Available online at www.garmian.edu.krd

Passer Journal

Passer 6 (Issue 2) (2024) 286-296

http://passer.garmian.edu.krd/

Analysis of CT Scan Medical Images to Diagnose COVID-19 Disease by Using Machine Learning and Image Enhancement Algorithms

Rangeen Yasin Ahmed[1], Azhin Taher Sabir[1*], Akar Hawree Taher[1]

[1]*Department of Software Engineering, Koya University, Koya, Kurdistan Region, Iraq.*

Received 20 September 2023; revised 24 February 2024;
accepted 3 March 2024; available online 12 May 2024

DOI: 10.24271/PSR.2024.417244.1393

ABSTRACT

The study presents a novel Artificial Intelligence (AI) system created to distinguish between COVID-19, normal lung states, and other lung illnesses by analysing Computed Tomography (CT) scans. The research uses sophisticated machine learning algorithms to pinpoint distinct characteristics and trends in CT images to achieve precise classification. The AI system's performance is thoroughly assessed using important metrics to tackle the issue of false negatives in early COVID-19 detection in comparison to Polymerase Chain Reaction (PCR) assays. Deep learning is crucial for improving the accuracy and efficiency of diagnostics. This study delves into the system's processing and analysis of CT images, emphasising the significance of internal and external validation and the use of primary algorithms for feature extraction and categorization. The study's contributions to early COVID-19 detection are highlighted through a comparative analysis with existing AI-assisted diagnostic techniques, demonstrating potential savings in labour and time requirements. The article discusses the importance of high-resolution imaging in CT scans for enhanced diagnostic accuracy and it explores the potential of AI in medical imaging for respiratory diseases, underscoring the study's novelty and objectives.

Keywords: Artificial intelligence**,** Covid-19, Deep learning, Preprocessing, Other lung disease, Before preprocessing, After preprocessing.

1. Introduction

The World Health Organization (WHO) announced the coronavirus disease pandemic in March 2020. It first appeared in December in Wuhan City, China. The SARS-CoV-2 virus was the cause of this pandemic, and it was named Corona Virus Disease 2019 (COVID-19[1]. When a new disease or pandemic appears, the diagnosis of each disease is the most essential step. The COVID-19 global pandemic has highlighted the critical requirement for swift and precise diagnostic instruments [2]. Computed Tomography (CT) scans are an essential diagnostic tool for identifying and assessing lung infections [3]. CT scans are a vital diagnostic tool for identifying and evaluating lung infections and are more accurate than chest X-rays [4]. In COVID-19, early detection from CT scans is sometimes more sensitive than PCR. According to that research, when a CT scan is taken, something detectable is detected, while at this early stage, the PCR test is negative. A few days later, the PCR test was positive. In addition, PCR has a false-negative rate at the beginning of the disease[5]. The COVID-19 global pandemic has highlighted the critical requirement for swift and precise diagnostic instruments. Differentiating COVID-19 from other lung disorders is difficult because of the similarities in radiographic appearances [2]. This intricacy requires the creation of an Artificial Intelligence-supported system that can accurately distinguish and diagnose[6].

* Corresponding author
E-mail address: azhin.sabir@koyauniversity.org (Instructor).
Peer-reviewed under the responsibility of the University of Garmian.

Artificial Intelligence in medical imaging has the potential to significantly improve diagnostic procedures. AI systems, especially those utilizing deep learning, can accurately interpret intricate patterns in medical images, providing a notable edge over conventional diagnostic techniques.

Deep Learning (DL)approaches are an efficient tool for the quick diagnosis of COVID-19 [7]. Although there have been significant gains, more research is needed to explore the integration of AI in identifying COVID-19 from other lung illnesses on CT scans[8-9]. Models have been created for COVID-19 diagnosis using pre-trained models with deep transfer learning and specialized DL architecture[10]. In the deep model, both feature extraction and classification are executed at the same time.

The extraction of features is an important step for detection. It provides the image's valuable characteristics. The Deep Neural Network (DNN) features from Residual Neural Networks (Resnet_50)[11] were extracted and classified. Then the next time, feature sets are classified using support vector machines. For the detection of COVID-19, researchers need datasets collected from different types and multiple sources. Most of the research uses datasets available online[12].

After doing a thorough evaluation of the research to identify the gaps in this subject and ascertain further research directions. Can focus on some points; most researchers use machine learning and deep learning to detect and also use public datasets, sometimes with private datasets. The weak point is that the number of images is limited, and there is little information about the images. Also, the data that is used for testing or validation is a sub-part of the data that is used for training because it contains little information about the images and may have duplicate or relevant data in the dataset. On the other hand, most researchers classify two classes of lung disease (COVID-19 and non-COVID-19) or only COVID-19 with the specific type of lung disease, for example; bacterial pneumonia or Sars. The researchers directly do not focus on a pre-processing effect on the results, which is another weakness. To propose a trusted model, it must be trained on a large dataset as The relationship between machine learning and training data is interactive and symbiotic. The quality, representativeness, and diversity of training data significantly impact the learning process and the subsequent performance of machine learning models. Thoughtful consideration and curation of training data are essential for achieving accurate and robust models.

This study addresses the existing gap by developing an AI system tailored for the differentiation of COVID-19, normal lung conditions, and other lung diseases. It introduces novel methodologies and algorithms for feature extraction and classification grounded in deep learning.

The aim is to enhance the accuracy, efficiency, and reliability of COVID-19 diagnosis using CT scans, thereby contributing significantly to the current body of knowledge. The importance of this work lies in its potential to facilitate early detection, improve patient outcomes, and reduce the burden on healthcare systems.

This paper's contents are structured as follows: Section 2 discusses related works. The background is provided in Section 3. Methodology, recommended approaches and implementation approaches are discussed in Section 4. The results are shown in Section 5. The discussions are given in Section 6. Section 7 presents details of limitations and future work, and Section 7 presents conclusions.

2. Related work

Regarding the imaging of lung parenchyma, CT is commonly regarded as the "gold standard" by doctors[13]. Extensive CT-based lung cancer screening programs in many areas of the world have led to a vast body of research on the application of machine learning to improve the efficiency and accuracy of lung cancer detection. Multiple studies have shown that CNNs trained with transfer learning can accurately detect lung nodules[3], [14]. This concentration directed researchers in this direction during the appearance of an epidemic, the researchers continued along these lines by applying CT scans and machine learning for COVID-19 detection.

