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Deep Learning Approach for Advanced COVID-19 Analysis

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Abstract*: Since the spread of the COVID-19 pandemic, the number of patients has increased dramatically, making it difficult for medical staff, including doctors, to cover hospitals and monitor patients. Therefore, this work relies on Computerised Tomography (CT) scan images to aid in the diagnosis of COVID-19. CT scan images are used to diagnose and determine the severity of the disease. On the other hand, Deep Learning (DL) is widely used in medical research, making significant progress in medical technologies. For the diagnosis process, the Convolutional Neural Network (CNN) algorithm is used as a type of DL algorithm. Hence, this work focuses on detecting COVID-19 from CT scan images and determining the severity of the illness. The proposed model is as follows: first, classifying CT scan images into infected or not infected using one of the CNN structures, Residual Neural Networks (ResNet50); second, applying a segmentation process for the infected images to identify lungs and pneumonia using the SegNet algorithm (a CNN architecture for semantic pixel-wise segmentation) so that the disease's severity can be determined; finally, applying linear regression to predict the disease's severity for any new image. The proposed approach achieved an accuracy of 95.7% in the classification process, as well as segmentation rates of 98.6% for lung and 96.2% for pneumonia, respectively. Furthermore, a regression process reached an accuracy of 98.29%.

Keywords*: Convolutional Neural Network (CNN), Deep Learning, Severity, SegNet, ResNet50, CT scan, VGG16.

I. INTRODUCTION

In January 2020, the coronavirus (COVID-19) pandemic started; since then, it has spread globally, causing millions of deaths, with enormous health implications for human lives. At the time of writing this paper, there were more than 768 million confirmed cases and more than 694 million deaths worldwide. Another measure found 388 million confirmed cases and 571 million deaths globally [1], [2]. There are several common symptoms of COVID-19, such as coughing, fever, dyspnea, musculoskeletal symptoms (myalgia, joint pain, fatigue), and gastrointestinal symptoms [3]. The attention given to COVID-19 has lowered recently, along with the restrictions and fear, but it is still responsible for a high percentage of death rates worldwide [1].

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Disease diagnosis is critical to epidemic management because it provides vital information on minor outbreaks that should be stopped before they spread. The disease is detected through several medical tests. The standard diagnostic technique for respiratory diseases is Reverse Transcription-Polymerase Chain Reaction (RT-PCR), which determines whether the patient is infected or not. However, it is not accurate enough: the follow-up CT chest scan shows the patient is infected [4]. RT-PCR with DNA sequencing is considered the most reliable and widely used method for detecting and identifying pathogens. Nevertheless, other tests are based on reported IgM/IgG antibodies [5].

Recently, applications of Artificial Intelligence (AI) and Deep Learning (DL) algorithms have been widely integrated and utilised to detect various diseases and assist doctors in more thorough investigations, particularly in medical image processing. Specifically, DL has achieved high performance results in disease classification, such as diabetes, attention deficit hyperactivity disorder (ADHD), and many others [6]. Therefore, radiologists and doctors can detect COVID-19 by checking the extracted data from the resulting X-ray images, which forms a good source to create a model based on AI to detect COVID-19 [7].

Deep Learning algorithms utilise various types of neural networks to accomplish a specific task. There are many types of DL algorithms, such as Convolutional Neural Networks (CNNs), Long Short-Term Memory Networks (LSTMs), and Recurrent Neural Networks (RNNs). CNN is the most used one, and it enables computational models consisting of multiple layers to learn data and make decisions [8].

Along with the rapid development of computer technology, digital image-processing technology has been widely applied in the medical field, including subsequent medical diagnosis via organ segmentation, image enhancement and repair. Deep CNNs were utilized to detect pulmonary perivisceral nodules, where CT images are typically divided into several small 2D/3D patches and classified into several pre-defined categories [9].

Technologies used to treat diseases are essential, including decision-making processes to inform the design of medical facilities. Public health policymakers need the accurate judgment of confirmed cases in the future as ML and DL algorithms take past data and use it to make predictions of the confirmed cases of COVID-19 numbers [10]. An AI-based global diagnostic index has increased diagnostic accuracy for therapeutic purposes [11], ML algorithms are used to analyze clinical data about patients to make a diagnosis [12].

CT scans detect inflammation and fluid in the lungs through imaging diagnostics.

These can lead to shortness of breath and other complications, such as hypoxia (a condition characterised by a lack of oxygen in the blood) and disruptions to certain bodily functions. It may be challenging to determine the extent of damage from the disease just by looking at the pictures and diagnosing them [13]. Therefore, this work proposes a model to detect COVID-19 by using DL algorithms to monitor the size of the inflammation and determine its location based on several characteristics, such as the percentage of white in the image, the extent of its spread, and the extent of inflammation in the lung.

The main objective of this work is to develop a CNN-based diagnostics model to detect COVID-19 from a CT scan of lung images as follows:

- A classification process to determine the status of the patient-infected or not-infected, based on CT scan images.
- A segmentation process to determine the location of inflammation in the lungs to specify the severity of the disease,
- The use of linear regression to predict the percentage of severity for any case.

The main objective of this work is to accelerate the diagnosis of COVID-19 pneumonia using DL algorithms. The automation of the process helps doctors further determine the oxygen dose. This paper proposes an approach to COVID-19 severity detection based on CNN and determines the location of inflammation in the lungs.

A. Deep Learning (DL)

DL has become increasingly popular in research and is used in many applications, including text mining, spam detection, image classification, and the retrieval of multimedia concepts [14]. The tremendous advances in the development of the ability to collect data have led to the constant emergence of innovative studies [15]. Computational models in DL algorithms consist of multiple processing layers to represent data in several abstraction layers. The model is trained to classify data such as images, text, or sounds, characterized by high precision [16]. In this case, DL can identify and classify diseases by analyzing medical images. It can also predict the mechanisms of disease treatment. Since the emergence of COVID-19, several studies and approaches have shown the use of DL to detect COVID-19 as quickly as possible [17]. In DL networks, three types of networks can be used: Recursive Neural Networks (RvNNs), Recurrent Neural Networks (RNNs), and CNNs [18]. This study uses CNNs.

CNNs are widely applied in image-recognition problems. CNN consists of three different layers: a convolutional layer, a pooling layer, and a fully connected layer, which work together to perform the process effectively. Both convolutional and pooling layers apply the feature-extraction process [19]. The convolutional layer is the base layer responsible for determining the pattern of features. In this layer, the image is passed through a filter. The filtering results produce a feature map. Kernels are applied in this layer to extract features in the pattern [16]. The pooling layer is the second layer in the CNN, used to apply corresponding mathematical computation on the feature map to reduce the number of feature maps [20]. Finally, the fully connected layer (FC) is the third layer of the CNN, functioning as a multi-layer perceptron. It uses a Rectified Linear Unit (ReLU), activation function, and SoftMax activation function to predict the output image [21]. The CNN algorithm comprises more than one architecture, and this is an essential aspect in optimising its performance. Some of these architectures are as follows [22]:

- A Residual Network (ResNet) is challenging to train; it requires a residual learning framework to train networks that are considerably deeper than those currently in use. A ResNet consists of many layers; each layer has its number of layers, such as 34, 50, 101, 152, and even 1202. ResNet50 is a well-known network with 49 convolutional layers and one FC [23].
- VGG16 was proposed by [24] as a CNN model. It was designed to evaluate the impact of the CNN model's depth on accuracy in a large-scale image recognition setup. Its main goal is to perform a comprehensive examination of networks with increasing depth using a stand-alone architecture with small convolution filters that show a significant improvement by pushing the depth into 16 weight layers with 1000 categories [25].

