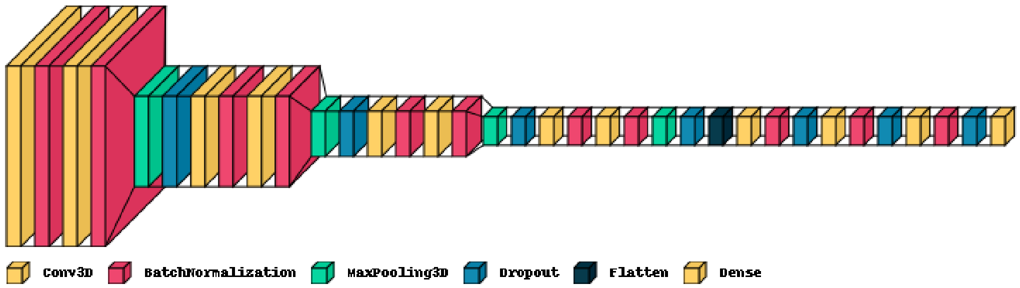

Figure 3: The architecture of the VGG-16 model, visualized using VisualKeras [1]. z-scale modified to fit the page.

4.4 Evaluation Metrics

In this section, the different evaluation metrics used in the litterature to evaluate the performance of the deep neural networks are presented. The first metric is the accuracy, the second metric is the specificity, the third metric is the sensitivity, and the fourth metric is the precision. The following abbreviations are used throughout the section :

- TP : True Positive; designate the amount of CT-scans with a covid+ label correctly identified as covid+ by the model.
- FP : False Positive; designate the amount of CT-scans with covid- label incorrectly identified as covid+ by the model.
- TN : true negative; designate the amount of CT-scans with a covid- label correctly identified as covid- by the model.
- FN : False negative; designate the amount of CT-scans with covid+ label incorrectly identified as covid- by the model.

4.4.1 Accuracy

Accuracy is the fraction of correctly identified predictions. It measures the overall performance of the model on the test set [31]

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{2}$$

4.4.2 Specificity

Specificity measures the proportion of negative class samples that were correctly identified [31].

$$Specificity = \frac{TN}{TN + FP} \tag{3}$$

4.4.3 Sensitivity / Recall

Sensitivity / Recall measures the proportion of positive class samples that were correctly identified [31].

$$Sensitivity = \frac{TP}{TP + FN} \tag{4}$$

4.4.4 Precision

precision gives the rate of the truly classified positive images among the classes [31].

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

4.4.5 F1-score

F1 score is a joint of Precision and Recall, expressed as a harmonic mean of this metrics [31].

$$F1 = 2 * \frac{precision * recall}{precision + recall} \tag{6}$$

Dataset	Covid+	Covid-
Training	957	643
Validation	248	152

Table 1: Proportion of Covid+ and Covid- CT-scans in the training and validation set.

5 Experimental Procedure

5.1 Dataset separation

The 2000 CT-scans are split into 80% for training and 20% for validation. The validation set is used to evaluate the performance of the model during the training process. The proportion of covid+ and covid- CT-scans in the training and validation set is presented in Table 1. The training set contains 1600 CT-scans, 957 covid+ and 643 covid- CT-scans. The validation set contains 400 CT-scans, 248 covid+ and 152 covid- CT-scans. This follows the proportion of Covid+ CT-scans in the full dataset [8]. The proportion of covid+ and covid- CT-scans in the training and validation set is presented in Table 1.

5.2 Hardware

As the STOIC2021 dataset containing CT-scans from 2000 patients is relatively large (original data = 250Gb, preprocessed data = 8Gb) , computation for this project were performed on High Performance Computing systems at the University of South Dakota, funded by NSF Award OAC-1626516. The specific node on which the computations were performed is composed of dual 12-core SkyLake 5000 series CPUs, an Nvidia Tesla 100V 32GB GPU, 192GB of RAM and 240GB SSD. Usage of the Lawrence supercomputer allowed for greatly reduced training times during the experimental phase of this research. USD research Computing staff Bill Cone provided valuable technical expertise and assistance to this project.

5.3 Training parameters

The training phase of this research was divided into two phases. The first phase was the experimental phase, where different architectures were trained for 40 to 50 epochs and compared. The second phase was the final phase, where the most stable architecture was trained for 20 epochs to see if the performances could be improved.

