CTCovid19: Automatic Covid-19 model for Computed Tomography Scans Using Deep Learning

Carlos Antunes[1], João M F Rodrigues[2] and António Cunha[1,3]

[1]Universidade de Trás-os-Montes e Alto Douro, Vila Real, Portugal
[2]NOVA LINCS & ISE, Universidade do Algarve, Faro, Portugal
[3]ALGORITMI Research Centre, University of Minho, Guimarães, Portugal

Summary: COVID-19 is an extremely contagious respiratory sickness instigated by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). Common symptoms encompass fever, cough, fatigue, and breathing difficulties, often leading to hospitalization and fatalities in severe cases. CTCovid19 is a novel model tailored for COVID-19 detection, specifically honing in on a distinct deep learning structure, ResNet-50 trained with ImageNet serves as the foundational framework for our model. To enhance its capability to capture pertinent features related to COVID-19 patterns in Computed Tomography scans, the network underwent fine-tuning through layer adjustments and the addition of new ones. The model achieved accuracy rates that went from 97.0% to 99.8% across three widely recognized and documented datasets dedicated to COVID-19 detection.

INTRODUCTION

COVID-19 is an extremely contagious respiratory sickness instigated by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). Its initial identification occurred in Wuhan, China, back in December 2019[1]. Since then, it has spread across the globe, culminating in a pandemic as declared by the World Health Organization (WHO). Common symptoms encompass fever, cough, fatigue, and breathing difficulties, often leading to hospitalization and fatalities in severe cases.

Traditional technologies to detect COVID-19 are very laborious, time-consuming, with high costs, and tend to fail sometimes, leading to detection failures at the initial stages of the disease, which can affect future treatment. One way to detect COVID-19 is by using Computed Tomography (CT) scan of the thorax, which produces fine-grained pictures of the heart, blood arteries, ribs, airways, and lymph nodes using specialized X-ray equipment.

While many nations and areas of the world allow the use of easily useable and accessible information and communication technology (ICT), this is not the case everywhere. In nations and areas with lower economic standing, doctors still face challenges in obtaining ICT resources to analyze medical images. On the other hand, all doctors need tools to help in the diagnosis that should be focused on their needs, and they (physicians) should/must be part of the design teams of any applications, i.e., any application designed for doctors/physicians should pass through a User-Centered Design development, which is an iterative design process in which designers focus on the users and their needs in each phase of the design process. For an application proposed by the authors with this purpose please see Antunes *et al.*[2], nevertheless, those applications need reliable COVID-19 detection models, that can cope with different "types" and "quality" of medical images, like (different) CT scans.

Based on the most modern Artificial Intelligence (AI) techniques for medical images (e.g., CT scans) Deep Learning (DL) techniques can be used to identify whether a patient has contracted the COVID-19 virus. Here, a new DL model is proposed, **CTCovid19,** to detect COVID-19 in CT scans. This model is an improvement of a previous model developed by the authors, CPAlexNet[2], which is focused on a specific DL architecture - AlexNet. In the present case, the model has the backbone of ResNet-50[3], trained with ImageNet, the network was fine-tuned by adjusting layers and adding new ones to better capture COVID-19 patterns in CT scans. It also briefly described the use of Explainable Artificial Intelligence (XAI) in CT scans to help with the process of explaining to the doctors how the detection was achieved. It is illustrated by two methods: Local Interpretable Model-agnostic Explanations (LIME)[4] and Gradient-weighted Class Activation Mapping (Grad-Cam)[5].

For testing the model it is used three different public datasets of CT scans with and without COVID-19, namely the Covid-19 lung CT Scans dataset[6], Extensive Covid-19 X-ray and Computed Tomography Chest Images dataset CoV-Healthy-6k[7], and the SARS-CoV-2 CT-scan dataset[8] to be possible to compare the results of the detection accuracy of the developed model with the work of other researchers on the same datasets.

The main contribution of the paper is to provide a novel accurate and practical mechanism for detecting COVID-19 on CT scans based on a DL model.

Section 2 presents the theoretical background, related work, and a brief explanation of the datasets used, section 3 the proposed model, section 4 tests and results, and the last section presents the conclusions and the future work. The disease COVID-19 is caused by the mutating virus severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) which has a spike protein that suffers mutations, a nucleocapsid protein, a membrane, an envelope and a single-stranded protein[1,9]. To enter the cells, the virus uses the Angiotensin-converting enzyme 2 (ACE2) cell receptor to anchor itself in the host, which is done via the spike. After, the S protein needs to be broken down by an enzyme to enter the cell. SARS-CoV-2 has a Ribonucleic Acid (RNA) nucleus and a lipid glycoprotein membrane, from which several proteins with different functions stand out. The SARS-CoV-2 multiplies easily, and the virus manages to reach the lungs causing serious symptoms, such as shortness of breath and consequently, less oxygenation of the organs of our body, which can be fatal[1,9].

THEORETICAL BACKGROUND AND RELATED WORK

Chest computed tomography scans have emerged as a promising alternative for COVID-19 diagnosis. CT scans provide high-resolution images of the lungs, which can reveal characteristic abnormalities associated with COVID-19, such as ground-glass opacities (GGOs). CT imaging has shown promise in aiding the diagnosis due to its ability to detect lung abnormalities associated with the virus[10]. Using DL for the detection of COVID-19 through CT scans has been an area of active research and application.

Chouat *et al.*[11] proposed a methodology to explore the potential of transfer learning in constructing a classifier for identifying COVID-19-positive patients using CT scans and X-ray images. To address overfitting and bolster the model's generalization, the authors employed data augmentation techniques to expand the training dataset. Their contribution lies in conducting a thorough assessment of several pre-trained deep neural networks, such as ResNet50, InceptionV3, VGGNet-19, and Xception leveraging data augmentation.