B. CT Scan Image Processing

Due to the critical importance of early disease detection for patient treatment and the need to isolate infected individuals to prevent the virus from spreading, various research efforts have been undertaken to develop more rapid and less expensive methods for detecting the virus. The standard test method, RT-PCR, is efficient in terms of time but limited in availability [26]. CT and X-Ray images of COVID-19 patients provide crucial information about their health. Virus-induced pneumonia has a variety of visual appearances [27]. There are several phases in the diagnosis of COVID-19 patients based on images from CT or X-ray scans. First, the lung images are processed, and then a CNN is used to extract the features. Finally, the traits are used in a diagnostic classification system [28].

II. RELATED WORK

Recently, several studies have been proposed to analyze and detect COVID-19 using DL from CT scans, and chest X-ray images.

[19] proposed a new model to detect COVID-19 based on a CNN algorithm using 100 chest X-ray images. Half of the patients had COVID-19, while the other half comprised the healthy group. The authors presented five models of CNN: ResNet-50, ResNet-101, ResNet-152, Inception-V3, and Inception-ResNet-V2. The results classified the patients into four categories: COVID-19, normal (healthy), viral pneumonia, and bacterial pneumonia. The proposed approach achieved a detection accuracy of 98%.

Moreover, in [21], a classification system to detect COVID-19 was proposed using multi-level thresholding and an SVM. The system is applied to lung X-ray images, where all photos were the same size, 512x512 pixels, and stored in JPEG format. The proposed system achieved a sensitivity of 95.76%, a specificity of 99.7%, and an accuracy of 97.48%.

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Several studies have been conducted to describe the process of identifying COVID-19 using CT scans. Before classification, most of these studies used lung segmentation. [29], with the DeepLabv3 model, described pulmonary segmentation. The authors employed a multi-specific paradigm of three classes, including COVID-19, ordinary pneumonia, and normal, with classification accuracies of 92.49% and 98.13%, respectively. This paper used 3D ResNet-18.

Similarly, [30] used Dense-Net 121 to create a lung mask for the segment of lungs and then used Dense-Net as the standard and COVID-19 clinical classifications structure and achieved accuracies of 90%, 78.93%, and 89.93%.

[31] used X-ray pictures and segments of the lungs by obtaining a mask of the lungs and then separating the lungs from the X-ray image with a fully connected DenseNet. The authors randomly selected several patches from the segments' ResNet-18 for classification in sizes of 224x224. The authors randomly selected K patches during the prediction process and, using majority voting, were able to predict whether the COVID-19 disease was present or not. In the test dataset, the authors reported an accuracy of 88.9%.

[32] showed how the lungs' involvement in COVID-19 should be considered serious. Each of the five pulmonary lobes received visual scores of 0 to 5, where 0 represents cases without participation and 5 represents more than 75% involvement. A total CT value between 0 (no participation) and 25 was determined as the lung-participation sum (maximum involvement). The study showed that patients with COVID-19 who had inferior lobes were more likely to have higher CT scores.

For each lung, [33] used the severity index. The lung score was added to give a final severity. Each lung was assigned a score of 0–4 based on the extent of consolidation involvement. The scores for each lung were added to the final severity score. This study found that chest X-ray findings often showed abnormalities in the lower area of both lungs among COVID-19 patients.

[34] provided the model for COVID-19 frontal chest X-ray pneumonia with a model for severity score prediction. The severity of lung infections with COVID-19 (and generally pneumonia) may be used to de-escalate or escalate care, as well as to assess the effectiveness of therapy control, particularly in ICUs. The images of a COVID-19 database were utilized for this investigation. Retrospectively, three specialists assessed these pictures in terms of lung involvement and the degree of opacity. Moreover, a pre-trained neural network model with massive (non-COVID-19) X-ray datasets will be utilized to build features that are predictive of our goal for COVID-19 images. The findings of this study reveal that a regression model based on a subset of outputs from the pre-workout X-ray chest model predicts the geographic extent score with a 1.14 MAE and 0.78 MAE in the presence of lung dysfunction. The results showed that the provided model may be utilised to determine the severity of COVID-19 lung infections, particularly in critical care units, for escalation or de-escalation, and to track treatment efficacy.

Moreover, [35] developed a new strategy for concurrently identifying diseases and predicting conversion times, considering challenges such as high-dimensional data, short sample sizes, outlier influence, and imbalance classification. To accomplish this, they devised a sparsity-regularisation term to conduct feature selection and learn the shared information across two tasks, as well as a novel approach to account for sample weights and the classification imbalance problem. They included 408 CT scan images. The results reveal that the approach achieves a classification accuracy of 85.91% and a regression correlation coefficient of 0.462. Moreover, the accuracy of the proposed approach is 76.97% percent.

III. PROPOSED WORK

This work presents an approach based on the Deep Learning CNN architecture to classify COVID-19 patients and predict disease severity using CT lung images. CNN algorithms have been significantly improved and are characterised by accurate algorithm classification operations. Moreover, the use of the CNN algorithm, due to its structure, eliminates the need for feature extraction. The CNN system is trained using image filters and convolution to build static properties that are passed to the next layer. Then, the features in the next layer use multiple filters to produce more diverse features until the final features are produced [22]. The proposed model is divided into three phases:

- Classification process: images are categorized into COVID-19-infected or non-infected using the ResNet50 structure. This output is represented as a CNN model. After the CNN model is generated, the test dataset is used to evaluate the model's effectiveness in classification.
- Severity detection using the segmentation process: another dataset was used that contains mask-segmentation images. The percentage of the disease mark (incision) is revealed through inflammation segmentation in the lung, where areas infected with the COVID-19 virus are identified, as these areas are segmented. The segmented area of the lung is used to calculate the percentage of lung tissue affected by inflammation. The system is then trained using images of COVID-19 patients, where some arithmetic (subtraction) and logical (XOR) operations are used to determine the size, location, and percentage of inflammation in the lung.
- Predicting severity through regression: Each image and its corresponding disease severity ratio are stored to prepare the data for the testing stage. All the collected data are trained using a linear regression algorithm to predict the incidence of the disease. The algorithm compares the expected values with the actual values to obtain the lowest error rate in predicting the disease incidence for a new image.