Farid et al.[15] Proposed a method to detect COVID-19 based on features and combinations of them. This model involves four image filters, and a suggested Composite Hybrid Feature Extraction (CHFE) method is used to extract features from CT scans using a combination of traditional statistics and machine learning techniques. Stack Hybrid Classification (SHC) was used to categorize the features that were chosen. The experimental investigation using actual data shows the feasibility and potential of the proposed method for the indicated cause. The dataset used in this paper is an online dataset consisting of two classes, COVID-19 and SARS. The total images are 51, separated to train and test by using 10-fold cross-validation, and the highest accuracy achieved is 94.13%.

A proposed method to distinguish COVID-19 and non-COVID cases from three types of modality images, X-ray, CT scan and ultrasound was proposed by Horry et al. [16]. All dataset sources are from four online datasets (COVID-19 chest X-ray dataset, National Institute of Health (NIH) Chest X-ray dataset, COVID-19 dataset, and the POCOVID-Net data set) Images have different sizes. The VGG19 model was used for the detection of COVID-19, and an accuracy of up to 86 % for X-ray, 100% for ultrasound, and 84% for CT scans was achieved.

In the study by Wang et al.[17], 1065 CT scans were gathered from 259 patients, 180 patients with typical viral pneumonia and 79 patients with COVID-19. The data are collected from three different hospitals. To build the method, they modified the inception transfer-learning model [17]. Then followed by internal and external validation. After that, the internal validation and external validation were executed; internal validation achieved an accuracy of 89.5% and external validation attained an accuracy of 79 % from the external dataset.

Inception Residual Recurrent Convolutional Neural Network (IRRCNN) was suggested by Alom et al.[18] for COVID-19 detection from X-ray and CT scan images and the NABLA-N method for segmentation. In addition, private datasets are used, including normal CT scans and COVID-19 CT scans. The COVID-19 CT images are from confirmed patients. The total number of images is 420, where 247 images are normal samples and 178 images are for COVID-19. The proposed model shows an accuracy of 84.67% from X-ray images and an accuracy of 98.78% from CT images. Also, this model determines the percentage of infection.

A pre-trained deep network, DenseNet 121, was proposed as a means of feature extraction by Kassani et al.[19]. From a total of 274 images, 117 X-rays and 20 CT scans were considered positive, while the remaining 117 X-rays and 20 CT scans were considered normal. More than two classifiers were utilized, with the bagging tree providing the highest accuracy at 99%.

Wu et al.[20] Gathered 495 patient chest CT scans from three Chinese hospitals. divided into two classes of data (368 COVID-19 and 127 other pneumonia cases) were randomly split into 8:1:1 training, validation, and test datasets. Using CT images with the most lung areas in the axial, coronal, and sagittal views, they built a multi-view fusion model with a deep learning network. Using the validation set, the multi-view deep learning fusion model attained an accuracy of 70% and an accuracy of 76% in the testing set.

3. Background

Two of machine learning's most essential activities are feature extraction and classification. To use the input data for categorization or other activities in the future, it must first undergo the process of feature extraction. Classification can then be performed using the retrieved features. The types of input data and the nature of the problem at hand determine which feature extraction and classification methods are most appropriate. In many cases involving COVID-19 identification, deep learning-based algorithms have demonstrated state-of-the-art performance. It is expected to be able to integrate feature extraction and classification into a single pipeline. One can use a deep convolutional neural network such as Residual Network (ResNet) to extract features from images and classify them [21].

Residual Network (ResNet) is a type of deep neural network that was introduced in 2015 by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in their paper "Deep Residual Learning for Image Recognition"[11]. ResNet is very effective for image recognition tasks. ResNet is available in various sizes, including versions with different numbers of layers (e.g., ResNet-18, ResNet-34, ResNet-101, etc.). ResNet-50, in particular, strikes a balance between model complexity and performance, making it a popular choice for many applications[22].

ResNet-50 has 50 layers; these layers are convolutional and fully connected. ResNet-50 uses residual blocks to train deep neural networks. ResNet-50 receives 224x224 RGB images as input. Then Residual Blocks The main innovation in ResNet is the residual block, which includes a "shortcut" or "skip connection" that bypasses one or more layers. This allows the network to learn the residual or the difference between the input and output of a block. Each residual block typically contains multiple convolutional layers with batch normalization and ReLU activation functions. The average pooling layer stops the network after the stack of residual blocks, reducing spatial dimensions to a single vector. Fully connected layers: A completely connected average pooling layer with a SoftMax activation function is classified next[22].

ResNet-50 excels at image classification, object detection, and image segmentation. In this setting, the modified pre-trained ResNet-50 model is used to extract features from input images, and those features are then used to categorize the images into the diagnosis of COVID-19 patients, normal and other lung diseases, or separate normal and abnormal cases; this is the first proposed approach.

In instances when there is a need for small amounts of data or more meaning, other ways such as Support Vector Machines (SVM) and decision trees may be considered appropriate[23]. In the realm of machine learning, Support Vector Machine (SVM) is a supervised technique used for classification and regression[23]. Commonly used for resolving binary classification issues, it may be expanded to manage multiclass classification as well. SVMs are well-known for their efficacy in classifying data by finding a hyperplane in a high-dimensional feature space. SVMs are based on the premise that data points can be represented as vectors in a feature space, with each feature standing in for a distinct attribute or characteristic of the data. Finding a hyperplane with the most significant margin (the distance between the hyperplane and the closest data points in each class) is the goal of the algorithm. To create a reliable and generalized separation between classes, SVMs aim to maximize the margin. Support Vectors, Kernel Functions, regularization, the AND margin, and the Decision Boundary are all essential parts of a support vector machine. Image and text recognition, text classification, bioinformatics, financial analysis, and medical diagnosis are just some of the many fields where SVMs have found widespread use. Because of their versatility and resistance to outliers, they are helpful in a wide variety of machine-learning applications. In the second proposed approach, a feature extracted from the average pooling layer from ResNet 50 is used for classification with SVM.