The results substantiate the efficacy of deep learning in COVID-19 detection. Specifically, upon evaluating each modality individually, the VGGNet-19 model surpassed the other three models when using the CT image dataset, achieving 88.5% precision, 86.0% recall, 86.5% F1-score, and 87.0% accuracy. Conversely, the refined Xception version delivers the highest precision, recall, F1-score, and accuracy of 98.0% when utilizing X-ray image datasets. Upon amalgamating the two modalities (X-ray and CT), the VGG-19 model demonstrated superior performance, attaining 90.5% accuracy and F1-score, 90.3% recall, and 91.5% precision.

Topff *et al.*[12] produced an AI-driven clinical support system using deep learning, potentially serving as an effective tool for concurrent assessment by clinicians. It utilized a newly curated European dataset comprising over 2,800 CT scans, demonstrating promise for aiding medical professionals in COVID-19 diagnosis. Alaiad *et al.*[13] utilized images sourced from King Abdullah University Hospital in Jordan, assembling a dataset comprising 875 cases encompassing 2,205 CT images. A radiologist categorized these images based on severity into four levels: normal, mild, moderate, and severe. Employing diverse DL algorithms, the authors aimed to forecast the severity of lung diseases. Among these algorithms, Resnet101 emerged as the most effective, achieving an accuracy score of 99.5% with a minimal data loss rate of 0.03%. In conclusion, the model proposed by the researchers played a crucial role in diagnosing and managing COVID-19 patients, contributing significantly to improved patient outcomes.

In Ulutas *et al.*[14] CT scans were employed to distinguish individuals among those with COVID-19, pneumonia, or those falling into the normal category. The classification was executed using two established CNN models namely ResNet50 and MobileNetv2, both well-known for image classification tasks. Additionally, a new CNN architecture, named CovidxNet-CT, was introduced, specifically tailored for diagnosing COVID-19 using CT scans categorized into three classes. To gauge the proposed method's effectiveness, K-fold cross-validation, a widely used technique in assessing DL performance, was utilized. The study also assessed the method's performance on two embedded system platforms, Jetson Nano and Tx2, demonstrating its viability for deployment in environments with limited resources. The system achieved an average accuracy of 98.83% and an AUC of 0.988 after training and validation using a 4-fold cross-validation approach. The encouraging results suggest that CovidxNet-CT holds promise in aiding radiologists and contributing to the collective efforts against COVID-19. The study proposes a fully automated, DL approach for COVID-19 diagnosis and prognostic analysis, specifically tailored for implementation on embedded platforms.

Foysal *et al.*[15] have used a deformable ResNet-50 to detect COVID-19 on CT scans, which demonstrated superior performance when compared to the proposed deformable CNN model. The application of Grad-Cam technique for visualizing and assessing the localization efforts in the targeted regions at the final convolutional layer has yielded excellent results.

For a more detailed state of the art please see also[2], and Tables 1 and 2, the 1st column presents the authors' name of the study, year and reference, the 2nd column summarizes the method, and the 3rd column the accuracy of the model.

As mentioned in the Introduction in this study it was used three datasets, going now into more detail. The Covid-19 lung CT Scans dataset[6] has more than 8,000 images of CT scans with COVID-19 and without, being 7,496 with COVID-19 and 944 normal. The images in this dataset were gathered from radiology departments at teaching hospitals in Tehran, Iran. The COVID-19 status of patients in the dataset was verified using reverse transcription-polymerase chain reaction (RT-PCR) tests.

On the extensive Covid-19 X-Ray and CT Chest Images dataset, CoV-Healthy-6k[7], can be found several X-rays and CT scans with and without COVID-19. Concerning the CT scans were used 5,427 with COVID-19 and 2,628 without. The inconsistency in the images on the extensive COVID-19 X-Ray and CT chest images dataset CoV-Healthy-6k arises from the diverse sources and equipment used to compile the dataset. Consequently, pre-processing becomes imperative before feeding the data into the model.

The SARS-CoV-2 CT-scan dataset[8] contains several CT scans with and without COVID-19. The proposed dataset is composed of 2,482 CT scan images, which is divided between 1,252 for patients infected by SARSCoV-2, and 1,230 CT scans for non-infected SARS-CoV-2 patients, but who presented other pulmonary diseases. Data was collected from hospitals in Sao Paulo, Brazil.

Of course, more datasets exist, please see e.g. Antunes *et al.*[2]. In the next section, it will be presented the proposed model.

CTCOVID19 MODEL

As mentioned in the Introduction, the present authors propose a model CPAlexNet[2] for COVID-19 detection, it was focused on a specific DL architecture, in the case of AlexNet trained with ImageNet, i.e., AlexNet is the backbone of the model. The network was fine-tuned by adjusting layers to detect COVID-19 and pneumonia, it is a more broadband model, details and results can be seen in Antunes *et al.*[2], and comparison results with the present model in Table 2.

In the present case, it is proposed CTCovid19, a different model, that has a backbone ResNet-50[3]. Understanding the architecture and function of each layer in ResNet-50 is crucial for adapting, fine-tuning, or exploring modifications to suit specific tasks like medical imaging or other specialized domains. Replacing and adding layers within the ResNet-50 architecture allowed it to enhance its ability to recognize COVID-19-related patterns. This involved inserting additional convolutional layers, adjusting pooling layers and integrating attention mechanisms to focus on relevant regions in CT scans.

The CTCovid19 model, built on the ResNet-50 architecture, underwent several modifications to enhance its ability to accurately detect COVID-19 from CT scans. To adapt the model to the specific task of COVID-19 detection, the final layers were replaced with a new learnable layer, a Softmax layer, and a classification layer, enabling the model to output probabilities for the two classes: COVID-19 positive and negative. Additionally, batch normalization layers were introduced to stabilize training by normalizing the input to each layer, preventing issues like vanishing or exploding gradients. ReLU activation functions were added to introduce non-linearity, allowing the model to learn complex patterns in the data. To improve the model's generalization ability, data preprocessing techniques were employed. Data balancing ensured that the model was trained on an equal number of COVID-19 and non-COVID-19 cases, preventing bias. Data augmentation techniques, such as rotation, flipping, and contrast adjustment, were applied to increase the diversity of the training data, enabling the model to recognize variations in CT scan images. The model was trained using the Adam optimizer, which is known for its efficiency in optimizing deep neural networks. The initial learning rate was set to 1e-4, and the model was trained for 100 epochs with a batch size of 8. These modifications and training strategies collectively contributed to the high accuracy achieved by the CTCovid19 model in detecting COVID-19 from CT scans.