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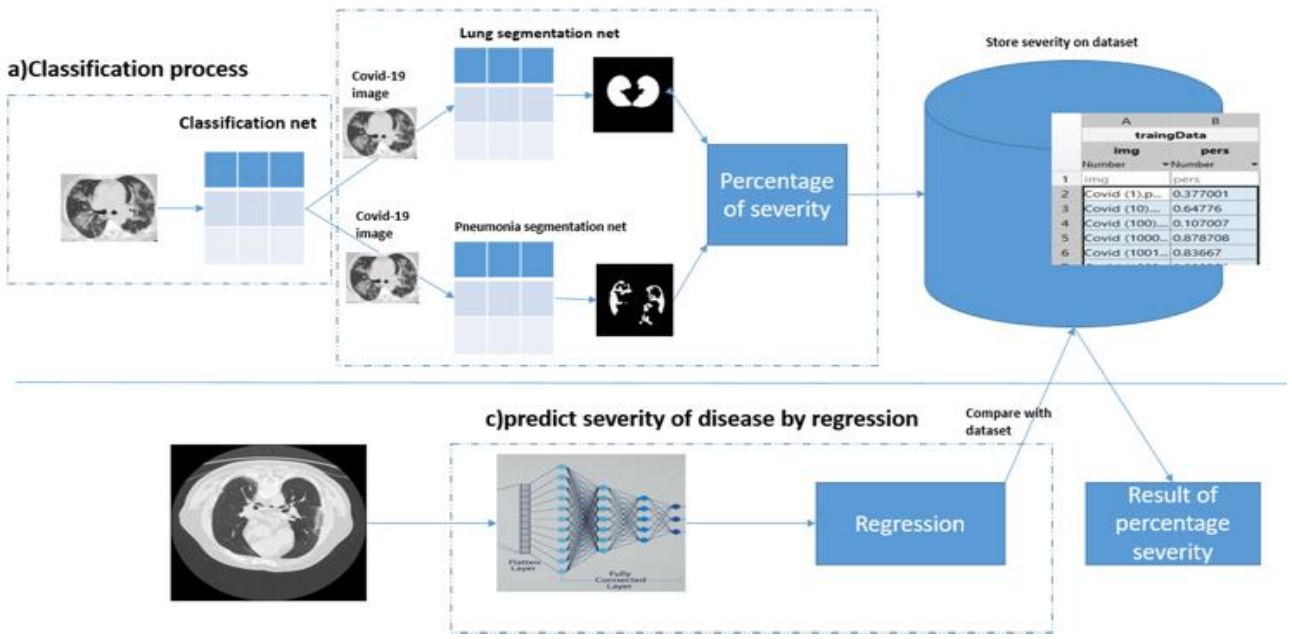

Fig. 1. The Proposed Model

All previous phases are shown in the block diagram in Fig. 1. Furthermore, in the pre-processing stage, the CT images of uninfected and COVID-19 patients are stored in the original dataset and processed to be ready for the training process.

A. Preprocessing

Image preprocessing refers to the operations applied to images at a basic level of abstraction to improve their quality. This is achieved by suppressing unwanted distortions and enhancing specific image features. This work used these steps: 1) conversion of the medical image to PNG format, 2) image augmenter reflection, and 3) histogram equalization.

The images in the dataset are converted into Portable Network Graphics (PNG) format to ensure they are suitable and accepted by DL algorithms. Then, the fixed-size pictures are used to train neural networks in the training stage. Therefore, all images containing a lung are resized to 224x224 pixels to be appropriate for the network.

Histogram equalization is a technique used in digital image processing, in which the contrast of an image is modified, and its histograms are as flat and distributed as possible [36]. This method typically enhances the contrast of many images, mainly when data are represented by contrast values that are closely spaced. Light intensity values are better distributed across the image histogram during the adjustment process; therefore, areas with little localised contrast can gain more contrast. This technique was applied to dark images, increasing the contrast by detecting the distribution of pixel densities in an image and plotting these pixel densities on a histogram. Fig. 2 illustrates an example of histogram equalisation applied to one of the images.

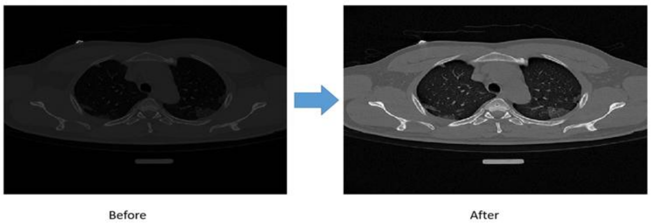

Fig. 2. Histogram Equalization Applied to One of the Images.

B. CNN Model

The CNN uses filters and image convolution to create static features whereby adjacent pixels are grouped, divided into classes, and then passed to the next layer. Then, the feature is wrapped in the next layer with different filters to obtain additional features, which are then combined to produce the final features. The advantage of the CNN algorithm is that it doesn't need to extract features because the CNN architecture extracts features on its own [8].

- **Input Layer**: In this layer, the images are utilized as input for the CNN, representing the images' pixel matrix, as shown in Fig. 3

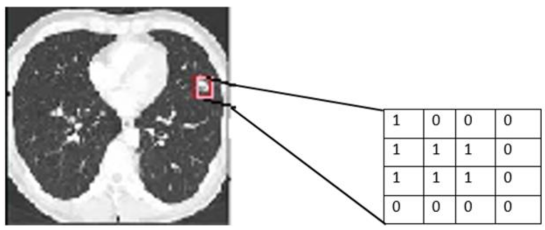

Fig. 3. Input Image Matrix

- **Convolution Layer**: This is the first layer and the most critical component of CNN design. It consists of a set of convolutional filters (so-called kernels). In this layer, the output feature map is created by convolving the input image, represented as an N-dimensional metric, with kernels. For example, a 4x4 grayscale image uses a 2x2 randomly initialised kernel to understand the convolutional operation better. First, the kernel moves horizontally and vertically across the entire image. In addition, the dot product between the input picture and the kernel is calculated. Their respective values are multiplied, and then the sum value of the dot product result is calculated to generate a single scalar value. The whole process is repeated until no further sliding is possible.

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Therefore, the calculated dot product values represent the feature map of the output. Fig. 4 illustrates the preliminary calculations executed at each step. In this figure, the light green colour represents 2x2 kernels, while the light blue colour represents a similar-sized area of the input image. After calculating the dot product results of the sum value (marked in light orange), the sum value serves as an input to the output feature map.

- **Pooling Layer**: The pooling layer subsamples the feature maps. In other words, this method reduces the size of enormous feature maps to create smaller ones. At the same time, it preserves most information (or characteristics) at each stage of the pooling process. Before the pooling process, both the stride and the kernel are assigned a size in the same way as the convolutional operation. Fig. 5 shows three pooling methods. They use the most significant number from each local cluster in the feature maps. The min-pooling method uses the lowest value, and the average pooling method uses the average value from the selected region. Flattening is performed after the pooling-layer process to convert all 2D arrays from pooled features into a single, long, continuous vector, as shown in Fig. 6. The output is used as input for the continuous layer.
- **Fully Connected Layer (FC):** The fully connected layer connects each neuron in this layer to all neurons in the previous layer. This layer receives its input from the previous pooling or convolutional layer. This input is formed as a vector by flattening the feature maps. Then, the output represents the final output of the CNN. In this phase, the flattened matrices are passed through the FC layer, and then the classification process begins.