During the experimental phase, the following parameters were used to obtain a first set of results :

- Epochs : 50 (40 for the Basic CNN)
- Loss Function : Binary Cross Entropy
- Optimizer : Adam
- Batch Size : 16
- Metrics : Accuracy, Loss

After determining the best performing architecture, the final phase of the training was performed. The following parameters were used to obtained the results presented in this paper :

- Epochs : 20
- Loss Function : Binary Cross Entropy
- Optimizer : Adam
- Batch Size : 16
- Metrics : Accuracy, Loss

Architecture	Validation Accuracy	Validation Loss	Time per epoch
Basic CNN	68.5%	0.9339	48s
ResNet34	72.0%	0.6150	70s
VGG16	70.75%	0.6007	114s

Table 2: Results for the experimental phase on the validation set.

Architecture	Training Accuracy	Training Loss	Time per epoch
Basic CNN	92.62%	0.2040	48s
ResNet34	72.69%	0.5450	70s
VGG16	73.62%	0.5327	114s

Table 3: Results for the experimental phase on the training set.

6 Results

6.1 Experimental phase

The results for the experimental phase are presented in Table 2. The results are presented in terms of accuracy and loss. The results are presented for the validation set. The results for the training set are presented in Table 3.

Analysing the behavior of the accuracy and the loss for each architecture can also be done by looking at the graphs in Figure 4. It can be seen that the VGG16 architecture is the one that seems to be the most stable.

6.2 Final phase

After training the VGG16 acrchitecture for 20 epochs, the accuracy reached a maximum of 63% on the validation set and 65.4% on the training set while the loss reached its lowest at 0.644 for the validation set and 0.642 for the