The last three layers of ResNet-50, specific to ImageNet classification, are removed. New convolutional layers are added to extract detailed features from the input images. Batch normalization layers are included to stabilize training and reduce overfitting. A fully connected layer maps the extracted features to the output classes (COVID-19 positive or negative), and a Softmax layer outputs the probabilities for each class, enabling probabilistic predictions. Rotations, flips, and shearing, were applied to increase the diversity of the training data. This helped the model learn more robust and generalizable features, preventing overfitting and improving its ability to accurately classify unseen CT scans as COVID-19 positive or negative. Leveraging transfer learning with ResNet-50 improves accuracy by transferring pre-trained weights from a large dataset, allowing the model to quickly learn relevant features from the medical image data.

This algorithm 1 outlines the operation of the Adam optimizer as applied to training a CT scan classification model, ensuring efficient learning while dynamically adapting the learning rates based on the gradients.

The Adam optimizer is particularly effective in the realm of deep learning due to its adaptive learning rate features and robustness across a variety of problems.

Algorithm 1: Adam Optimizer for Training CT Scan Classification Model

Input:
Training dataset D_{train} (augmented CT scan images and labels)
Learning rate α (initial learning rate: 1e−4)
Mini-batch size m (8)
Number of epochs E (100)
Model architecture (ResNet50 with modified final layers)
Output:
Trained model parameters θ
Training metrics (accuracy and loss)

Steps:
1: Initialize Variables
Set θ to initial parameters of the model.
Initialize first moment estimate $m_t = 0$ for all parameters.
Initialize second moment estimate $v_t = 0$ for all parameters.
Set hyperparameters $\beta 1 = 0.9,\ \beta 2 = 0.999$ and $\epsilon = 1e - 8$.
2: **For** each epoch e from 1 to E:
Shuffle the training dataset D_{train}
For each mini-batch b in D_{train}:
2.1: Forward Pass
Compute predictions $\hat{y}$ using the model with current parameters θ.
Calculate the loss $L(\hat{y}, y)$ between predictions and actual labels.
2.2: Compute Gradients
Calculate gradients $g_t = \nabla L(\hat{y}, y)$ for the loss with respect to parameters θ.
2.3: Update First Moment
Update the first moment estimate: $mt = \beta 1 \cdot mt + (1 - \beta 1) \cdot gt$
2.4: Update Second Moment
Update the second moment estimate: $\beta_2 \cdot v_t + (1 - \beta_2) \cdot g_t^2$
2.5: Bias Correction
Compute bias-corrected estimates:
$\widehat{\mathrm{m}}_{\mathrm{t}} = \frac{m_t}{1-\beta_1^e}$
$\hat{\mathrm{v}}_{\mathrm{t}} = \frac{v_t}{1-\beta_2^e}$
2.6: Parameter Update
Update model parameters: $\theta = \theta - \frac{\alpha}{\sqrt{\hat{v}_t + \epsilon}} \cdot \widehat{m}_t$
3: Return Trained Model
After completing all epochs, return the trained model parameters θ along with training metrics.

Figure 1 shows CTCovid19 model taking into consideration the ResNet-50 architecture as backbone, the final layers were altered to suit the specific classification needs for COVID-19 detection. This involved adjusting the number of output nodes and reconfiguring the architecture to accommodate binary (COVID-19 vs. non-COVID-19) classification. Changing the last layers, where a new learnable layer with a weight learn factor of 10 and a bias learn rate factor also of 10 is added to the model replacing the current "fc1000". A Softmax layer is created to replace the current "fc1000_softmax" layer and a classification layer is also created to replace the "ClassificationLayer_fc1000". Also, a new batch normalization layer is created to replace the "activation_49_relu" and a new RELU layer to replace the "avg_pool". The code used to develop the model was adapted from Narayanan *et al.*[16].

The initial layer accepts the input images, typically of size 224 × 224 pixels in three colour channels (RGB). The minimum batch size was 8, and the optimizer used was Adam. The model was trained for 100 epochs, the initial learning rate was 1e-4. Moreover, adjustments included the creation of a new batch normalization layer to substitute "activation_49_relu", and a new RELU layer was implemented in place of "avg_pool".

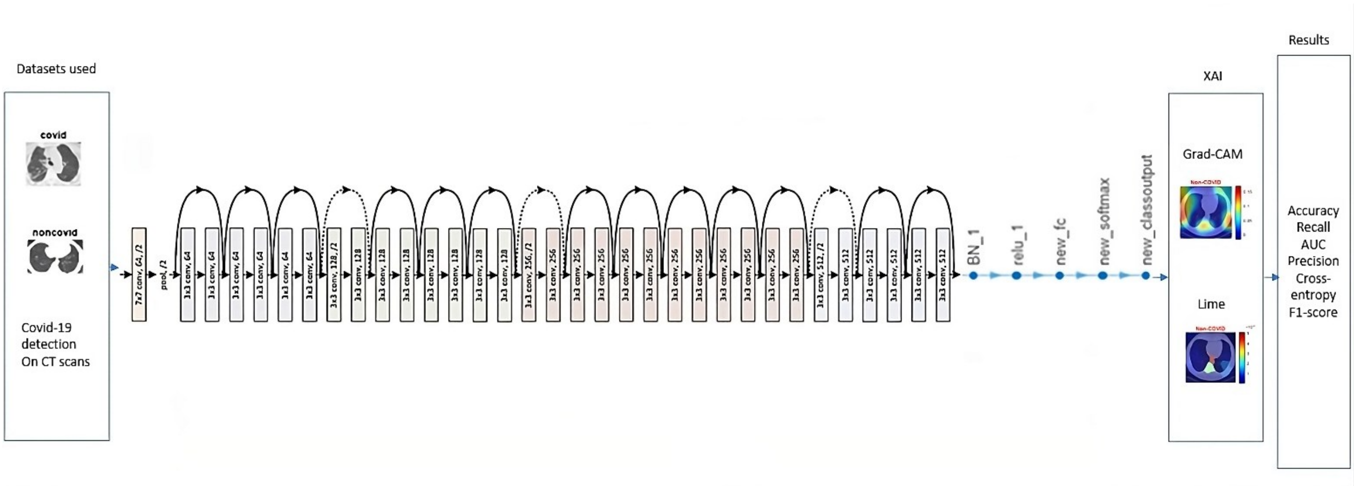

Figure 1. Schematic representation of CTCovid model.