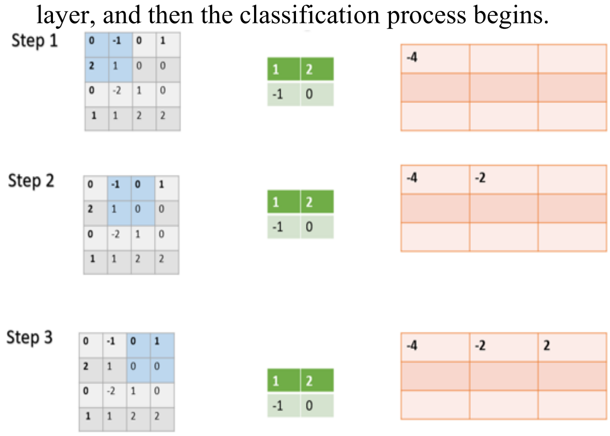

Fig. 4. Convolution Operation

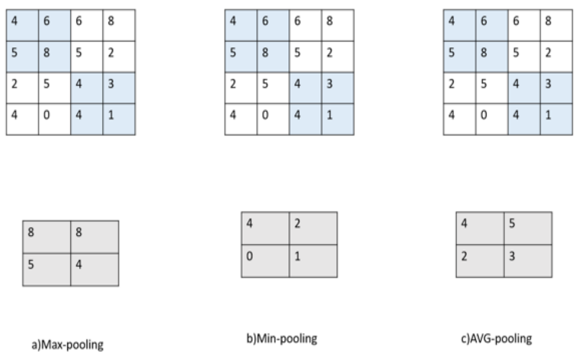

Fig. 5. Pooling Layer Results

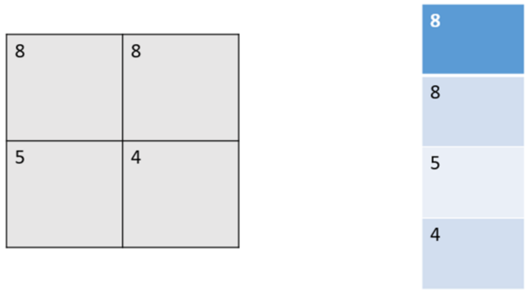

Fig. 6. Flatting Process

C. CNN Architectures

The significant improvement in CNN performance was mainly attributable to the restructuring of processing units and the development of new blocks. Utilizing the depth network to perform the novelist breakthroughs in CNN designs. The architecture of a model is a critical aspect when it comes to increasing the performance of many applications on various architectures such as ResNet and VGG [37].

- **Res Net** is divided into four stages: the network inputs images with heights and widths that are multiples of 32 and a channel width of 3. The input size is assumed to be 224 × 224 × 3. For initial convolution and max pooling, every ResNet-50 design uses 7x7 and 3x3 kernel sizes. After that, the first stage starts with three residual blocks, each containing three layers. The kernels utilised to conduct the convolution operation in all three layers of the first-stage block are 64, 64, and 28.
- **VGG**: during the training process, an RGB fixed-size image 224x224 was input into the VGG16 model ConvNets to preprocess each pixel by subtracting the average RGB value computed on the training set. The image is sent through a stack of convolutional layers. The receiving field is a 3x3 filter. The VGG16 model utilises 1x1 convolutional filters in a single setup. Spatial grouping is accomplished using five levels of grouping to follow some of the layer transformations. In the second step, the max-pooling is performed using a 2x2 pixel window. There is a SegNet design (a CNN architecture for semantic pixel-wise segmentation) for segmentation and an architecture consisting of an encoder network and a broad global semantic hashing structure, followed by a decoder network. The encoder in this experiment depends on the VGG16 classification network, followed by a decoder for this network. SegNet consists of a network encoder and a network decoder, followed by a pixel-wise classification layer. The Cypher network contains 13 convolutional layers, which correspond to the 13 primary convolutional layers of the VGG16 network used in the classification process. The decoder network consists of 13 layers, as each encoder layer has a corresponding decoder layer. The final decoder output is sent to a multi-class SoftMax classifier, which individually generates class probabilities for each pixel [38].

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IV. PROPOSED METHODOLOGY

The proposed method is a stage in which the severity of the disease is determined through three steps: 1) classifying COVID-19 and non-infected patients, 2) detecting the severity of the disease, and 3) carrying out the regression process that predicts the severity of the disease.

A. Classification Process for Detecting COVID-19 Patients

Classification is a process related to categorisation, where ideas and objects are recognised, distinguished, and understood. In this methodology, the primary goal of CNN training is to classify image data based on features and find the convenient feature. The ResNet50 training network is used in this work. To classify lung images as infected or non-infected, ResNet50 models are trained on optimised pictures obtained from the previous stage. These models are then used to classify any image after the preprocessing process, improving tomography and incorporating it into the training process.

In the proposed model, a neural network was trained to classify the image into two classes: COVID-19 or non-COVID-19. A large dataset of CT scan images, specifically a publicly available COVID-19 CT scan dataset, was utilised to identify COVID-19. The dataset comprises 1,252 CT scan images that are positive for COVID-19 and 1,230 CT scan images that are negative for COVID-19, totalling 2,482 CT scan images. These data were collected from real patients in hospitals from São Paulo, Brazil, and data are available in [39].

The training process is designed to extract features based on specific criteria. If an area appears white in the lung image, this whiteness is often found in the lower region of the lung, as indicated by medical studies and research. When the layer initially captures basic image features such as edges and blocks, they are considered as basic features grouped via the FC in each layer. These features are distributed into classes, which are determined in each layer. After each operation, the features are distributed to other classes in the second layer. Then, the convolutions of these classes are grouped to determine which final class they belong to. The feature can be visualised by examining the weight of the mesh filter from the first convolution layer, where the raw features are extracted after the first convolutional layer.

After all the layers are processed, the last layer is processed in the ResNet50 product feature for all classes; this feature must be activated, and the training of the features maps must be saved, as they are labeled in the training for the classifier, to use this feature map in the training model to classify the output result. Finally, in this step, a multi-layer product is used to complete the training with an error-correction output model.

B. The Severity Detection Process

The process of determining the severity of the disease is carried out in three steps: 1) segmenting the inflammatory area, 2) segmenting the lung area, and 3) using the trained segmentation to determine the severity of the disease.

C. The Pneumonia-Segmentation Process

The classification process results are presented, whether the patient has COVID-19 or not. In this step, the CT scan is used to detect areas representing pneumonia in the image by determining the percentage and extent of whiteness in the lungs. Image segmentation is one of the most complex phases of understanding image content due to changes in lighting, size, and orientation. %% ref

Therefore, a fixed method of image-processing algorithms cannot be used, especially for medical images. To address this issue, neural networks are employed to train the computer to segment the image, thereby handling image states dynamically and effectively. SegNet depends on VGG16, which is used for semantic segmentation. The pixel-classification layer is performed to predict the categorical label of each pixel in the input image. The dataset of COVID-19 CT scan images used in this network comprises 100 axial CT images from more than 40 patients with COVID-19, with 70% of the images allocated for training and 30% for testing. Fig. 7 and Fig. 8 illustrate the flowcharts representing pneumonia and lung segmentation, respectively.

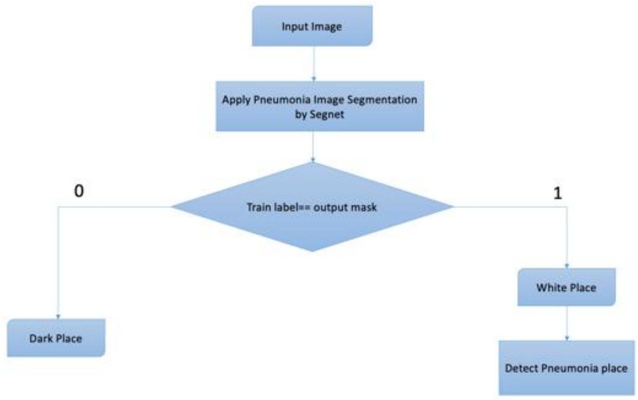

Fig. 7. Flowchart Representing Pneumonia Segmentation.