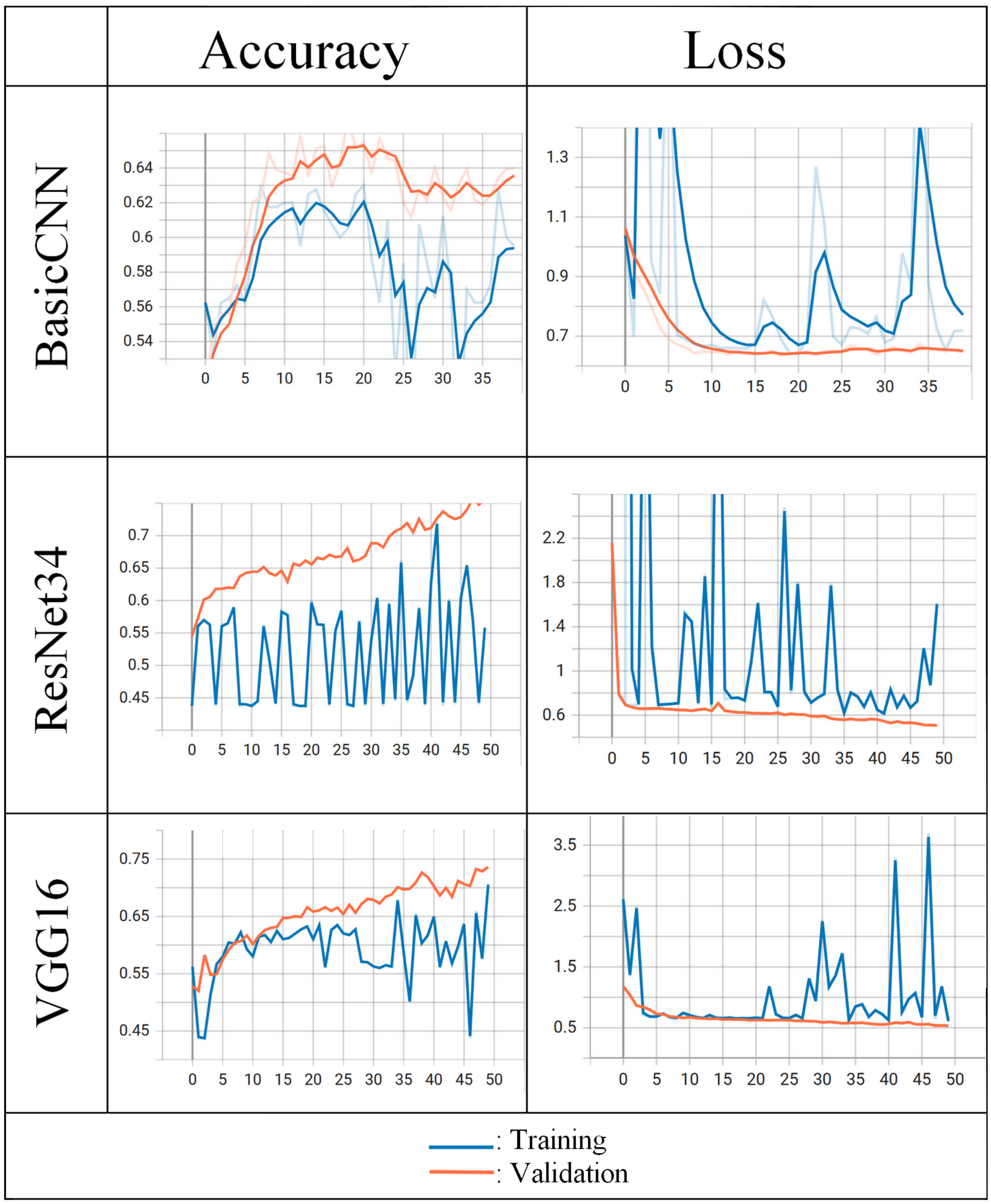

Figure 4: Graphs of the accuracy and loss for the experimental phase.

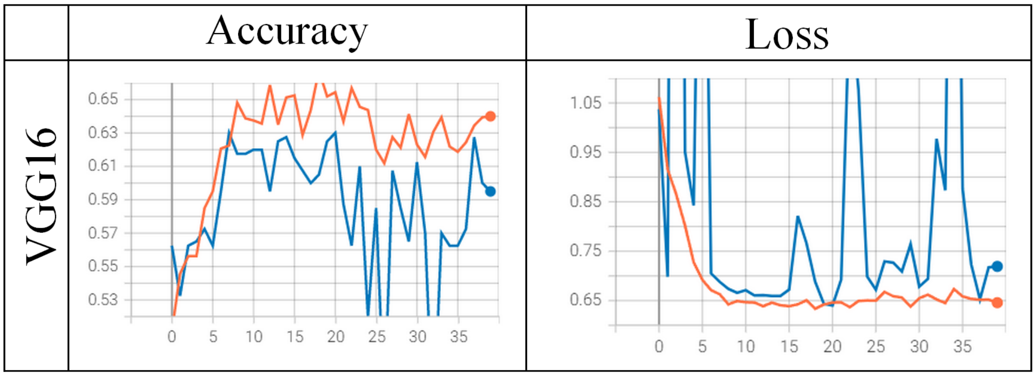

Figure 5: Graphs of the accuracy and loss for the final phase.

training set.

The graphs of the accuracy and loss for the final phase are presented in Figure 5.

7 Discussion

This study demonstrated the potential of deep learning models to improve the accuracy and efficiency of COVID-19 diagnosis using CT scans. Our 3D CNN model achieved promising results in detecting COVID-19 from CT scans with an accuracy of 65.44% on the validation dataset. This result is comparable to the performance of other state-of-the-art models reported in the literature. However, further validation and refinement of the model are necessary to improve its accuracy and reliability for clinical use.

One limitation of our study is that we used a relatively large dataset of 2000 CT scans for training and validation. This came at the cost of a heavy preprocessing in order to reduce the size of the dataset, and thus losing some data in the process. Future studies could explore the potential of using a ligther preprocessing and keep a higher resolution input shape, if they have the necessary computational resources.

Another limitation of our study is that we used CT scans as the sole imaging modality for COVID-19 diagnosis. While CT scans are a cost-effective option, they may not be readily available in all settings. Future studies could explore the potential of combining CT scans with other imaging modalities, such as X-rays or ultrasound, to improve the accuracy of COVID-19 diagnosis.

Overall, our proposed 3D deep learning model has the potential to be a valuable diagnostic tool for COVID-19, particularly in resource-constrained settings. The use of AI-guided tools can facilitate accurate analysis of COVID-19 evidence even in regions where other diagnostic modalities may not be available. Our study highlights the potential of AI to improve the efficiency and accuracy of COVID-19 diagnosis and underscores the need for further validation and refinement of deep learning models for clinical use.