This study utilises performance metrics involving accuracy, confusion matrix, recall(sensitivity), and precision. The confusion matrix is a tabular representation that documents the frequency of occurrences between two raters, specifically the target/actual classification and the predicted/output classification, as depicted in all the tables are shown as a confusion matrix, accuracy is shown diagonally, precision is on the right, and recall (sensitivity) is at the bottom of the image.

Accuracy is a widely employed metric for assessing the efficacy of classification models in the field of machine learning. The accuracy formula can be expressed as

$$Accuracy = \frac{number\ of\ correct\ predictions}{total\ number\ of\ prediction}$$

Precision is defined as the ratio of True Positive elements to the total number of positively predicted units. Specifically, True Positive refers to the elements that have been classified as positive by the model and are indeed positive. In contrast, False Positive refers to the elements that have been classified as positive by the model but are actually negative.

The precision formula can be expressed as:

$$precision = \frac{number\ of\ true\ positive}{true\ positive + falsepositive}$$

Recall, which is alternatively referred to as sensitivity or actual positive rate, holds significant importance as an evaluation parameter within the field of machine learning.

$$Recall(\text{sensitivity}) = \frac{number\ of\ true\ positive}{true\ positive + false\ negative}$$

4. Methods and Materials

The methodology section explains how the AI system distinguishes COVID-19 from other lung disorders by analyzing CT data. The approach is based on a machine learning algorithm that has been taught to recognize distinct characteristics and patterns that are associated with COVID-19, distinguishing them from normal lung states and other lung disorders. The features consist of ground-glass opacities, consolidation patterns, and the distribution of lung lesions.

The study utilizes convolutional neural networks (residual networks) to accurately classify data by effectively handling spatial and temporal patterns. Algorithms like Support Vector Machines (SVMs) are used for classification due to their established effectiveness in medical image analysis.

The CT scans go through a sequence of preprocessing procedures to improve image quality and isolate essential characteristics. The process involves denoising, and normalization to enhance the resilience and applicability of the AI models. Performance indicators like accuracy, sensitivity, recall, and confusion matrix are used to assess the models' effectiveness.

Validation activities are carried out internally and externally to evaluate the AI system's reliability and suitability for various datasets and clinical environments. This thorough evaluation framework guarantees that the models' performance is both statistically significant and therapeutically relevant. All steps in the methodology are shown in **Error! Reference source not found.**.

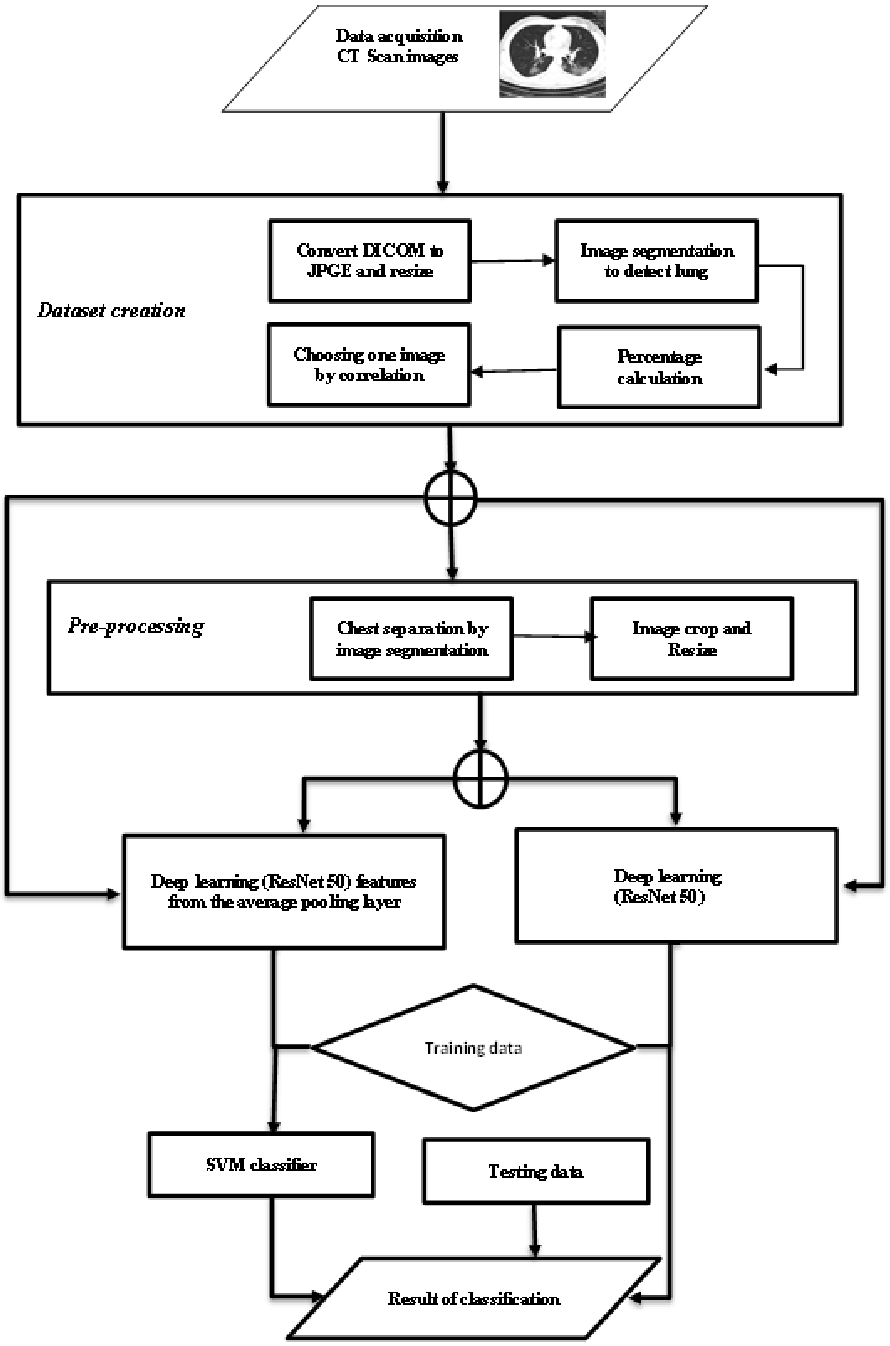
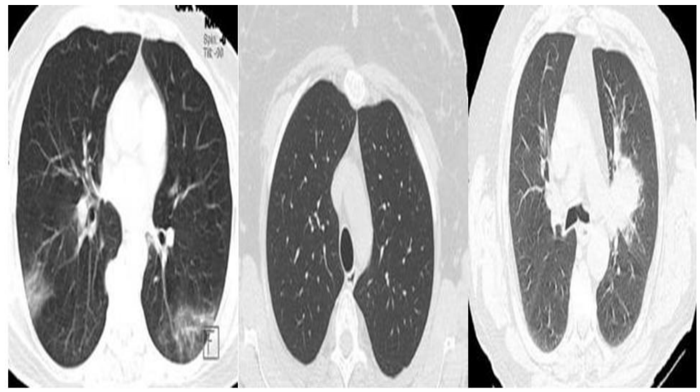


Figure 1: Proposed approach diagram.