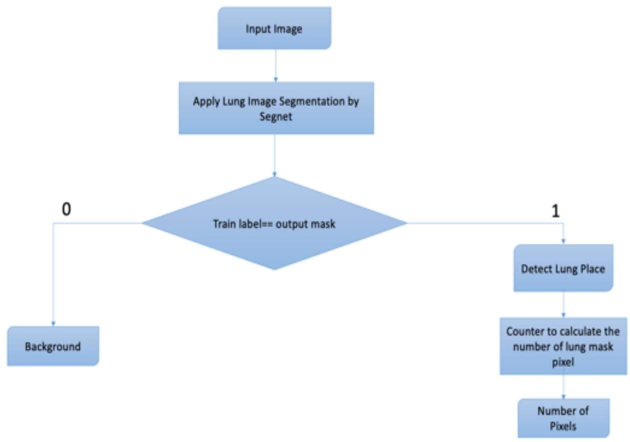

Fig. 8. Flowchart Representing Lung Segmentation.

The SegNet network defines the input and output images that indicate the segmentation mask images. The network is trained to identify the output image in the database using mask images of inflammation for each image. These images are trained such that the weight of the input image equals the weight of the output image. The last layer, which determines the category and

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provides the weight of the output image, is removed to train the images to reach the weight of the mask label by calculating the total number of white pixels, the total number of black pixels, and the ratio of the image to calculate the weight of the image.
Fig. 9, Fig. 10, and Fig. 11 show the result after applying the hash training model. Moreover, the training model recreates intrapulmonary pneumonia as shown in the hash-mask form. It also detects the lung boundaries as pneumonitis, meaning that there are regions incorrectly identified as areas with pneumonitis. Therefore, the lung area needs to be discovered.

Fig. 9. The Original Image

Fig. 10. Segmentation Mask

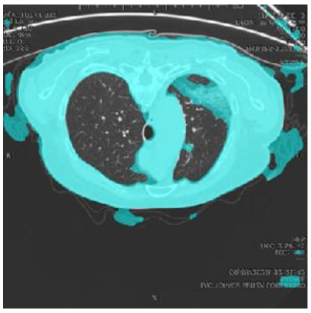

Fig. 11. Overlay Mask.

D. Lung Segmentation Process

The severity of COVID-19 in the lungs is determined by identifying the edges of the lungs. VGG16 exhibits a high level of self-learning, adaptability, and generalisation ability, with a high training speed and accuracy in lung image recognition. Another semantic segmentation network was implemented using SegNet on VGG16. This type of network needs to define the input and output images, which refer to the hash mask image that represents the lung areas in the image. The network is trained to produce the output image through the database, where mask images for each image are stored. These images label the mask by counting the total number of pixels in white and the number of pixels in black, and their proportion to the image to calculate the weight of the image. This value will be incorporated into the weight of the resulting image and serve as a mask for inflammation. The training data are applied to the same images in the inflammation segmentation but with different segmentation-mask image files so that when the lung is located and the network is saved, then the lung and inflammation training network are called and saved in the previous step to calculate and classify the lung opacity to discover the lung information in the images.

E. Using Segmentation Steps to Detect the Disease Severity

The VGG16 network is a Keras-based trained network. Keras is a neural network library that has been trained. These libraries make it easy to train images and preserve the learned networks. ImageNet was used to train it on millions of images from a range of classifications [40].
Although training a CNN model from scratch takes longer than training a pre-trained model, it is less computationally costly when the dataset comprises fewer images. To categorise these characteristics, the fully connected neural network rule is employed, and the final layer is modified to provide it with a weighted representation of the output in the [0, 1] range, where 1 denotes pneumonia and 0 represents the mask. After using the output of the lung image segmentation, the training network, and the output of the inflammation image segmentation, both contain image information and main features. Then, it will be straightforward to determine the location of inflammation in the lung using a set of computational steps and the corresponding area. As shown in Fig. 12, this model was applied to the same lung image to obtain a lung mask. The result of the lung mask was then subtracted from the pneumonia mask until the areas that did not require it were reached. All-white areas outside the lung area were identified, which represent bones and other non-interesting areas. Exclusive OR (XOR), a logical process, was applied. This process calculates the XOR between the image of the product of the subtraction process and the pneumonia mask, resulting in the location of lung inflammation in the vital area.

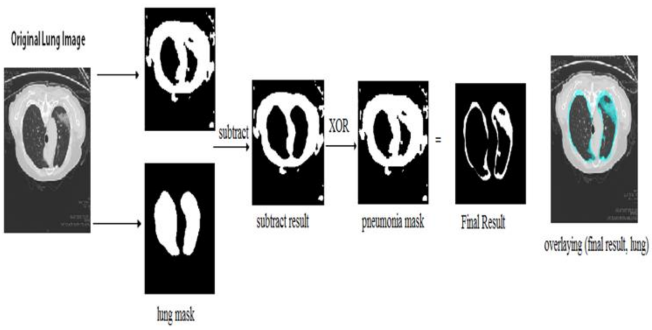

Fig. 12. The Detection of Pneumonia in the Lungs

Then, this result is applied to the original image to understand the location of the inflammation in the image. To calculate the severity, these steps are applied to all images and stored in a database that contains the image number and disease percentage, as shown in Table I, which is a sample of the data. This data is then prepared for the testing stage. These data are trained on CNN algorithms, and linear regression is

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applied to train the model to predict disease severity.

Table I: Regression Dataset Sample

Image No.	Training Data No.
Covid (1000).png	0.878708
Covid (1001).png	0.83667
Covid (1002).png	0.890259
Covid (1003).png	0.926618
Covid (1004).png	0.915866

F. Regression Process

Regression analysis is a set of statistical methods used to estimate the relationships between a dependent variable and one or more variables in statistical modeling [41]. In this work, linear regression was used for analysis because the relationship between images and the proportion of inflammation is direct. At this stage, the dataset was collected and entered into the model to identify the disease, determine lung inflammation, and calculate the disease severity for each image. These images were stored along with the corresponding percentage in the database, as shown in Fig. 13, which illustrates the number of images associated with the severity of the disease; this information is utilised later in the training and testing processes.

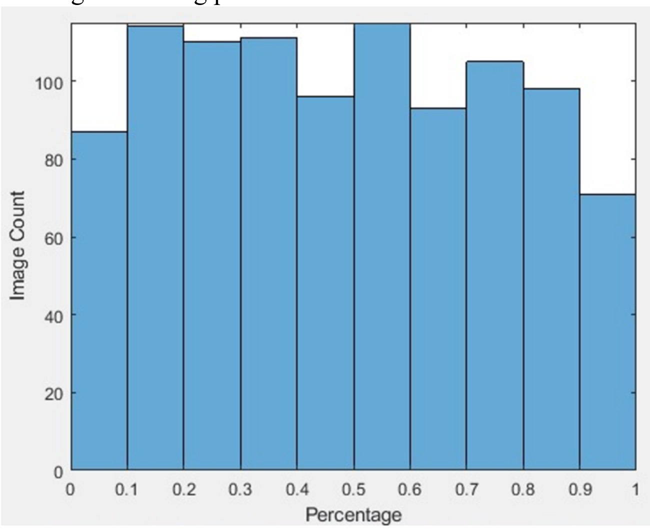

Fig. 13. The Number of Images with the Extent of the Severity of the Disease.