8 Conclusions and Future Work

The accuracy of this model in detecting the presence of COVID-19 on CT-scans shows that Deep Learning models can be useful tools for mass screening. Deep learning tools could in this case facilitate the triage of COVID-19 and nonCOVID-19 patients, and thus improve diagnosis on thoracic symptoms as well as limit the spread of the most contagious virus. In the future, this project could be combined with other well-known deep learning models trained on different image data types such as chest x-rays to employ multimodal learning and representation for COVID-19 screening. This could possibly provide more information in detecting anomaly patterns due to COVID-19. Further research could also try to improve the performances of this project by using a higher-resolution preprocessed data or by experimenting with data augmentation techniques and/or transfer learning techniques.

References

[1] P. Gavrikov, "visualkeras," https://github.com/paulgavrikov/visualkeras, 2020.

[2] W. H. Organization, "Who sprp 2021 mid-term report - who strategic action against covid 19," *WHO SPRP 2021 Mid-term Report - WHO Strategic Action Against COVID 19*, Oct 2021. [Online]. Available: https://www.who.int/publications/m/item/2021-mid-year-report—who-strategic-action-against-covid-19

[3] ——, "Maintaining infection prevention and control measures for covid-19 in health care facilities: Policy brief, 7 june 2022," *Maintaining infection prevention and control measures for COVID-19 in health care facilities: Policy brief, 7 June 2022*, Jun 2022. [Online]. Available: https://www.who.int/publications/i/item/WHO-2019-nCoV-Policy—brief-IPC-HCF-2022.1

[4] M. Teymouri, S. Mollazadeh, H. Mortazavi, Z. N. Ghale-noie, V. Keyvani, F. Aghababaei, M. R. Hamblin, G. Abbaszadeh-Goudarzi, H. Pourghadamyari, S. M. Hashemian, and H. Mirzaei, "Recent advances and challenges of rt-pcr tests for the diagnosis of covid-19." *Pathology Research and Practice*, 2021.

[5] V. Shah, R. Keniya, A. Shridharani, M. Punjabi, J. Shah, and N. Mehen-

dale, "Diagnosis of covid-19 using ct scan images and deep learning techniques." *Emergency Radiology*, 2021.

[6] Y. Fang, H. Zhang, J. Xie, J. Xie, M. Lin, L. Ying, P. Pang, W. Ji, and W. Ji, "Sensitivity of chest ct for covid-19: Comparison to rt-pcr," *Radiology*, 2020.

[7] K. C. Santosh, S. Ghosh, S. Ghosh, and S. Ghosh, "Covid-19 imaging tools: How big data is big?" *Journal of Medical Systems*, 2021.

[8] "Stoic2021 training dataset access," https://registry.opendata.aws/stoic2021-training/, accessed: 2022-06-12.

[9] F. Altaf, S. Islam, and N. Akhtar, "Resetting the baseline: Ct-based covid-19 diagnosis with deep transfer learning is not as accurate as widely thought." *arXiv: Computer Vision and Pattern Recognition*, 2021.

[10] P. Angelov, E. A. Soares, 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*, 2020.

[11] J. Zhao, X. Yang, X. He, J. Zhao, Y. Zhang, Y. Zhang, S. Zhang, and P. Xie, "Covid-ct-dataset: A ct scan dataset about covid-19," *arXiv: Learning*, 2020.

[12] M. Turkoglu, "Covid-19 detection system using chest ct images and mul-

tiple kernels-extreme learning machine based on deep neural network." *Irbm*, 2021.

[13] S. Sen, S. Sen, S. Sen, S. Saha, S. Chatterjee, S. Mirjalili, and R. Sarkar, "A bi-stage feature selection approach for covid-19 prediction using chest ct images," *Applied Intelligence*, 2021.

[14] N. Ghassemi, A. Shoeibi, M. Khodatars, J. Heras, J. Heras, A. Rahimi, A. Zare, R. B. Pachori, R. B. Pachori, R. B. Pachori, R. B. Pachori, J. M. Gorriz, and J. M. Górriz, "Automatic diagnosis of covid-19 from ct images using cyclegan and transfer learning," *arXiv: Image and Video Processing*, 2021.