To address the concern about overfitting during training, we employed several strategies. Early stopping was implemented to halt training when validation loss increased, indicating overfitting. Data augmentation techniques, such as random rotations, flips, and noise addition, were applied to enhance data diversity and improve generalization. L2 regularization was utilized to penalize large weights, preventing overfitting. Additionally, careful hyperparameter tuning was performed to optimize the training process. By combining these approaches, we effectively mitigated overfitting and achieved robust performance in our model.

Algorithm 2 shows the methodology used that processes CT scan images in several steps. First, the image is preprocessed by resizing and normalizing pixel values. Next, the preprocessed image is fed into a ResNet-50 backbone to extract high-level features. These features are then passed through fine-tuned layers, including additional convolutional and pooling layers, and attention mechanisms to focus on relevant regions. The output of these layers is fed into a fully connected layer, followed by a Softmax activation function to obtain probabilities for each class (COVID-19 positive or negative). The class with the highest probability is selected as the final prediction. The source code used can be found at [17].

The algorithm 2 represents a significant advancement in the use of deep learning for medical image classification, particularly in the context of a global health crisis like COVID-19. By employing a robust model architecture in conjunction with k-fold cross-validation, the algorithm enhances the reliability and validity of its predictions. Moreover, the integration of explainable AI techniques not only fosters trust in automated diagnostic systems but also aids healthcare professionals in understanding and interpreting model outputs, ultimately improving clinical decision-making and patient management.

Through meticulous training and evaluation using k-fold cross-validation, the algorithm achieves high accuracy and robust performance metrics, underscoring its effectiveness in clinical scenarios. The integration of Grad-CAM and LIME not only enhances the interpretability of the model's predictions but also bridges the gap between advanced machine learning techniques and practical healthcare applications.

Algorithm 2: CTCovid19 - Image Classification with Modified ResNet50 and Explainable AI

Input:
Image Data Path: Directory containing CT scan images.
Number of Folds: Integer value for k-fold cross-validation (e.g., num_folds = 2).
Training Parameters:
MaxEpochs = 100
MiniBatchSize = 8
InitialLearnRate = 1e-4
XAI Options: Flags to indicate the use of Grad-CAM and LIME for explainability.

Output:
Trained Models: Saved models for each fold of cross-validation.
Predicted Labels: Classification results for the test images.
Performance Metrics: Confusion matrix, ROC curve, precision, recall, and F1 score.
XAI Visualizations: Explanatory visuals for model predictions using Grad-CAM and LIME.

Steps of the CTCovid19 Algorithm
1: Initialize Workspace
Clear all variables, close figures, and clear the command window.
2: Set Image Data Path
Define the path to the dataset containing CT scan images.
3: Create Image Datastore
Load images from the specified path, including subfolders, and use folder names as labels.
4; Count Images per Label
Analyze the distribution of images across various categories.
5: Visualize Random Images
Randomly select and display 6 images from the dataset for initial inspection.
6: Define Number of Folds
Set the number of folds for k-fold cross-validation (num_folds = 2).
7: **For** Each Fold (from 1 to num_folds)
Print Current Fold Number
Determine Test Indices
Compute test_idx = fold_idx:num_folds:num_images for the current fold.
Create Train/Test Sets
Use subset to create training and testing datasets based on the computed indices.
Load ResNet50 Architecture
Load the pre-trained ResNet50 model, initializing its architecture for feature extraction.
Replace Final Layers
If numClasses > 0:
Replace the last fully connected layer with a custom layer tailored for the specific number of classes.
Substitute the softmax and classification layers to align with the new output structure.
End If
Preprocess Images
Define a preprocessing function that normalizes and augments the training and testing images.
Set Training Options
Define training parameters:
MaxEpochs = 100
MiniBatchSize = 8
InitialLearnRate = 1e-4
Define Data Augmentation Techniques
Configure augmentation parameters such as random rotations, flips, and scaling to enhance dataset variability.
Resize Images
Resize all images to [224, 224] to meet ResNet50 input requirements.
Train the Model
Execute training using the augmented training dataset with specified training options.
Test the Model
Classify the test images and store predicted labels along with posterior probabilities.
Save the Model
Persist the trained model for the current fold to facilitate later evaluation.
Clear Unnecessary Variables
Employ clearvars to manage memory and optimize computational resources.
End For

8: Generate Confusion Matrix
Compute and visualize the confusion matrix to evaluate classification performance.
9: Calculate ROC Curve
Assess model performance through Receiver Operating Characteristic (ROC) analysis.
10: Calculate Performance Metrics
Derive precision, recall, and F1 score using the confusion matrix for comprehensive evaluation.
11: Implement Explainable AI Techniques
For Each Test Image
If use_gradcam:
Apply Grad-CAM to generate visual saliency maps, identifying critical regions influencing predictions.
End If
If use_lime:
Utilize LIME to produce local explanations for individual predictions, highlighting feature contributions.
End If
End For

Algorithm 2 is a sophisticated framework tailored for the classification of CT scan images, specifically targeting COVID-19 detection. By harnessing the capabilities of the ResNet50 architecture, this algorithm utilizes transfer learning to adapt a pre-trained deep neural network to the nuances of CT imaging data.