Before the training process begins, each image is converted into values to be read during the regression analysis process and converted into a 4D array, as shown in Fig. 14, because the regression analysis deals with values rather than images.

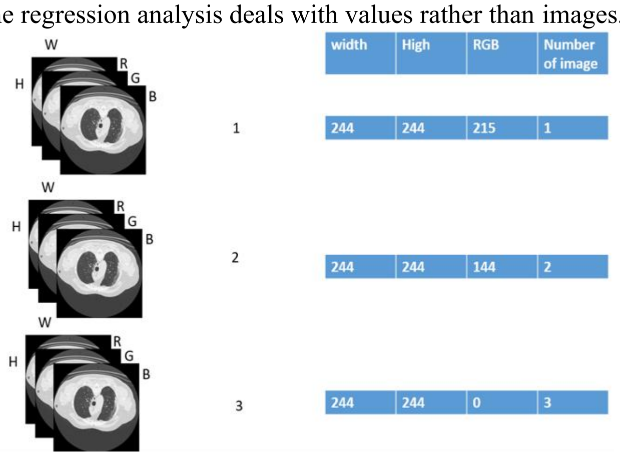

Fig. 14. Converting an Image to a 4D Array.

These data are applied to a CNN algorithm that builds nine layers of a CNN, which takes a range of real numbers and returns an output value from 0 to 1. The hidden layers in the CNN architecture contain four convolutional filters in the convolutional layer. The next layer is the maximum pool with sub-sampling ratios of 2x2. Fig. 15 represents a CNN model. The output layer is converted into a regression layer to train the network to predict the disease severity.

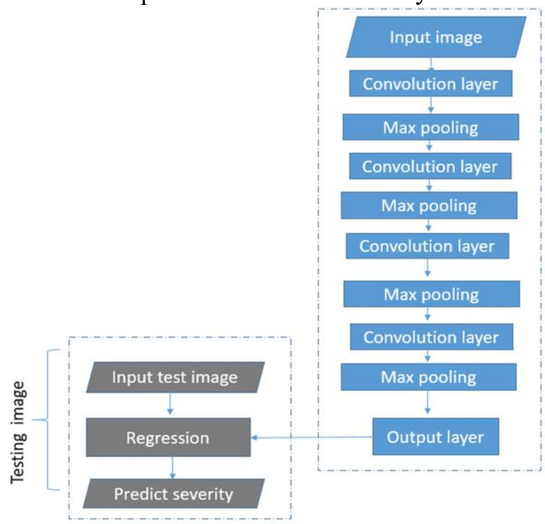

Fig. 15. The CNN Model for the Regression Step.

The method consists of two main parts of implementation and data operations. First, the training phase involves inputting the images into the ResNet50 network to identify COVID-19 patients, thereby transferring the learned knowledge to the segmentation phase, where the images are segmented. Both inflammation and lungs were analysed using the VGG16 network to determine the location of inflammation in the lungs. Second, the testing phase compiles these images with the severity of each image in the database to train the data to predict disease severity using linear regression. The CNN model is used to predict and identify the relationship between independent and dependent variables. Each image is compared with its corresponding disease severity rate. A value is expected for each image, and the equation is applied to calculate the error ratio between the actual value and the predicted value by the algorithm. This relationship is represented between the variables shown in Fig. 16.

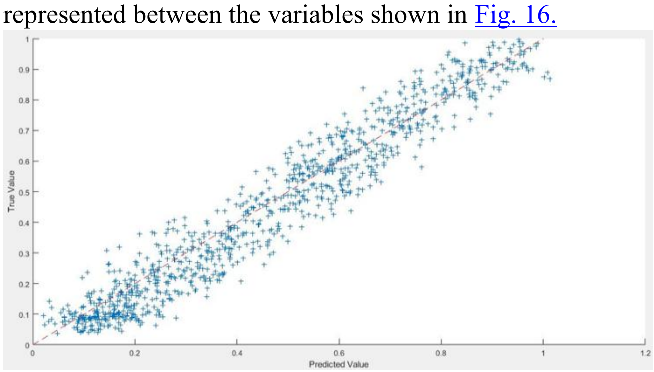

Fig. 16. The Relationship between the Predicted Value and the True Value.

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In the first step, a matrix is constructed that contains the input images as input to the hash generator, creating a database of images with a satisfactory severity percentage. In the regression stage, the difference between the actual and expected values is calculated, and the Root Mean Square Error (RMSE) equation is applied. RMSE has been used as a standard statistical metric to measure model performance in meteorology. In this step, the threshold value is set to 0.15, chosen randomly based on previous experiments. It is necessary to determine this value because the result is based on the threshold value, which represents the percentage of error in calculating the difference between the percentage of actual image severity in the database and the expected percentage of disease severity for the test images.

V. RESULTS

CNN relies on its ability to detect important features automatically without any human intervention. Data were trained on the ResNet50 network to classify patients with COVID-19 using CT images. The presence of pneumonia in the image is determined by classifying the inflammation as the white areas of the lung, which are filled with fluid that leads to pneumonia. The photos of COVID-19 patients were trained to determine disease severity using SegNet based on the VGG16 network and a 13-layer deep CNN. The value of the last layer was changed, with a label of 0 or 1. A database of 170 images was used to locate the lungs and quantify pneumonia, utilising a segmentation mask for accurate comparison. The percentage of lung inflammation was measured by calculating the area of inflammation in the lung relative to the total lung area, which provides the percentage of the lung volume occupied by inflammation. Then, the severity of the disease was calculated for all the images collected in the database. Each image, along with its corresponding percentage severity of the disease, was used in the linear regression process to predict the disease severity.

A. Dataset

The dataset used in this work is defined as follows.

- The data were completed as truncated images containing positive images for 1252 COVID-19 images with COVID-19 infection and 1230 CT images without COVID-19 infection, for a total of 2482 CT images, to transfer the learning to the segmentation process, i.e., Kaggle [39].
- In the segmentation process, a dataset of 100 axial CT images of more than 40 patients infected with COVID-19 was taken and converted from JPG files. For the segmentation process of inflammation and disease from the radio, the data contains the segmentation mask for both lungs and the inflammation used in the training process. Fig. 17 and Fig. 18 show sample data images and image masks for lungs, respectively. Fig. 19 shows the overlying image mask used to obtain the lung location and its boundaries.

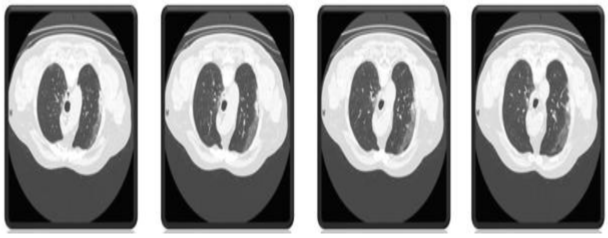

Fig. 17. Sample of Image Data.

Fig. 18. An Image Mask of Lungs.

Fig. 19. Overlying Mask on Original Image.

MATLAB libraries were utilised to implement the research method, starting with data preprocessing, followed by filtering and feature extraction, and concluding with classification.

B. Testing and Training

The training, validating, and testing of the data were performed in this work. The sizes into which the data were split were 80% and 20%, 70% and 30%, and 50% and 50% for the training and testing sets, respectively. During the training phase, the data were split and shuffled to achieve the best accuracy. In the testing phase, the model was tested for all possible data and cases in the dataset. The results from the training and testing phases are shown in Table II.