4.1. Data acquisition

Data collection is the first step in research when using a private dataset. At starting this research, a large dataset was not available in our region, and online data was not available for the large number of patients in the three classes. The maximum number of patients available is 85. This dataset has three classes but doesn't have enough information about them; maybe it has repeat images, and one-by-one patients are not separated. Because of that, we decided to create a data set that had a larger number of patients and included three classes. In this paper, 735 cases were collected, each for one patient. The three classes consisted of: the first class is COVID-19 from 245 patients. The second class is normal (not infected) from 245 patients, and the third class is other lung disease from 245 patients, An Example of each class is shown in **Error! Reference source not found.**. And there is n o imbalance in the number of patients. Regarding the third class, there are more than 5 lung diseases (bacterial pneumonia, mass, emphysema bullae, calcification, bronchiectasis, cancer, fibrosis, and pleural effusion). In some cases, more than one lung disease appears at the same time, like 2 or 3 diseases on a CT scan[2]. This diversity in one class directly affects the classification[24]. The lungs have different shapes and sizes. Moreover, age and gender have a direct relationship to it. Lung diseases do not have constant shapes; they differ from one patient to another[2].

CT scans were collected from four medical imaging centers in different locations in the Kurdistan region of Iraq, as shown in **Error! Reference source not found.**.



(A) (B) (C)

Figure 2: samples of the CT scan images (A) COVID-19, (B) Normal, (C) Other lung diseases.

Table 1: Table of CT scan imaging dataset sources with number of cases.

Name of a medical imaging centre	Number of COVID-19 cases	Number of Normal cases	Number of other lung disease cases
Gardoon radiology center	145	133	121
Shar Hospital Radiology Center	55	52	63
Radiology Center in Sulaymaniyah	15	11	18
Rania imaging centre	30	49	43
Total	245	245	245

The COVID-19 CT scan cases contain patients from the beginning of the COVID-19 pandemic (early 2020) until the end of the year 2022. At the same time, the other two classes (normal and other lung diseases) contain some cases before the pandemic. Ground Glass Opacity (GGO) is a main feature used to describe COVID-19 that appears in a CT scan[25]. The total number of images for 735 patients is 156,797 images (one case contains multiple images). These images are divided in this way: for patients affected by COVID-19, there are 70319 images; for normal patients, 53377 images; for patients with other lung diseases, 33101 images. Finally, only 735 images were chosen, with each class receiving 245 images. The data collected from each medical center is different because of having different types of CT scan devices.

4.2. Dataset creation

After data collection, many steps are taken to create a dataset.

- Image conversion and Resizing: the first step is converting the image format from Digital Imaging and Communications in Medicine (DICOM) to JPEG and resizing it to 512 x 512 pixels.
- Image segmentation: is used to detect lung only and calculate the percentage of lung size in the image; for segmentation, by using erosion morphological technique a square shape and neighborhoods of 3 pixels[26], and then fill image regions and holes by morphological reconstruction[27].
- Lung size detection: calculating the percentage of lungs to remove images if the lung is tiny or does not appear is the first step in removing unnecessary images. If the rate is greater than 10%, this image remains. This step is executed

by calculating the histogram for the grey colour value between 20 and 150 in the image.

- Best image selection: The decision to choose one image for one patient to prevent redundant and identical data. For the COVID-19 image, using image correlations reduced the number of images with the same information and then selected the largest lung. This step was repeated until there was only one image remaining. For the normal cases, the biggest lung slices were chosen when calculating the lung percentage, and for other lung disease images, the correlation between images was used to find the most different ones because, in some cases, the change appears in only one image.

4.3. Preprocessing

Image segmentation and separation of the chest are critical because the area around the chest includes something unnecessary, like the patient's name and some personal information, and sometimes has artefacts. One curial of medical ethics is patient privacy protection, the preprocessing step executes this point[28]. In this step, the first time the image is converted to black and white, the same previous image segmentation technique is used as mentioned above (morphology filter) in the database creation. After separation of the chest, assume the background has a 0 value and remove all rows and columns when values are zero. At this time, the size of the image is different and then it is resized to 512 by 512. After some redundant data remained in the backgrounds, the image automatically was cropped with a fixed number of pixels for each side; For above and down 50 pixels and for right and left 35 pixels. After that, the image resizes to 224 by 224 with three channel colours.

4.4. Proposed model for feature extraction and classification

This section discusses the two primary proposed models to identify COVID-19 cases. The first model the modified ResNet 50, also has both feature extraction and classification in the same pipeline, this new model can also take new additional training data and modified neural layers[17].

First model (Adopted ResNet 50 Network): The suggested method (the detection of COVID-19) relies heavily on the weights, bias, and features learnt while training on the pre-trained ResNet 50. The next step is to utilize these settings when training on our fresh input dataset, which consists of CT scan images. The creation of architectures from scratch that can detect COVID-19, is more time-consuming and requires a lot of processing power compared to training a CNN network using random weight values and then tuning up the pre-trained network, especially when the interested dataset does not include many images. However, we replace the pre-trained network's final levels with our own custom layers in order to use them for our assignment as shown in **Error! Reference source not found.**.

