AI-Based Image Processing for COVID-19 Detection in Chest CT Scan Images

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ABSTRACT

Big data analysts and artificial intelligence experts are paying attention to the COVID-19 outbreak. The classification of computed tomography (CT) chest pictures as normal or diseased necessitates a large amount of data and an unique AI module design. By studying CT chest scan pictures, we present a platform that encompasses various layers of analysis and classification of normal and pathological characteristics of COVID-19. Specifically, the platform augments the training dataset with a reliable collection of photos, segmenting/detecting suspicious portions in the images, and evaluating these regions in order to return the correct classification. We also integrate AI algorithms after selecting the most appropriate module for our research. Finally, we compare the efficacy of our design to other strategies published in the literature. The collected findings indicate that the suggested design is 95% accurate.

COVID-19, corona score, medical imaging analysis, AI medical platform, deep learning, computed tomography, segmentation

Keywords: COVID-19, corona score, medical imaging analysis, AI medical platform, deep learning, computed tomography, segmentation

1 INTRODUCTION

Artificial intelligence has made a significant contribution to medical diagnostics and drug development. Artificial intelligence, according to experts, will have a significant impact by providing radiologists with tools to make faster and more accurate diagnoses and prognoses, resulting in more effective treatment. Because computers will be able to process massive amounts of patient data, big data and artificial intelligence will change the way radiologists work, allowing them to become experts on very specific tasks (Shen et al., 2017a). Artificial intelligence has already been successful in solving problems such as chronic illnesses and skin cancer (Esteva et al., 2017). Scientists now anticipate artificial intelligence to play a significant part in the hunt for a cure for the new corona virus, and therefore in reducing the terror that has gripped the globe.

Due to the COVID-19 pandemic, the health-care system has recently faced significant challenges in terms of supporting an ever-increasing number of patients and associated costs. As a result, the recent effect of COVID-19 necessitates a mental change in the health-care industry. As a result, using current technology such as artificial intelligence in order to build and develop intelligent and autonomous health-care solutions has become critical. When compared to other viruses, COVID-19 is notable for its rapid dissemination, which allowed it to become a global pandemic in record time. The medical and health-care systems are still researching and analysing it in order to get more trustworthy information and obtain a better understanding of this critical issue of rapid spread. As a result, accurately simulating the COVID-19 transmission remains a top goal in the fight against this virus. The detection of viral RNA from sputum or a nasopharyngeal swab using real-time reverse transcription–polymerase chain reaction (RT–PCR) is now the most widely utilised diagnosing approach. These tests, on the other hand, need human interaction, have a low positive rate at early stages of infection, and may take up to 6 hours to provide findings. Thus, quick and early diagnostic tools are needed to speed up the control of this pandemic, particularly in the long run, when lockdowns are entirely removed, testing should be conducted on a broad scale to avoid the pandemic from resuming.

Due to a lack of resources and technology in certain nations, testing has been confined to individuals who have symptoms, and in many instances, several symptoms. It goes without saying that the enormous burden that the situation has placed on national health-care systems and personnel, even in the most industrialised nations, exacerbates the difficulty of recognising and monitoring potential cases.

Artificial intelligence algorithms, which are approaches used to implement AI systems, assist with a variety of pandemic-related questions, ranging from vaccine and drug development to tracking people's mobility and how and whether they follow social distancing guidelines, to evaluating lung CT scans and X-rays for faster diagnosis and tracking the progression of such patients.

COVID-19 is now being diagnosed by a series of incremental attempts based on AI algorithms. Advanced neural networks are being utilised to categorise patients based on their breathing pattern in a large-scale viral screening (Wang et al., 2020). In the research by Gozes et al., the identification of COVID-19 was targeted by analysing chest CT images (2020). The development of automated diagnostic systems improves the accuracy and speed of diagnosis while also protecting health-care professionals by informing them of the severity of each infected patient's condition (Alimadadi et al., 2020).