With the MaxEpochs parameter set to 100, the training process is designed to maximize the model's learning capacity, enabling it to capture complex patterns indicative of COVID-19 pathology. This extended training period is critical in clinical settings where diagnostic accuracy can significantly impact patient outcomes. The choice of a mini-batch size of 8 effectively balances computational efficiency with gradient stability, promoting reliable convergence during training. Additionally, the initial learning rate of 1e−41e-41e−4 facilitates gradual weight adjustments, minimizing the risk of overshooting optimal solutions in the high-dimensional parameter space. The integration of Explainable AI methodologies, including Grad-CAM and LIME, significantly enhances the interpretability of model predictions. Grad-CAM generates visual saliency maps, elucidating the critical anatomical regions that drive the model's decisions, thereby providing essential insights for clinical validation. Meanwhile, LIME offers localized explanations, allowing clinicians to understand the contribution of specific image features to the model's outputs. In conclusion, algorithm 2 not only aspires to achieve high classification accuracy but also underscores the necessity of interpretability in AI applications within the medical domain. By ensuring that model predictions are explainable, the algorithm enhances clinical decision-making processes, fostering greater trust in automated diagnostic tools and ultimately improving patient management and treatment strategies in the fight against COVID-19.

The workflow in Figure 2 outlines a sophisticated approach for classifying CT scan images to detect COVID-19 using deep learning techniques, specifically employing a modified ResNet50 architecture. It initiates by setting the data path and creating an image datastore, followed by analyzing the distribution of samples across classes. Utilizing k-fold cross-validation, the algorithm iterates through defined folds, adapting the model for classification tasks with tailored final layers and setting training parameters, including 100 epochs, a mini-batch size of 8, and an initial learning rate of 1e−41e-41e−4. The model is trained with augmented data, evaluated on unseen samples, and assessed using performance metrics such as confusion matrices, ROC curves, precision, recall, and F1 scores. Additionally, Explainable AI techniques like Grad-CAM and LIME are integrated to enhance model interpretability, providing insights into the decision-making process, thereby improving diagnostic accuracy and fostering transparency in clinical applications of AI.

Figure 2. Demonstration of the algorithm used to deploy the CTCovid model.

The datasets comprised publicly available CT scan images, organized into structured image datastores for efficient management, with a comprehensive analysis of data distribution performed to assess class balance. The model was trained for a maximum of 100 epochs, using a mini-batch size of 8 and an initial learning rate of 1e−41e-41e−4 to optimize convergence while minimizing the risk of overshooting in the high-dimensional parameter space. Data augmentation techniques, including random rotations and flips, enhanced the diversity of the training dataset. Rigorous evaluation through k-fold cross-validation yielded high accuracy results, demonstrating the model's capability to classify CT scan images with notable precision. The integration of Explainable AI techniques, such as Grad-CAM and LIME, provided insights into the model's decision-making process, enhancing interpretability and fostering trust among healthcare professionals. This study underscores the potential of deep learning methodologies to improve COVID-19 diagnostic accuracy, contributing to ongoing efforts to leverage advanced technologies for better patient outcomes in the context of the pandemic.

TESTS, ANALYSIS, VALIDATIONS AND RESULTS DISCUSSION

Analyzing the practicality of CTCovid19 is crucial, as assessing its potential for assisting doctors, radiologists and healthcare professionals in diagnosing COVID-19. CTCovid19's performance is assessed based on standard metrics, accuracy, sensitivity, specificity, precision, recall, F1-score, and area under the curve (AUC). Using the same dataset for comparison results (accuracy, AUC, etc.) with other authors ensures consistency and fairness in evaluating the model's performance. It establishes a level playing field for different models and methodologies, allowing direct comparisons based on the dataset's characteristics and nuances.

With this purpose, as already mentioned, this study took into consideration the detection of COVID-19 on three different CT scans datasets, namely: Dataset #1 - Covid-19 lung CT Scans dataset[6]; Dataset #2 - CoV-Healthy-6k[7]; Dataset #3 - SARS-CoV-2 CT-scan dataset[8], all obtained from public sources. Figure 3 shows examples of CT scans images from Dataset #2.

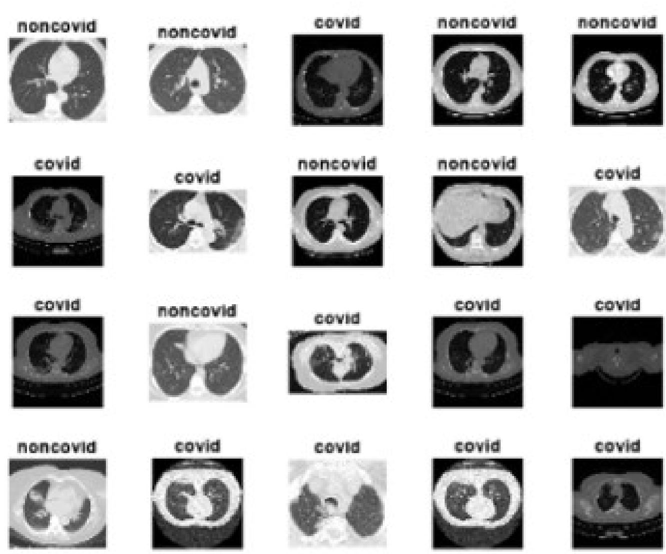

Figure 3. Examples of CT scans from Dataset #2.