Table II: The Modeling Results of the Splitting Data

Phase	Dataset Size	Step 1	Step 2	Step 3
Classification process	2458	95.9%	95.7%	94.9%
Lung-segmentation process	174	98.72%	98.6%	98.1%
Pneumonia-segmentation process	174	96.5%	96.2%	95.5%
Regression process	1252	98.6%	98.29%	98%

Using several confusion-matrix-based performance matrices, the proposed DL-based COVID-19 classification model was tested using the following metrics: precision, recall, specificity, sensitivity, and accuracy.

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C. Cross-Validation Accuracy

Cross-validation is a technique used to evaluate the performance of an individual model on a data sample concerning future data by dividing the data into two groups: the training set, comprising the data on which the application is carried out, and the testing set, comprising the data on which the percentage of the resulting error is calculated. Cross-validation is typically used in statistics to perform regression on a dataset, select the best model to solve a particular problem, and utilise it in classification. Five features were applied for validation, as represented in Table III, for the four phases used: classification, lung and pneumonia, and regression.

Table III: 5-fold Cross Validation Results

Phase	*k*= 1	*k*= 2	*k*= 3	*k*= 4	*k*= 5
Classification	95.3%	94.8%	94.6%	95.55%	96.2%
lung	98.5%	97.8%	98.5%	98.3%	98.9%
Pneumonia	94%	95.7%	96.1%	95.9%	95.9%
Regression	98.0%	97.5%	98.2%	98.35%	98.9%

D. Detection Results

The work is divided into (1) the classification of COVID-19 patients using ResNet50, (2) the image segmentation of COVID-19 patients, (3) the detection of the severity of disease in the lung, and (4) the prediction process based on the linear regression algorithm to predict the severity of the patients' disease.

E. Classification of COVID-19 Patients Using ResNet5

This study used DL to classify COVID-19 cases using a CNN model based on the ResNet50 architecture. To do so, 1253 images of COVID-19 patients and 1230 images of non-patients were used. We chose the ResNet50 network because it is one of the most widely used networks for classification, with an accuracy of 95.3% in training the data, as shown in Fig. 20.

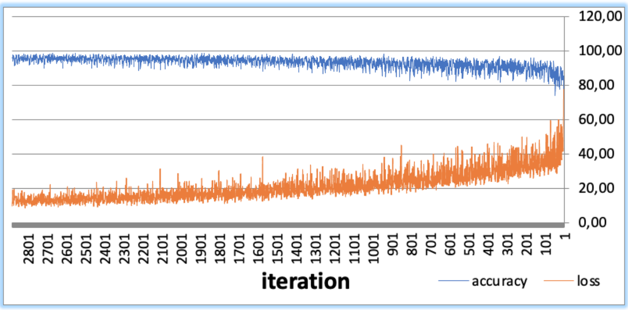

Fig. 20. The Training Accuracy of the Classification Process in ResNet50.

This step aims to determine whether the human is infected with COVID-19 or not. The confusion matrix shows that the model obtained the following values: a false negative of 0.0425, a true negative of 0.954, a true positive of 0.957, and a false positive of 0.045. Depending on the number of correct and incorrect predictions, the classifier performs well. The following performance measures are used to validate the proposed model's performance for the classification process, as shown in Table IV. The proposed framework yielded a high performance in the classification process. These values proved the reliability of the proposed framework in determining whether the given CT scan represented COVID-19 or not. The dataset was trained with 15 epochs using the ResNet50 method with a batch size of 24.

Table IV: The Classification Process Performance

Metric	Value
Accuracy	95.7%
Sensitivity	96.0%
Specificity	95.69%
Recall	95.7%
Precision	96.0%

F. Image Segmentation of COVID-19 Patients

There were significant differences between patients' CT scans, allowing the CNN to identify these differences. The images are segmented into two phases: inflammation (pneumonia) area segmentation and lung area segmentation, using SegNet based on the VGG16 network.

G. Segmentation of the Pneumonia Area

To identify the location of the inflammation and compare the input image to the output image of the segmentation mask, several experiments were conducted on randomly selected images from the entire dataset to determine the most suitable parameters for achieving optimal segmentation performance. The dataset was divided into two parts: training datasets (0.7) and testing datasets (0.3). The total number of samples was 170, with an image size of 340 × 340 pixels. The training accuracy was 95.8%, as shown in Fig. 21, which displays both the training accuracy and training loss; the model achieves a high training accuracy. Moreover, it yields the best results in training, offering a high degree of flexibility, as it approaches all points with the lowest validation and training loss.

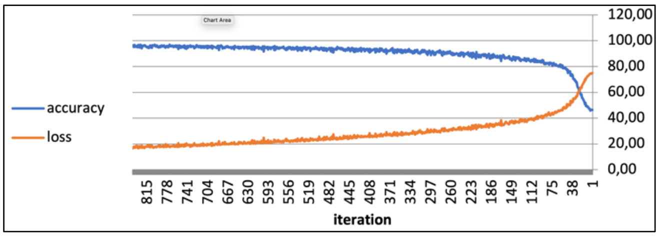

Fig. 21. Results of the Segmentation Process for Pneumonia Areas.

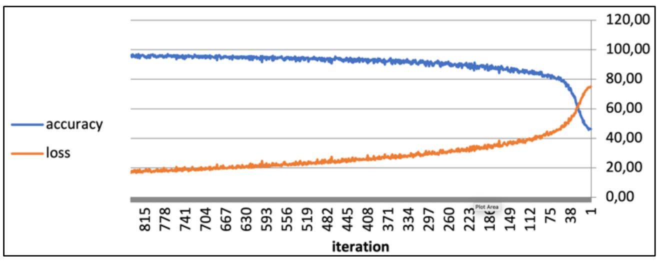

Fig. 22. Results of the Segmentation Process for both Lung Areas.

This step aims to segment the image into two parts by classifying them into labels, where 1 represents inflammation (white regions) and 0 represents non-inflammation regions. The training dataset was used up to a maximum of 100 Epochs using SegNet with a batch size of 3. The Performance of the pneumonia and lung segmentation processes is

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shown in Tables V and VI, respectively.

Table V: Pneumonia Segmentation Process Results

Metric	Value
Accuracy	96.2%
Sensitivity	96.3%
Specificity	96.1%
Recall	96.27%
Precision	96.27%

Table VI: Lung Segmentation Process Results

Metric	Value
Accuracy	98.6%
Sensitivity	98.65%
Specificity	98.6%
Recall	98.6%
Precision	98.58%

H. Segmentation of the Lung Area

To determine the location of the lung using a segmentation mask image, several experiments were conducted on randomly selected images. The dataset was divided into two parts: a training dataset with a ratio of 0.7 and a validation dataset with a ratio of 0.3. In the same sample, 170 images were used with an image size of 340x340. The training results are shown in Fig. 22, where the accuracy is 98.3%. To evaluate the performance, the training dataset was processed for up to 100 epochs using the SegNet with a batch size of 3. Results are shown in Table VI.

I. Detection of Disease Severity

One of the calculated results is the percentage of pneumonia, where sufficient information is available regarding lung and pneumonia areas, allowing for the determination of the disease state and the severity of the inflammation. As shown in Fig. 23, the percentage was calculated in several pathological conditions by subtracting the lung segmentation mask images from the segmented inflammation mask images. Furthermore, the XOR process was performed between the resulting image from the subtraction process and the image of the pneumonia mask to identify the critical area, which corresponds to the area of pneumonia in the lung.