In this context, we propose an AI medical platform that intends to gather multimodal data from many sources, combining both network and medical sensory systems, with the objective of effectively participating in the global pandemic fight. When confronted with large-scale pandemics like COVID-19, the goal is to solve various issues encountered by low- and middle-income nations owing to people's restricted access to excellent treatment and limited medical resources accessible or supplied by governments.

In the literature, there are a variety of segmentation approaches. However, for the purposes of this research, we concentrated on AI-based methodologies and conducted a comprehensive literature review. It's important to note that this piece is part of a larger study. We plan to examine alternative kinds of segmentation algorithms and compare findings based on accuracy and efficiency in order to arrive at an ideal solution.

This article's outline is as follows: Section 2 includes an overview of the literature on AI applications in medical imaging, as well as a short discussion of each deep learning approach employed. Many strategies for detecting COVID-19, as well as its severity, are included in the literature review. The technique used in the creation of the platform is covered in Section 3. The AI medical hub platform's outcomes are presented in Section 4. Finally, Section 5 brings the essay to a close with information on various ways to use the platform.

RELATED WORK

We include a broad range of material in this part that relates to the use of artificial intelligence algorithms in diverse medical imaging applications. In connection to COVID-19 medical diagnosis, this section also includes several computer vision and image processing approaches. Medical Imaging and Artificial Intelligence

The task of classifying photographs into one of many categories is known as image classification. It's a simple computer vision problem. Other computer vision operations such as detection, segmentation, and localization are built on top of it. Deep learning models that employ numerous layers of nonlinear acquired knowledge processing for function extraction and transformation, as well as pattern classification and analysis, have been used to handle this sort of challenge in recent years (Rawat and Wang, 2017).

In the field of medical imaging, computer-assisted image processing has shown to be crucial. Recent advances in artificial intelligence (AI), especially deep learning, have resulted in a huge breakthrough in the field of image interpretation, allowing computers to detect, categorise, and quantify patterns in medical pictures (Shen et al., 2017b). The use of hierarchical function representations derived only from data, rather than handmade features that frequently focused on domain-specific information, is the cornerstone of the advancements. Deep learning looks to be the next building block for increasing efficiency in a variety of medical applications (Shen et al., 2017b).

The desire for improving quality and efficacy in clinical therapy was a driving driver behind the development of AI in medical imaging. Radiology imaging data tends to grow at a rapid rate in comparison to the number of qualified readers accessible. As a result, health-care providers have been under pressure to compensate by becoming more efficient when processing photographs (Wu et al., 2016).

Deep learning has been used to claim remarkable advancements in various AI technologies in the literature. These accomplishments drew researchers into the field of computational medical imaging to investigate the capabilities of deep learning in medical pictures recorded using computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography PET, and X-ray. Deep learning applications for picture localisation, cell structure identification, tissue segmentation, and computer-aided illness diagnosis are shown below (Shen et al., 2017b).

Artificial neural networks are a kind of AI model that mimics the structural beauty of the human brain system in order to perceive and learn from hidden patterns via a large number of observations. The perceptron was the first trainable neural network with just one layer (Rosenblatt, 1958). The modified perceptron is a linear model with many output units that prohibits applications from dealing with complicated input patterns, even when nonlinear functions are used in the output layer. By adding a hidden layer between the input and output layers, this limitation is successfully avoided. A two-layer neural network with a finite number of hidden layers can estimate any continuous function when certain assumptions on the activation function are taken into account (Chen et al., 1995), and is hence referred to as a universal approximator. However, utilising a deep design, which has more than two layers and fewer units in total, it is generally feasible to predict functions with the same accuracy (Bengio, 2009). As a result, the number of trainable parameters may be reduced, making the training process easier with a smaller dataset (Schwarz, 1978). COVID-19 Detection Using Artificial Intelligence.