The development of the CTCovid19 model involved a multi-faceted approach, utilizing a combination of powerful tools and libraries. MatLab, a versatile programming environment, was instrumental in data preprocessing, visualization, and initial exploratory data analysis. This included tasks such as image loading, resizing, and normalization. Subsequently, Python, a popular programming language for machine learning, was employed to construct and train the deep learning model. Leveraging the capabilities of

TensorFlow and Keras, the model was designed, optimized, and evaluated. TensorFlow provided the underlying infrastructure for tensor operations and automatic differentiation, while Keras offered a user-friendly interface for building and training neural networks. This integrated approach allowed for efficient development, training, and evaluation of the CTCovid19 model. For training and testing, it was used a desktop with CPU Intel i7 – 1165G7 2.8 GHz, RAM 8Gb GPU Intel UHD Graphics. The normalization techniques used, employed color constancy normalization to reduce the impact of varying lighting conditions. This involved calculating the mean intensity of each color channel and scaling the channels to have a similar mean intensity. Additionally, spatial normalization is applied by resizing images to a standard size [224, 224] pixels, ensuring consistent input dimensions for the neural network. The lungs were segmented from the CT scan images to isolate the region of interest for analysis. This step involved identifying and separating the lung parenchyma from other structures such as bones, heart, and mediastinum. CT scans can contain noise due to various factors, including scanning parameters and patient movement. Color constancy normalization was applied to mitigate the impact of varying lighting conditions, while image resizing ensured consistent input dimensions. Rotations and flips, further improved the model's ability to generalize to diverse image variations. These combined strategies contributed to the model's resilience to noise and other image artifacts, leading to improved performance and reliability.

For the tests done with the standard architectures (see below), it was used 80% of the samples for training these architectures and 20% for testing. The CTCovid19 was trained on the three mentioned datasets, which were divided into sets for training, validation, and testing sets (80:10:10), except for the datasets where that division is already done.

Table 1 shows, for different datasets, the accuracy level (3rd column) of the present model against several state-of-the-art models by different authors to detect COVID-19 on datasets of CT scans of the thorax. The present model has better results than the models presented in the table, being our result, the average of the results achieved using the three datasets mentioned above. In summary, the analysis and conclusions drawn from applying CTCovid19 on multiple public datasets of CT scans understand the model's performance and its potential for real-world deployment in aiding COVID-19 diagnosis and patient care.

Additionally, models such as Yasar & Ceylan (2020) with a 23-layer deep CNN and Amyar et al. (2020) utilizing multitask deep learning achieved accuracies of 95.9% and 94.6%, respectively. Other models, including Wang et al. (2020) with 3D-ResNets and Jaiswal et al. (2020) employing various transfer learning techniques, demonstrated accuracies ranging from 90.9% to 93.3%. Overall, the CTCovid19 model not only outperforms the majority of the listed models but also showcases its potential as a robust tool for enhancing diagnostic accuracy in COVID-19 detection using CT scans.

Table 1. Comparison between CTCovid19 and different state-of-the-art models (different datasets).

Authors	**Summarized model**	**Accuracy**
Yasar & Ceylan, 2020[18]	23-layer deep CNN	95.9%
Han et al., 2020[19]	C3D, DeCoVNet and AD3D-MIL Algorithm	96,8%
Ardakani et al., 2020[20]	Pre-processing (Cropped / Input Image Size: 60x60) and Transfer Learning with Convolutional Neural Networks (AlexNet, VGG-16, VGG-19, SqueezeNet, GoogleNet, MobileNet-V2, ResNet-18, ResNet-50, ResNet-101, and Xception)	78,9%
Amyar et al., 2020[21]	Multitask DL (with the encoder and the decoder)	94.6%
Wang et al., 2020[22]	3D-ResNets	93.3%
Jaiswal et al., 2020[23]	Transfer Learning with Convolutional Neural Networks (VGG16, Inception ResNet, ResNet 152V2, DenseNet201)	90,9%
Sun et al., 2020[24]	AFS-DF	91.7%
Ouyang et al., 2020[25]	Convolutional Neural Network (3D ResNet34) and Uniform Sam- pling, Size-balanced Sampling, Dual-Sampling	87.5%
Hasan et al., 2021[26]	DenseNet-121	92.0%
Pathak et al., 2022[27]	Transfer Learning with Convolutional Neural Networks (Transfer from ResNet-50 Network to a New CNN Architecture)	93.0%
CTCovid19	**Present model**	**98.3%**

Nevertheless, this is not enough to show the practicality of the model. With this purpose, Table 2 compares the present model with different state-of-the-art models focusing (specifically) on Dataset #1, #2 and #3. In the selected datasets the present model archives better accuracy results than the state-of-the-art models, the exception is the authors' models for Dataset #2. This is expected, once from our previous study, it was noticed that the backbone of AlexNet architecture can extract explicitly very reliable information (features) from Dataset #2.

Pursuing the analysis of the model practicality, Figure 4 shows the confusion matrixes of the research concerning the detection of COVID-19 on CT scans, displaying the obtained using standard architectures ResNet-50 (on the left), AlexNet (on the right) for Dataset #1 and Figure 5 the same but for the CTCovid19 on the left Dataset #1, middle Dataset #2, and right Dataset #3. It is quite easy to see that the present models show much better results than the ResNet and AlexNet standard models, and also that the bad classification mostly occurs in situations where there is COVID-19, and the models say that there isn't. This still needs improvement.

Analyzing ROC curves, for ResNet-50 the AUC = 0.9467, AlexNet the AUC= 0.8985 for Dataset #1, and the present proposed model for Dataset #1 the AUC=0.9996, Dataset #2 the AUC=0.9778 and Dataset #3 the AUC=0.9962. Figure 6 shows the curves respectively from top to bottom, left to right of ResNet-

50 (Dataset #1), AlexNet (Dataset #1), and CTCovid19 Dataset #1-#3.

Table 2. Comparison of the results obtained with different state-of-the-art on Dataset #1- #3.

Authors	**Models**	**Accuracy**
	Dataset #1	
Dhivya & Sharmila, 2023[28]	Ensemble Deep Lung Disease Predictor (EDepLDP)	92.0%
Kordnoori *et al.*, 2023[29]	NASNet	96.0%
CPAlexNet[2]	Previous Authors model	95.1%
CTCovid19	**Present model**	**99.8%**
	Dataset #2	
Masud *et al.*, 2021[30]	Developed CNN-based diagnostic model	96.0%
Elpeltagy & Sallam, 2021[31]	Modified ResNet-50	97.7%
CPAlexNet[2]	Previous Authors model	**99.8%**
CTCovid19	**Present model**	98.0%
	Dataset #3	
Lawton & Viriri, 2021[32]	VGG-19 implemented with the Contrast Limited Adaptive Histogram Equalization.	95.8%
Alhichri, 2021[33]	DL method to classify CT chest images based on the light-weight pre-trained EfficientNet-B3 CNN model and ensemble techniques	88.2%
CPAlexNet[2]	Previous Authors model	94.4%
CTCovid19	**Present model**	**97.0%**

For the CPAlexNet[2], the AUC for Dataset #1- #3 was 99.4%, 99.8% and 99.3%. Table 3 summarizes the accuracy, precision, recall, AUC, specificity and F1-Score using ResNet-50, the AlexNet for Dataset #1, and the CTCovid19 for the three datasets.