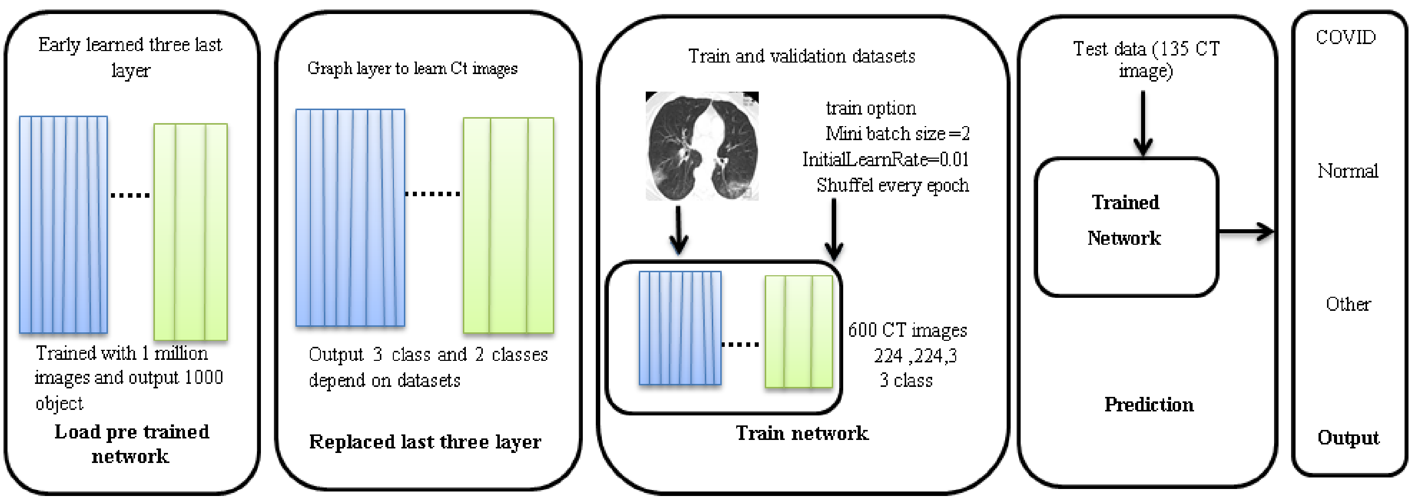


Figure 3: Modified ResNet 50 network for detection of COVID-19.

During the training of the CNN model, the number of epochs, minimum batch size, initial learning rate, and optimizer are set to 30, 20,0.01, and stochastic gradient descent with momentum (SGDM)[29].

The image data were processed on an Intel Core i7 10750H CPU with 32 GB of RAM and a 12.8 GHz processor on a MATLAB R2021a platform. The results of this model for each scenario are five results because, using 5-fold cross-validation, each fold has a result for validation and testing. The second proposed model is ResNet 50 with an SVM classifier

The second model (ResNet 50 network and SVM classifier): In this study, when features are extracted from the average pooling layer from the ResNet 50 network, there are 2048 features. These features are classified by SVM to diagnose COVID-19.

5. Results and Discussions

The results section showcases the AI system's efficacy in accurately identifying COVID-19 cases from CT scans, compared to other lung conditions. The models demonstrate high accuracy, sensitivity, and recall.

In this study, the dataset was used in four different scenarios. The first and second scenarios contain three classes (COVID-19, normal, and other lung diseases) when there was the pandemic; the first scenario contains images before preprocessing, and the second scenario includes images after preprocessing. The third and fourth scenarios contain two classes (normal and abnormal) to differentiate healthy cases from unhealthy cases at all times. The third scenario involves images before preprocessing, and the fourth scenario contains images after preprocessing. The first and second scenarios have 735 images divided into 600 images with a rate of 8:2 for training and validation and 135 images for testing, every 45 images for one class. The third and fourth scenarios contain 535 images: 400 for training and validation (200 normal and 200 abnormal), with a rate of 8:2, respectively. Abnormal contains 100 for COVID-19 and 100 others. Then there are 135 images for testing. The testing images contain 45 images for normal and 90 images for abnormal. Each image used for the test was not utilized before for training or validation.

5.1. First scenario results

In the first scenario with the ResNet 50, the best accuracy achieved between the 5 folds is 81.7% for the validations with fold 5, as shown in t**Error! Reference source not found.**. For t he tested data, the accuracy was 77% with fold 3, as shown in **Error! Reference source not found.**. The average accuracy for t hese models is 74% in validation and 70% in test data, but if we put all training and validation data into training and test the model with test data, the result is near the average result, as shown in **Error! Reference source not found.**.

Table 2: Table of Accuracy of Modified ResNet50 network with all scenarios and folds.

	Scenario 1		**Scenario 2**		**Scenario 3**		**Scenario 4**	
	Validation Acc	Testing Acc	Validation Acc	Testing Acc	Validation Acc	Testing Acc	Validation Acc	Testing Acc
fold 1	63.3%	60%	79.2%	91.1%	71.2%	75.6%	86.2%	91.1%
fold 2	76.7%	71.1%	80%	82.2%	75%	71.1%	86.2%	88.1%
Fold 3	77.5%	77%	85%	84.4%	88%	80%	92.5	93.3%
fold 4	70.8%	70.4%	86.7%	85.2%	87.5%	75.6%	90%	89.6%
fold 5	81.7%	72.6%	75%	86.7%	90%	80%	81.2%	92.6%
Average	74%	70.2%	81.2%	85.9%	82.3%	76.5%	87.2%	91.1%

Table 3: Accuracy Result of average pooling layer feature from ResNet 50 network with SVM classifier with all scenarios by using Automatic five-fold cross-validation.

	Validation accuracy	**Testing accuracy**
Scenario 1	76.5%	66.7%
Scenario 2	78.2%	80.7%
Scenario 3	88.2%	76.1%
Scenario 4	89.8%	93.3%

Table 4: Confusion matrix table with evaluation metrics with scenario 1 of the ResNet 50 model with testing data.

Confusion Matrix					
Output class	COVID-19	38	5	9	73.1%
	Normal	2	30	9	73.2%
	Other	5	10	27	64.3%
		84.4%	66.7%	60.0%	70.4%
		COVID-19	Normal	Other	
Actual class					

The accuracy results achieved with the SVM classifier are 76.2% for validation as shown in**Error! Reference source not found.**, a nd then tested with test data, performance was lower than validation achieved, and this accuracy is 65.2%, as shown in **Error! Reference source not found.**.