In this worldwide health disaster, the medical community is looking for new ways to detect and control the COVID-19 (coronavirus) pandemic. Artificial intelligence is a tool that scientists can trust since it can instantly diagnose high-risk individuals, track the virus's evolution, and control the epidemic efficiently in real time. This technology can also estimate the severity of cases by looking at prior patients' data, although the rates of accuracy, true negatives, and false positives may still be improved to prevent medical misunderstanding (Haleem et al., 2020; Bai et al., 2020; Hu et al., 2020). The key use of AI in the COVID-19 pandemic, which this research focuses on, is early infection identification and diagnosis. Artificial intelligence might quickly identify problems based on symptoms and so-called red flags, alerting patients and health-care providers (Ai et al., 2020; Luo et al., 2020). It develops a low-cost, quick-decision-making algorithm. Modern COVID-19 situations may be discovered and handled in a classified framework using a variety of AI methods. Computed tomography (CT) and magnetic resonance imaging (MRI) are useful inputs for AI algorithms that scan human body regions for diagnostic purposes.

Segmentation is the first step in image processing and interpretation for detecting and assessing COVID-19. It specifies the areas of interest (ROIs) acquired in chest X-rays or CT scans, which are the most important aspect for the AI algorithm. These split areas may be used to produce self-learned or even created attributes (Shi et al., 2020a).
In the field of COVID-19 detection, computed tomography is one of the most important sources of high-quality 3D pictures. U-Net (Cao et al., 2020; Gozes et al., 2020; Huang et al., 2020; Li et al., 2020; Qi et al., 2020; Zheng et al., 2020), U-Net++ (Chen et al., 2020; Jin et al., 2020), and VB-Net (Shan+ et al., 2021) are the most popular deep learning Despite the fact that X-ray pictures are more difficult to segment than CT images in the medical field owing to their accessibility, the segmentation procedure in X-ray images is more difficult. The visual contrast in the 2D projection of ribs onto soft tissue causes this.

In the case of COVID-19, segmentation is shown to be a critical component in the virus's interpretation. Gaál and his colleagues (2020) suggested Attention-U-Net for lung segmentation that can extract pneumonia-related characteristics. A approach like this might be used to diagnose coronavirus (Shi et al., 2020a).There are two types of lung segmentation mechanisms: region-based segmentation and damage-based segmentation. The first step in any application targeting COVID-19 is to differentiate the lung and its lobes from other areas using X-ray or CT (Cao et al., 2020; Gozes et al., 2020; Huang et al., 2020; Jin et al., 2020; Qi et al., 2020; Shan+ et al., 2021; Tang et al., 2020a; Zheng et al., Cao et al., 2020; Chen et al., 2020; Gozes et al., 2020; Huang et al., 2020; Jin et al., 2020; Li et al., 2020; Qi et al., 2020; Shan+ et al., 2021; Shen et al., 2020; Tang et al., 2020a; Tang et al., 2020a; Tang et al Because the form and texture of these lesions varies, recognising them is a difficult process. Gaál et al. (2020) provided an attention mechanism that was deemed an effective localization strategy for screening lesions. This technique may be used to monitor COVID-19-related damage. To return to the first group, Jin et al. (2020) developed a two-stage pipelined approach for capturing COVID-19 in CT images, the first of which is to identify the lung area. U-Net++ was used to create this technique.
Several approaches for lung segmentation have been proposed in the literature, each aiming towards a different purpose (Cicek et al., 2016; Milletari et al., 2016; Isensee et al., 2018; Zhou et al., 2018). U-Net is one of the most often utilised strategies in COVID-19 applications (Cao et al., 2020; Huang et al., 2020; Qi et al., 2020; Zheng et al., 2020). In each of the previously described groups, this strategy proved to be effective. The father of U-Net, Ronneberger (Ronneberger et al., 2015), defined this technique as a completely CNN with a U-shape structure and symmetry in both the encoding and decoding directions. If the layers are linked along these routes, a shortcut connection is introduced at each level. As a consequence, visual semantics and textures, which are the most important considerations in medical segmentation, may be learnt quickly. In the COVID-19 field, a more sophisticated version of U-Net has been created. Cicek et al. (2016) developed a higher-dimensional U-Net (3D), in which the layers in this technology were replaced with a 3D model. U-Net++ (Zhou et al., 2018) is a more adaptable model in which a layered convolutional architecture is introduced between the encoding and decoding channels. Through damage localisation in COVID-19 diagnosis, this method also helps to pandemic remedies (Chen et al., 2020). A composite technique combining the attention mechanism and U-Net was able to extract precise features in medical pictures, making it a suitable segmentation method for COVID-19. V-Net (Milletari et al., 2016) is another segmentation approach that uses a residual module as the basic convolutional module and Dice loss as the optimizer. VB-net achieves efficient segmentation by introducing a bottleneck to the convolutional module (Shan+ et al., 2021). All of these networks perform well in terms of segmentation. The key problem, however, is how the training method will be carried out. The main restriction for training a segmentation technique is having enough labelled data. The availability of sufficient data was a challenge in COVID-19 picture segmentation since handmade depiction of lesions takes a lot of time and effort. Researchers and radiologists are working together to find a solution to this challenge. The U-Net algorithm converges toward an acceptable threshold once an initial seed is given into it (Qi et al., 2020). In order to build a pseudo-segmentation mask for CT images, Zheng et al. (2020) reorganised the issue as an unsupervised technique. Due to a lack of tagged medical pictures, the COVID-19 literature suggests that unsupervised and poorly supervised learning processes are preferred strategies.
The literature on segmentation in COVID-19 applications is extensive. Using U-Net on chest CT, Li et al. (2020) conducted lung segmentation to distinguish between coronavirus and pneumonia. The most critical component in safeguarding the population is early identification of COVID, hence quick AI approaches should be