The CTCovid19 model applied for Covid-19 detection via CT scans using the Covid-19 lung CT Scans dataset[6] (Dataset #1), exhibited robust performance. It attained 99.8% accuracy, a 100.0% recall rate, 99.7% precision, an F1-score of 99.4%, 97.9% specificity, and a 99.9% area under the curve, showcasing its strong capabilities. When applied to CoV-Healthy-6k[7], Dataset #2 (for CT scans) achieved an accuracy of 98.0%, a recall rate of 98.8%, a precision of 98.2%, an F1-score of 98.5%, a specificity of 96.2%, and an area under the curve of 99.7%. For the last dataset, the SARS-CoV-2 CT-scan[8] dataset (Dataset #3), CTCovid19 achieved an accuracy of 97.0%, a recall rate of 97.2%, a precision of 96.8%, an F1-score of 96.9%, specificity of 96.2%, and an area under the curve of 99.7%.

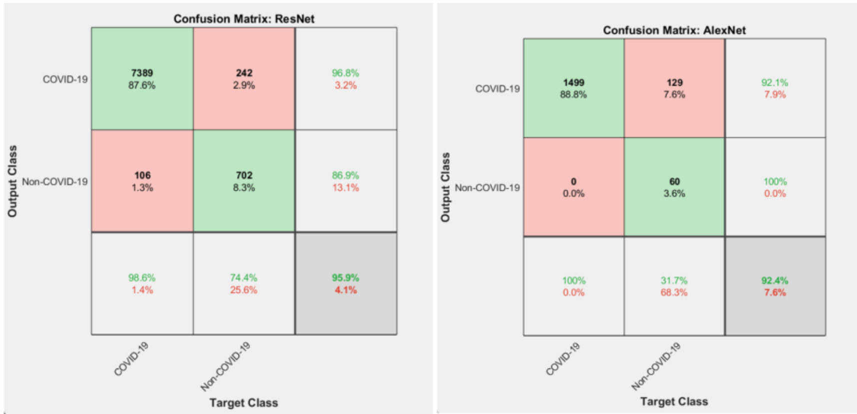

Figure 4. Confusion matrices of the standard models (Dataset #1), on the left ResNet-50, and on the right AlexNet.

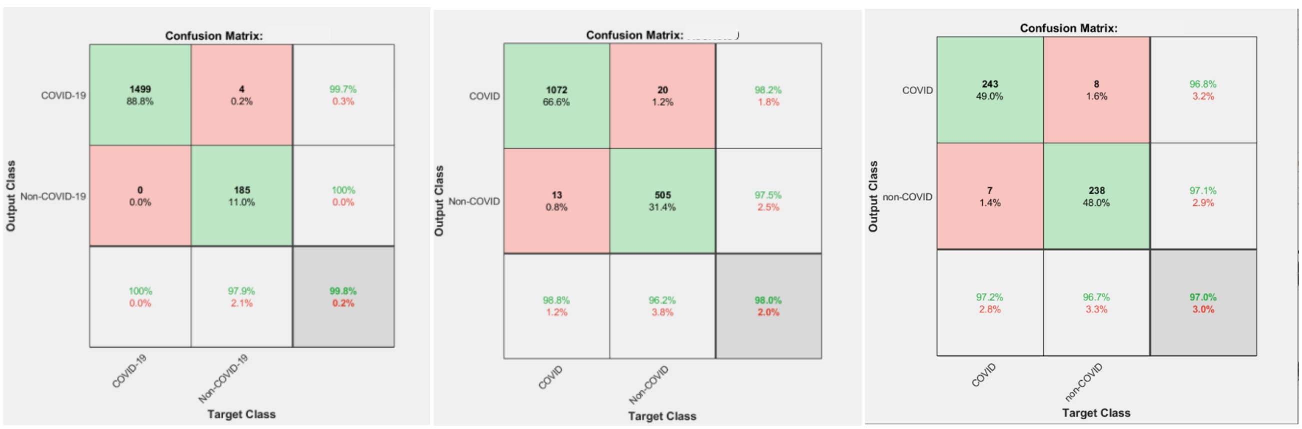

Figure 5. Confusion matrices CTCovid19, top to bottom results for Dataset #1 (left), Dataset #2 (middle), and Dataset #3 (right).

The present model only loses CPAlexNet[2] in accuracy and AUC for Dataset #2 and it ties in with the standard AlexNet model in Recall, once again we think this is due to the "very good" features that AlexNet backbone can extract from Dataset #2.

In summary, CTCovid19 exhibited unwavering performance (see Table 3) consistency across various datasets, affirming its reliability, stability and practicality. Demonstrated adaptability and generalization capabilities across different imaging datasets, suggesting its potential applicability in diverse clinical scenarios. Competed favourably with established models, indicating its status as a good-performing model in COVID-19 detection tasks across multiple datasets.