Fig. 23. Detection of Disease Severity in Lungs

By applying the classification to distinguish between images with and without COVID-19, the segmentation operations were then applied to extract the inflammation area using the trained lung mask extraction network and the inflammation mask-extraction network. Then, by subtracting the lung mask from the inflammation mask, applying the XOR process on the image resulting from the subtraction process with the inflammation mask to obtain the inflammation area in the lung, and then dividing the number of pixels for each of the inflammation areas in the lung by the number of pixels in the lung, the percentage of inflammation is obtained for the image size. Fig. 24 shows the disease severity ratio of 0.1439.

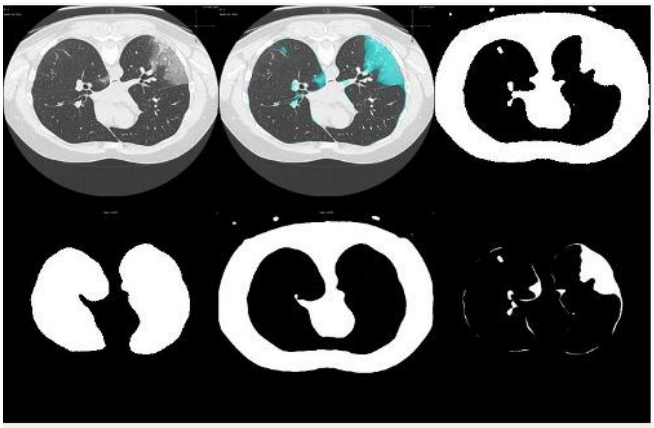

Fig. 24. The Percentage of Severity of Disease Value 0.1439

Furthermore, the other cases, which represent different severity levels of various images, are shown in the Figure. 17 The same method was applied to determine the severity. The greater the inflammation in the lung area, the more severe the disease, as illustrated in the sixth case (Fig. 25).

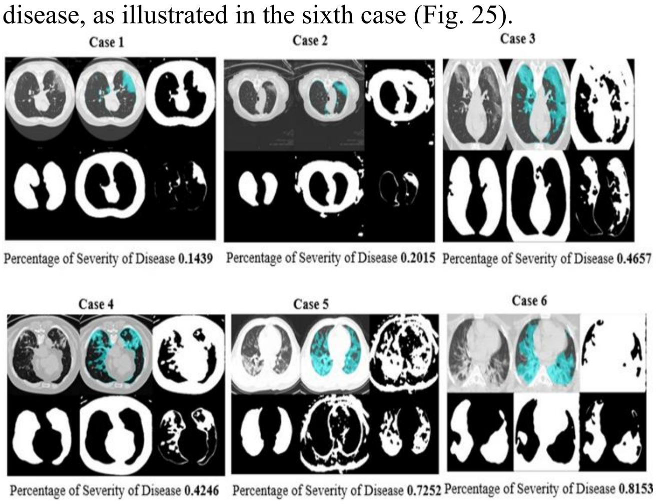

Fig. 25. Different Cases for the Detection of Severity

J. Regression Analysis Process

After the image dataset is created, it is compared with the dataset to predict the severity of the disease. For the prediction phase, any input images can be used to compare them with the database. In this step, the threshold value was 0.15, and it is necessary to be decided because the result is based on the threshold value. The prediction is performed by calculating the difference between the image in the database and the new images. The percentage of the prediction error is calculated by subtracting the actual values from the expected values. The RMSE is also calculated, which is the square root of the arithmetic mean of the sum of the squares of the error rate. The threshold value is 0.15 and is used to calculate the number of images that match the expected ratio, which is close to the proper ratio, with a margin of error determined by dividing the sum of the actual images by the training RMSE. The training reached an RMSE of 0.07 and an accuracy of 98.29%.

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VI. COMPARISON WITH PREVIOUS STUDIES

Table VII shows that the proposed model achieved the highest accuracy in the four different processes using CT images of COVID-19 patients. All these studies used CT scan images.

Table VII: Comparison of the Proposed Model with Previous Studies

Ref.	Data Size	Dataset	Algorithm	Accuracy
[42]	2458	classification	ResNet50	95.7%
[43]	170	segmentation	CNN	98.6%
[44]	408	Regression	CNN	85.9%, RMSE = 0.49
The proposed model	2458	classification	ResNet50	95.7%
The proposed model	1252	regression	CNN	98.29%, RMSE = 0.07

The ResNet50 model achieved better results in the classification process on CT images due to improvements made to the pictures, specifically in enhancing essential parts. After several training stages, the preprocessing of the images played a crucial role in influencing the model, which led to the clarification of the image features. Moreover, the segmentation model achieved a higher accuracy rate using the same database employed in the segmentation process. The image segmentation mask plays a key role in determining the region's accuracy. The proposed model was based on lung segmentation using a segmentation mask. This was achieved by training the data to match the weight of the mask image, ensuring accurate segmentation of the image based on the output. Moreover, the regression model achieved a higher accuracy rate using the same CNN approach employed in other research and image regression training, which yielded a better result for RMSE based on the database generated from the process of determining disease severity, compared to the proposed model.

VII. CONCLUSION

This work proposes a systematic approach to COVID-19 detection, lung and lesion segmentation, and patient course grading from CT images. The proposed approach, utilising cascaded models, achieved high performance levels in both segmentation and classification processes. The proposed approach, utilising the ResNet50 model, achieved the highest accuracy of 96.1% in terms of COVID-19 Detection performance. The proposed model can classify COVID-19 patients. For lung segmentation, SegNet is used to conduct feature extraction. The proposed pneumonia-segmentation pipeline can generate better lung and lesion masks for small lung areas. This study demonstrated lung segmentation using VGG16, achieving the highest accuracy of 98.3% for lung segmentation and 95.8% for pneumonia detection. In summary, the system was able to classify the severity of COVID-19 in patients; computer-aided detection and quantification is an accurate, easy, and feasible method for diagnosing COVID-19 cases. For future work, the proposed framework can be extended to solve more complex diagnostic problems, such as diagnosing the disease based on the doctors' diagnosis of critical and normal cases, analyzing these opinions based on each disease case, and finding the common factor of chronic diseases and their relationship with the affected person's impact on the disease. In addition, the aim is to develop a different methodology using different data, such as the pathological record with the percentage of inflammation and the relationship between the pathological record and the extent of the disease's impact on the body.

DECLARATION STATEMENT

Authors are required to include a declaration of accountability in the article, including review-type articles, that stipulates the involvement of each author. The level of detail differs; some subjects yield articles that consist of isolated efforts that can be easily detailed, while other areas function as group efforts at all stages. It should be after the conclusion and before the references.

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Ethical Approval and Consent to Participate	No, the article does not require ethical approval or consent to participate, as it presents evidence that is not subject to interpretation.
Availability of Data and Material/ Data Access Statement	Not relevant.
Authors Contributions	Mohammad Abbadi and Rania Alhalaseh conceptualized the idea of the work. Rania Alhalaseh provided methodology and validation. Sura Kassasbeh performed software implementation and visualization. Writing---original-draft preparation was performed by Sura Kassasbeh, and writing---review and editing were performed by Rania Alhalaseh and Mohammad Abbadi. Mohammad Abbadi performed project administration.

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