Table 5: Confusion matrix table with evaluation metrics with scenario 1 of model 2 (ResNet 50+SVM) with testing.

Confusion Matrix					
Output class	COVID-19	29	4	10	67.4%
	Normal	5	30	4	76.9%
	Other	11	11	31	58.4%
		64.4%	66.7%	68.9%	66.7%
		COVID-19	Normal	Other	
Actual class					

5.2. Second scenario results

After the preprocessing step, all results changed for the better with the ResNet 50. The best accuracy achieved between the 5 folds was 86% for validation with fold 4, but in the test data, it was 91.1% with fold 1, as shown in table 2 **Error! Reference s ource not found.**. The average accuracy is 80% in validation and 85.8% in test data. When we put all training and validation data in training and then tested it with the tested data, the accuracy achieved was 86.7%, as shown in table 6.

Table 6: Confusion matrix table with evaluation metrics with scenario 2 of the ResNet 50 model with testing data.

Confusion Matrix					
Output class	COVID-19	36	0	2	94.7%
	Normal	5	44	6	80.0%
	Other	4	1	37	88.1%
		80.0%	97.8%	82.2%	86.7%
		COVID-19	Normal	Other	
Actual class					

The second scenario accuracy shown table 2, with the SVM classifier for validation is 78.2%, and when tested with test data, it shows higher performance than validation accuracy, which is 80.7%, as shown in table 7.

Table 7: Confusion matrix table with evaluation metrics with scenario 2 of model 2 (ResNet 50+SVM) with testing.

Confusion Matrix					
Output class	COVID-19	33		6	84.6%
	Normal	2	41	4	87.2%
	Other	10	4	35	71.4%
		73.3%	91.1%	77.7%	80.7%
		COVID-19	Normal	Other	
Actual class					

5.3. Third scenario results

As discussed, the third scenario contains two classes, except during a pandemic time, which can be used at all times to distinguish normal from abnormal cases (healthy and unhealthy).

In this scenario with ResNet 50, the highest accuracy achieved is 90% with fold 3 in validation, and the accuracy of the tested data is 80% with the same fold as shown table2. Table 8 shows the average that was achieved when we put all training and validation data in training and then tested it with test data, which is an accuracy of 75.6%.

Table 8: confusion matrix table with evaluation metrics with scenario 3 of the ResNet 50 model with testing data.

Confusion Matrix				
Output class	Abnormal	69	12	85.2%
	Normal	21	33	61.1%
		76.7%	73.3%	75.6%
		Abnormal	Normal	
Actual class				

The results of accuracy with the SVM classifier are shown in **Error! Reference source not found.**. The highest accuracy a chieved for validation is 88.2%, and with test data, 76.1%, which is a lower performance than validation accuracy, as shown in table 9.

Table 9: Confusion matrix table with evaluation metrics with scenario 3 of model 2 (ResNet 50+SVM) with testing data.

Confusion Matrix				
Output class	Abnormal	67	10	87.0%
	Normal	23	35	60.3%
		74.4%	77.8%	76.1%
		Abnormal	Normal	
Actual class				

5.4. Forth scenario results

In the final scenario, the highest accuracy achieved was 92.5% in validation with fold 4 and 93.3% in test data with fold 3, as shown in table 2. This is the highest accuracy achieved among all folds. Like all previous scenarios, when putting all training and validation data into training and testing it with the test data, the average accuracy is 91.9%, as shown in table 10.

The result of the fourth scenario with the SVM classifier presents the highest accuracy in both step validation and test data, compared with the same classifier with other scenarios, showing an accuracy of 89.8% and 92.6%, respectively, as shown in table 3. Table 11 shows the result of the average test data.

Table 10: Confusion matrix table with evaluation metrics with scenario 4 of the ResNet 50 model with testing data.

Confusion Matrix				
Output class	Abnormal	79	0	100%
	Normal	11	45	80.4%
		87.8%	100%	91.9%
		Abnormal	Normal	
Actual class				

Table 11: Confusion matrix table with evaluation metrics with scenario 4 of model 2 (ResNet 50+SVM) with testing data.

Confusion Matrix				
Output class	Abnormal	82	2	97.6%
	Normal	8	43	84.3%
		91.1%	95.5%	93.3%
		Abnormal	Normal	
Actual class				

5.5. comparison state art

In this part, the results of two studies are explained and compared with this study. In the first step, our dataset is organized like their dataset classes (COVID and NON-COVID), but with two scenarios before preprocessing and after preprocessing. The data that are used for the test contain 45 images for COVID and 90 images for NON-COVID. Kaur et al.[30] explain in their study that they achieved an accuracy of 98.35% with the ResNet 50 network with the Soares[31] Dataset. When reimplemented for comparison, the accuracy result was 96.8% with the same steps and dataset. It was tested with the above datasets and achieved an accuracy of 56.2% with test data before pre-processing and 58.89% with test data after pre-processing, as shown in table 12.

The second comparison was done with the study of Maghdid et al. [32]. Their proposed approach involves two models: simple CNN and modified pre-trained AlexNet. This AlexNet model achieved higher accuracy than simple CNN, as shown in table 13 our four dataset scenarios.

After showing the results, it can now be discussed why other research achieved very high accuracy (up to an accuracy of 99%) compared with these results, where the highest accuracy achieved was 91.9% for the dataset containing three classes and 92.6 for the dataset containing two classes. This high accuracy is due to the form recognition of the lung for the same person and the correct case detection. The main factor is that in this study, a private dataset was used that contains each image chosen from one case, according to the research by Silva et al.[12]. Completely explains this situation and shows the effects on the result. When re-implemented another study clearly showed the result, as shown in table 12. Completely explains and supports this situation and shows the effects on the result. Another factor is that an image was chosen when the lung is the biggest; maybe in this image, the COVID-19 features do not appear because in some cases where COVID-19 is little, they only appear in the lower lobe of the lung.

5.6. Discussion

The consequences of incorporating AI technology in the early identification and diagnosis of COVID-19 are significant. The AI solution provides a scalable and efficient alternative for healthcare systems globally by decreasing the need for labour-intensive manual analysis and overcoming the inherent constraints of PCR testing.

Table 12: Reimplements Kaur et al model and test it with our data.