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implemented in the diagnostic process. Jin et al. (2020) suggested an approach that used CT slices as input to the model, with the slices resulting from a segmentation network. To summarise, the segmentation method is a cornerstone in the world of COVID-19 applications since it simplifies the life of radiologists by providing them with accurate detection of areas of interest and reliable viral diagnosis.

Picture preprocessing is another effective way for ignoring unneeded sections of an image. In COVID-19 applications, this may be used for segmentation. Image preprocessing is separated into two categories: picture restoration and image reconstruction. The most basic method of picture restoration is to use filtering to remove noise. Multilayer neural network–based filters have been created to identify picture edges and improve the noise detection method (Suzuki et al., 2001; Suzuki et al., 2002a; Suzuki et al., 2002b;Suzuki et al., 2004). When dealing with noisy data that includes nonlinearity, reconstructing medical pictures may be a difficult task. As a result, this issue was deemed ill-conditioned, and it could only be solved by loosening requirements and making simplified assumptions. Because they create a linear approximation of the noisy data, feed forward (Nejatali and Ciric, 1998; El et al., 2000) and Kohonen neural networks (Adler and Guardo, 1995; Comtat and Morel, 1995) are popular approaches in the field of reconstruction.

A quick review of the phases of radiography patterns in CT images is required before addressing the classification of COVID-19 from other illnesses and the severity of the virus infecting specific individuals. These patterns are evaluated in four steps, according to Pan et al. (2020). The first stage is the early stage (day 0 to day 4), during which first symptoms appear and lesions' areas may be seen in the lower lobes of the lung using a chest CT. Lesions grow out and thicken in stage two (days 5–8), attaining multilobes. Lesions are widespread with a dense intensity in the third stage (days 9 to 14); this is the most hazardous period. The penultimate step in which the virus is confined is known as the absorption stage. The classification and severity analysis of the infection state rely heavily on these patterns.