[15] M. Aria, E. Nourani, and A. G. Oskouei, "Ada-covid: Adversarial deep domain adaptation-based diagnosis of covid-19 from lung ct scans using triplet embeddings," *Computational Intelligence and Neuroscience*, 2022.

[16] E. D. Carvalho, R. R. V. e Silva, F. H. D. Araújo, R. A. L. Rabelo, and A. O. de Carvalho Filho, "An approach to the classification of covid-19 based on ct scans using convolutional features and genetic algorithms." *Computers in Biology and Medicine*, 2021.

[17] A. Jaiswal, N. Gianchandani, D. Singh, V. Kumar, and M. Kaur, "Classification of the covid-19 infected patients using densenet201 based deep transfer learning." *Journal of Biomolecular Structure & Dynamics*, 2020.

[18] V. Arora, E. Y. K. Ng, R. S. Leekha, M. Darshan, and A. Singh, "Transfer learning-based approach for detecting covid-19 ailment in lung ct scan." *Computers in Biology and Medicine*, 2021.

[19] G. Singh, G. Singh, G. Singh, and K.-C. Yow, "Object or background: An interpretable deep learning model for covid-19 detection from ct-scan images." *Diagnostics*, 2021.

[20] K. Gunraj, "Kaggle. covidx ct-2 dataset," 2021, accessed: 2023-01-01. [Online]. Available: https://www.kaggle.com/datasets/hgunraj/covidxct

[21] 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." *Biomedical Signal Processing and Control*, 2021.

[22] L. Yang, S.-H. Wang, and Y. Zhang, "Ednc: Ensemble deep neural network for covid-19 recognition," *Tomography*, 2022.

[23] M. Loey, G. Manogaran, and N. E. M. Khalifa, "A deep transfer learning model with classical data augmentation and cgan to detect covid-19 from chest ct radiography digital images." *Neural computing & applications*, 2020.

[24] H. A. Alshazly, C. Linse, E. Barth, and T. Martinetz, "Explainable covid-19 detection using chest ct scans and deep learning." *arXiv: Image and Video Processing*, 2020.

[25] A. Heidari, S. Toumaj, N. J. Navimipour, and M. Unal, "A privacy-aware method for covid-19 detection in chest ct images using lightweight deep conventional neural network and blockchain," *Computers in Biology and Medicine*, 2022.

[26] C. Zhao, Y. Xu, Z. He, J. Tang, Y. Zhang, J. Han, Y. Shi, and W. Zhou, "Lung segmentation and automatic detection of covid-19 using radiomic features from chest ct images." *Pattern Recognition*, 2021.

[27] M.-P. Revel, S. Boussouar, C. de Margerie-Mellon, I. Saab, T. Lapotre, D. Mompoint, G. Chassagnon, A. Milon, M. Lederlin, S. Bennani, S. Molière, M.-P. Debray, F. Bompard, S. Dangeard, C. Hani, M. Ohana, S. Bommart, C. Jalaber, M. E. Hajjam, I. Petit, L. Fournier, A. Khalil, P.-Y. Brillet, M.-F. Bellin, A. Redheuil, L. Rocher, V. Bousson, P. Rousset, J. Gregory, J.-F. Deux, E. Dion, D. Valeyre, R. Porcher, L. Jilet, and H. Abdoul, "Study of thoracic ct in covid-19: The stoic project." *Radiology*, 2021.

[28] C.-C. J. Kuo, "Understanding convolutional neural networks with a mathematical model," *Journal of Visual Communication and Image Representation*, vol. 41, pp. 406–413, 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1047320316302267

[29] M. Shafiq and Z. Gu, "Deep residual learning for image recognition: A survey," *Applied Sciences*, vol. 12, no. 18, p. 8972, Sep 2022. [Online]. Available: http://dx.doi.org/10.3390/app12188972

[30] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556*, 2014.

[31] R. Karthik, R. Menaka, M. Hariharan, and G. Kathiresan, "Ai for covid-19 detection from radiographs: Incisive analysis of state of the art techniques, key challenges and future directions." *Irbm*, 2021.