	Kaur et al.*[33] *validation (ResNet50 network) ACC	***Reimplemented validation (ResNet50) ACC***	***Testing ACC before preprocessing the dataset***	***Testing ACC after pre-processing***
Soares et al. [34] *dataset*	*98.35%*	*96.8%*	*56.67%*	*58.89%*

Table 13: Comparison between Maghdid et al models with different scenarios for datasets.

	AlexNet model ACC	***CNN ACC***	***ResNet50 ACC***	***ResNet50+SVM ACC***
Maghdid et al.[35] *dataset*	*98%*	*94%*		
Scenario 1	*60%*	*54%*	*70.4%*	*65.2%*

Scenario 2	*80%*	*62.2%*	*86.7%*	*80.7%*
Scenario 3	*73.3%*	*59%*	*75.6%*	*75%*
Scenario 4	*89.6%*	*77.4%*	*91.9%*	*92.6%*

The conversation also explores the possible future uses of AI and machine learning in identifying respiratory illnesses other than COVID-19. The progress in AI-powered image processing is poised to transform medical imaging, enhancing diagnostic precision and patient results across many ailments. This study's contributions establish a groundwork for future research and advancement in the field, indicating a transition towards more automated, accurate, and swift diagnostic procedures.

The rewrite thoroughly addresses the original comments by enhancing the paper from abstract to discussion, resulting in a more detailed and scientifically solid document that meets the standards for a significant contribution to the field of AI-assisted medical diagnostics.

5.7. *Limitation and Future Work*

Certain constraints of the study will require rectification in the future. Firstly, augment the sample size, particularly for different lung illness categories, and categorize each lung disease as a distinct class. Secondly, achieving a precise separation of the lung from the chest without losing any details, particularly when they are adjacent and have similar colours.

The encouraging outcomes set the stage for additional exploration of AI's capabilities in medical imaging, specifically focusing on respiratory illnesses. Future research could investigate incorporating AI into regular diagnostic procedures, creating advanced models for diverse medical illnesses, and utilizing this technology in resource-constrained environments to enhance global health outcomes. focus on globalizing the dataset by expanding the number of instances and including comprehensive information along with patient images.

Conclusion

The study introduces a new AI system that can effectively distinguish between COVID-19, normal lung states, and other lung disorders by analyzing CT scans. The system's utilization of deep learning algorithms greatly enhances diagnostic precision, overcoming the constraints of PCR testing and conventional diagnostic techniques. The AI technology helps detect and diagnose COVID-19 early, providing a scalable and effective solution that could lessen the strain on healthcare systems. CT scans' high-resolution imaging, when paired with AI processing, provide precise and detailed diagnostic data, improving patient care.

This study highlights the role of data, techniques of image processing, and the use of machine learning for feature extraction and classification. showing the direct effect of the private dataset and choosing data that has a direct relationship with the classification. Using this private dataset in four scenarios Then we classified these scenarios with two different proposed approaches, the first by using a pre-trained transfer learning network (ResNet 50) with some modifications and 5-fold cross-validation. The second approach is extracting features from ResNet 50 and classifying them with SVM. In the classification with ResNet 50, the highest performance with a three-class dataset is an accuracy of 91.1% after the preprocessing step, and the highest performance with a two-class dataset is an accuracy of 93.3% after the preprocessing step. In the second proposed approach, Resnet 50 with SVM classifier, the highest performance achieved for the three-class dataset is 80.7% accuracy after the preprocessing step, and the highest performance for the two-class dataset is 92.6% accuracy after the preprocessing step. All results show that the preprocessing step plays a great role.

Author Contribution

In all aspects of this work, beginning from the conception and development of the research design to a careful analysis of the results obtained as well as the comprehensive drafting of the manuscript, authors played an equal role. They were involved in different stages of research, including implementation, design, analysis and composition phases; thus, their contributions covered almost the entire spectrum of this process.

Conflict of interests

None

References

1. D. Wu, T. Wu, Q. Liu, and Z. Yang, “The SARS-CoV-2 outbreak: What we know,” *International Journal of Infectious Diseases*, vol. 94. Elsevier B.V., pp. 44–48, May 01, 2020. doi: 10.1016/j.ijid.2020.03.004.
2. A. Ulhaq, J. Born, A. Khan, D. P. S. Gomes, S. Chakraborty, and M. Paul, “COVID-19 Control by Computer Vision Approaches: A Survey,” *IEEE Access*, vol. 8, no. October, pp. 179437–179456, 2020, doi 10.1109/access.2020.3027685.
3. T. K. Sajja, R. M. Devarapalli, and H. K. Kalluri, "Lung Cancer Detection Based on CT Scan Images by Using Deep Transfer Learning Traitement du Signal Lung Cancer Detection Based on CT Scan Images by Using Deep Transfer Learning," no. October 2019, doi 10.18280/ts.360406.
4. M. A. Speidel, “Scanning-beam digital x-ray „ SBDX … technology for interventional and diagnostic cardiac angiography,” pp. 2714–2727, 2006, doi: 10.1118/1.2208736.
5. G. A. Govindrao, “Textbook of oral radiology-E-Book“, Elsevier Health Sciences, 2016.
6. A. Borakati, Perera Perera, J. Johnson, and T. Sood, "Diagnostic X-ray ray versus CT matched in COVID-19 : a propensity- database study,” pp. 1–14, 2020, doi: 10.1136/bmjopen-2020-042946.
7. S. Yusuf, H. Ahmad, R. Zeb, U. Zeb, and A. A. Zeb, “High-Resolution CT Chest Findings in Suspected COVID-19 Pneumonia Patients With Negative Real-Time Polymerase Chain Reaction Assay,” vol. 13, no. 3, 2021, doi: 10.7759/cureus.14023.
8. I. Ozsahin, B. Sekeroglu, M. S. Musa, M. T. Mustapha, and D. U. Ozsahin, “Review on Diagnosis of COVID-19 from Chest CT Images Using Artificial Intelligence,” vol. 2020, 2020.