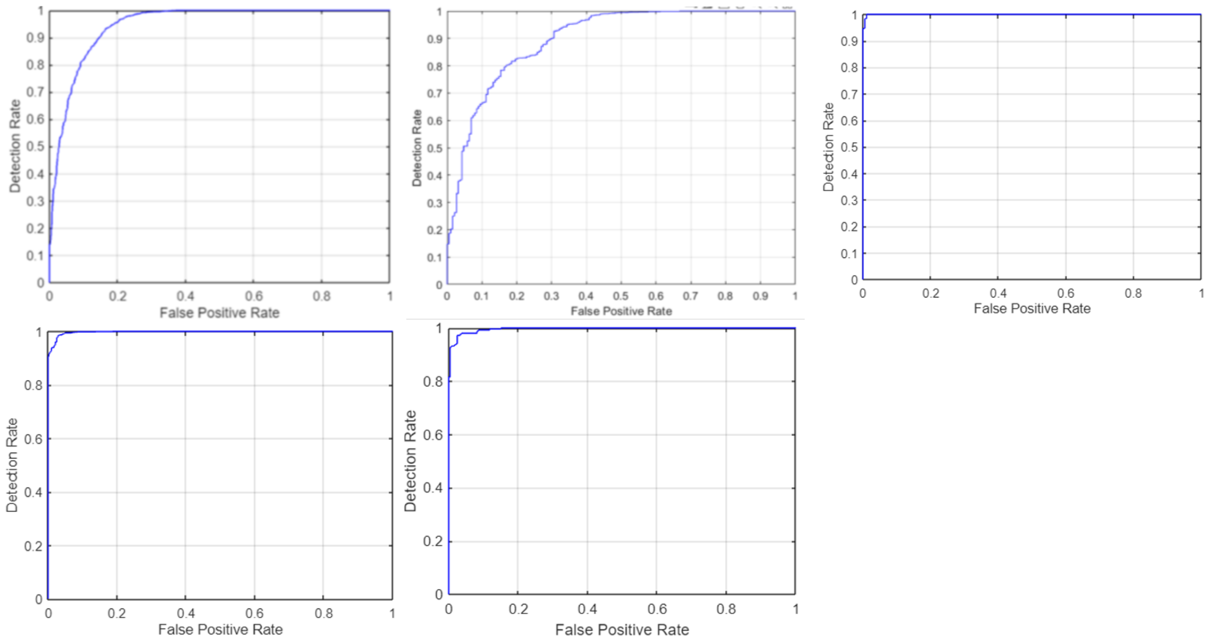

Figure 6. ROC curves (see text).

Table 3. Performance metrics.

Model	Accuracy	Precision	Recall	AUC	F1-score
ResNet-50	95.9%	96.8%	98.6%	94.6%	95.6%
AlexNet	92.4%	92.1%	**100.0%**	89.8%	92.2%
			CTCovid19		
Dataset #1	**99.8%**	**99.7%**	**100.0%**	**99.9%**	**99.8%**
Dataset #2	98.0%	98.2%	98.8%	99.7%	98.49%
Dataset #3	97.0%	96.8%	97.2%	99.6%	96.9%

Finally, is briefly presented Grad-CAM[5] and LIME[4] applied to CT scans, which are essential in clinical scenarios to gain insights into how these models analyze CT scan data to make predictions. Figure 7 left two columns present Grad-CAM predicted classifications and right two columns show LIME on the predicted classifications.

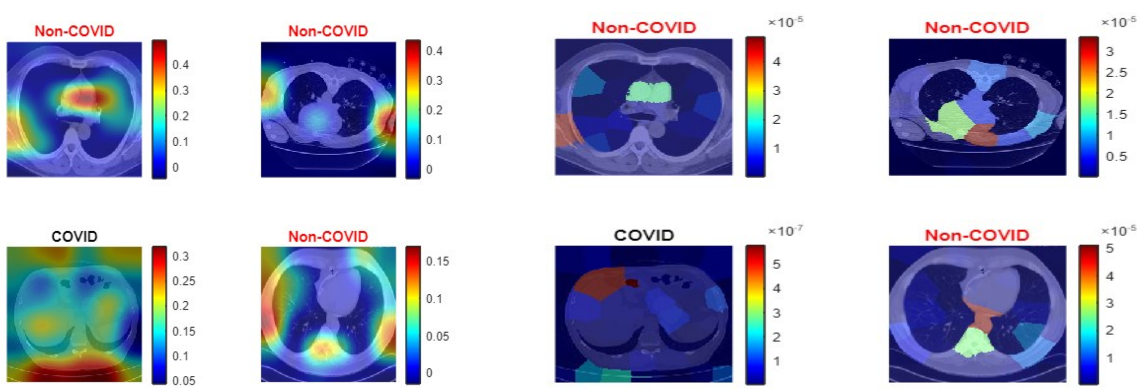

Figure 7. Left the Grad-CAM predicted classifications, and right LIME predicted classifications.

CONCLUSIONS

The research on the detection of COVID-19 using CT scans has demonstrated significant strides in leveraging artificial intelligence and deep learning techniques. The utilization of DL models has shown promise in accurately identifying patterns associated with COVID-19 infections from CT scans.

The findings indicate that these CTCovid19 exhibit a high level of sensitivity and specificity, showcasing its potential as a valuable tool for early and efficient detection of COVID-19 cases. The validation and testing process allowed us to evaluate the model's (CTCovid19) performance on a separate validation dataset to ensure it generalizes well to new, unseen data. The results showed model accuracy from 97.0% to 99.8%, and AUC 99.6% to 99.9%. The fine-tuning process allowed the adjustment of hyperparameters and model architecture validating the results to enhance performance, so the test of the trained model can be applied to a different set of CT scan images, including those it has never encountered during training.

The application of DL models in detecting COVID-19 from medical imaging provides a non-invasive and potentially rapid method for screening and diagnosing these conditions. This is another step in Human-Centered AI (HCAI) principles, for using AI to enhance human activities. All this investigation fits under the EU AI Act.

Last but not least, following the goal of giving health professionals better tools to help to do their activity, independent of where they are located around the world, in Antunes *et al.*[2] the current authors presented mainly a graphical interface (and initial model that can cope with CT scans), in the present work they present a reliable and practicality model to detect COVID-19 in CT scans, future work will focus in developing an XAI reliable and practicality model that can inform correctly doctors, not only for their diagnostic but also as a tool the can show the patients.

ACKNOWLEDGES

This work was supported by the Portuguese Foundation for Science and Technology (FCT) project NOVA LINCS (UIDB/04516/2020) and by FCT project ALGORITMI (UIDB/00319/2020).

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