9. L. Review, “Applications of Artificial Intelligence in Battling Against Covid-19: A Literature Review,” *Chaos, Solitons and Fractals: the interdisciplinary journal of Nonlinear Science, and Nonequilibrium and Complex Phenomena*, p. 110338, 2020, doi: 10.1016/j.chaos.2020.110338.
10. F. Karray, R. Alhajj, and J. I. A. Zeng, “A Review on Deep Learning Techniques for the Diagnosis of Novel Coronavirus (COVID-19),” pp. 30551–30572, 2021, doi: 10.1109/ACCESS.2021.3058537.
11. N. Subramanian, O. Elharrouss, S. Al-Maadeed, and M. Chowdhury, “A review of deep learning-based detection methods for COVID-19,” *Computers in Biology and Medicine*, vol. 143. Elsevier Ltd, Apr. 01, 2022. doi: 10.1016/j.compbiomed.2022.105233.
12. K. He and J. Sun, “Deep Residual Learning for Image Recognition,” pp. 1–9.
13. P. Silva *et al.*, “COVID-19 detection in CT images with deep learning: A voting-based scheme and cross-datasets analysis,” *Inform Med Unlocked*, vol. 20, p. 100427, 2020, doi: 10.1016/j.imu.2020.100427.
14. J. A. Verschakelen and W. De Wever, “Computed Tomography of the Lung : A Pattern Approach,” vol. 49, no. 1, p. 45757, 2008, doi: 10.2967/jnumed.107.045757.
15. A. Masood, P. O. Yang, B. I. N. Sheng, H. Li, P. Li, and D. D. Feng, “Cloud-Based Automated Clinical Decision Support System for Detection and Diagnosis of Lung Cancer in Chest CT,” *IEEE J Transl Eng Health Med*, vol. 8, no. December, pp. 1–13, 2019, doi 10.1109/JTEHM.2019.2955458.
16. A. A. Farid, G. I. Selim, and H. A. A. Khater, “A Novel Approach of CT Images Feature Analysis and Prediction to Screen for Corona Virus Disease (COVID-19),” *Int J Sci Eng Res*, vol. 11, no. 03, pp. 1141–1149, 2020, doi: 10.14299/ijser.2020.03.02.
17. M. J. Horry *et al.*, “COVID-19 Detection through Transfer Learning Using Multimodal Imaging Data,” *IEEE Access*, vol. 8, pp. 149808–149824, 2020, doi: 10.1109/ACCESS.2020.3016780.
18. S. Wang *et al.*, "A deep learning algorithm using CT images to screen for Coronavirus disease (COVID-19)," *Eur Radiol*, vol. 31, no. 8, pp. 6096–6104, 2021, doi: 10.1007/s00330-021-07715-1.
19. M. Z. Alom, M. M. Shaifur Rahman, S. Nasrin, T. M. Taha, and V. K. Asari, “COVID_MTNet: COVID-19 detection with multi-task deep learning approaches,” *ArXiv*, 2020.
20. S. H. Kassania, P. H. Kassanib, M. J. Wesolowskic, K. A. Schneidera, and R. Detersa, “Automatic Detection of Coronavirus Disease (COVID-19) in X-ray and CT Images: A Machine Learning Based Approach,” *Biocybern Biomed Eng*, vol. 41, no. 3, pp. 867–879, 2021, doi: 10.1016/j.bbe.2021.05.013.
21. X. Wu *et al.*, “Deep learning-based multi-view fusion model for screening 2019 novel coronavirus pneumonia : A multicentre study,” vol. 128, no. April, pp. 1–9, 2020, doi: 10.1016/j.ejrad.2020.109041.
22. H. Liang, X. Sun, Y. Sun, and Y. Gao, “Text feature extraction based on deep learning: a review,” *Eurasip Journal on Wireless Communications and Networking*, vol. 2017, no. 1. Springer International Publishing, Dec. 01, 2017. doi: 10.1186/s13638-017-0993-1.
23. F. Z. Hamlili, M. Beladgham, M. Khelifi, and A. Bouida, “Transfer learning with Resnet-50 for detecting COVID-19 in chest X-ray images,” *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 25, no. 3, pp. 1458–1468, Mar. 2022, doi: 10.11591/ijeecs.v25.i3.pp1458-1468.
24. M. A. Hearst, S. T. Dumais, E. Osuna, J. Platt, and B. Scholkopf, “Support vector machines,” no. 1, pp. 1–11.
25. N. Japkowicz and S. Stephen, “The class imbalance problem : A systematic study,” vol. 6, pp. 429–449, 2002.
26. D. Cozzi, E. Cavigli, C. Moroni, O. Smorchkova, G. Zantonelli, and S. Pradella, “Ground - glass opacity (GGO): a review of the differential diagnosis in the era of COVID - 19,” *Jpn J Radiol*, vol. 39, no. 8, pp. 721–732, 2021, doi: 10.1007/s11604-021-01120-w.
27. P. Srisombut, “Morphological Image Processing,” 2004.
28. S. Chakraborty and K. Mali, “A morphology-based radiological image segmentation approach for efficient screening of COVID-19,” *Biomed Signal Process Control*, vol. 69, Aug. 2021, doi: 10.1016/j.bspc.2021.102800.
29. R. Ball and / Corbis, *WORLD MEDICAL ASSOCIATION Medical student holding a newborn Medical Ethics Manual*. 2015.
30. P. K. Chaudhary and R. B. Pachori, “FBSED based automatic diagnosis of COVID-19 using X-ray and CT images,” *Comput Biol Med*, vol. 134, no. February, p. 104454, 2021, doi: 10.1016/j.compbiomed.2021.104454.
31. T. Kaur and T. K. Gandhi, “Classifier Fusion for Detection of COVID-19 from CT Scans,” *Circuits Syst Signal Process*, vol. 41, no. 6, pp. 3397–3414, Jun. 2022, doi: 10.1007/s00034-021-01939-8.
32. E. Soares, P. Angelov, S. Biaso, M. Higa Froes, and D. K. Abe, “SARS-CoV-2 CT-scan dataset: A large dataset of real patients CT scans for SARS-CoV-2 identification”, doi: 10.1101/2020.04.24.20078584.
33. H. Maghdid, A. T. Asaad, K. Z. G. Ghafoor, A. S. Sadiq, S. Mirjalili, and M. K. K. Khan, "Diagnosing COVID-19 pneumonia from X-ray and CT images using deep learning and transfer learning algorithms," SPIE-Intl Soc Optical Eng, Apr. 2021, p. 26. doi: 10.1117/12.2588672.