Distinguishing COVID-19 patients from other patients is a difficult undertaking that has been the focus of current research. COVID-19 and non–COVID-19 patients were labelled using the segmentation model acquired by U-Net++. In this study, segmented lesions were enough to predict the label and differentiate COVID-19 individuals from those with other disorders. The researchers classified 106 CT pictures of patients. These contributions help radiologists save time while reading. Another article (Zheng et al., 2020) combined the U-Net model for segmentation with a 3D convolutional neural network that determines the likelihood of labelling based on the output of the preceding model. The following rates were obtained using a dataset of 540 chest CT images: sensitivity of 0.907, specificity of 0.911, and accuracy of 0.959. Another technique (Jin et al., 2020) used a combination of U-Net++ for lesion localisation and ResNet50 for classification. Based on 1,136 chest CT scans, the method had higher specificity and sensitivity (0.922 and 0.974, respectively).

The severity evaluation is another important consideration in medical therapy. In the investigation by Shi et al., Vb-Net was utilised to detect this component (2020b). In order to train the RF architecture, the segmentation was done based on infection volumes in the areas of interest. Tang et al. (2020b) used another RF-based architecture to identify the COVID-19 level as severe or non-severe, based on 176 chest CT scans. The accuracy rate of the architecture was 0.875. As a result, the researchers devised potential ways for diagnosing COVID-19 using artificial intelligence. These studies' findings are regarded as trustworthy when it comes to categorising patients. In addition, severity estimate is an important part of the treatment process since it decides whether or not an ICU is required, for example.

THE COVID-19 DETECTION SYSTEM

This section discusses the platform's development technique. It offers a full description of the design, as well as definitions of each block and its characteristics, as well as examples of the evaluation measures and calibration metrics that were used. Overview of Architecture and Challenges

The scarcity of resources is one of the most significant issues in any health-care system (Abdellatif et al., 2019; Abdellatif et al., 2020). The study's and architecture's dependability and quality are determined by the availability and quality of data. To assure the aforementioned influences of data availability, using CT scans necessitates a big dataset. As a result, a huge dataset of 6,752 CT scans was used in this investigation (see Section 4.1).

We propose an AI-based medical hub platform that combines AI and image processing to identify various serious medical issues early. This platform is designed to address medical imaging-related issues. It detects irregularities and categorises them according to their severity. COVID-19 is a priority medical condition for the purposes of this research. As illustrated in Figure 1, the chest photos in the dataset pass through various blocks in this design.

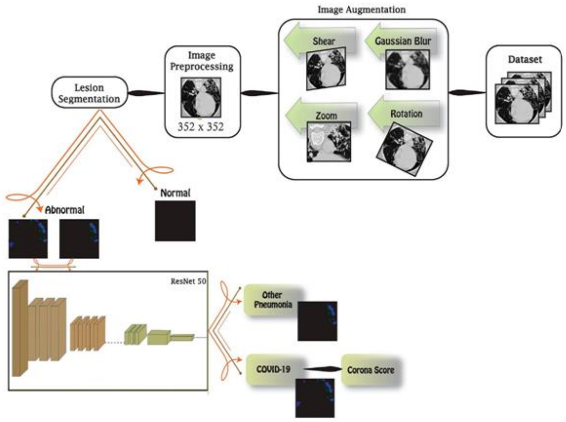

FIGURE 1 | Block diagram of the proposed architecture.

First, the data is enhanced to add additional photos to the latter blocks and to emphasise important aspects that must be identified. Rotating, shearing, zooming, and blurring pictures accomplish this. After that, the supplemented data goes through two steps of preprocessing: standardisation and normalisation. These phases are necessary for the data sent into the network to be unified. The preprocessed pictures are supplied into the lesion segmentation block, which employs InfNet to handle aberrant aspects and features in order to locate anomalies in images. We are allowing it to determine the severity of the issue via additional picture analysis in addition to early detection utilising this block. Finally, in order to discriminate between COVID-19 and other viral pneumonia diseases, the aberrant pictures are fed into a deep network using the transfer learning approach. In the next sections, we'll go through each block in further detail. Augmentation of images

Data augmentation is a technique for extracting more information from an existing dataset. In this situation, it makes perturbed duplicates of the existing photos. The primary purpose is to strengthen the neural network with diverse diversities, resulting in a network that can discriminate between significant and irrelevant dataset properties. Several strategies are available for image enhancement. When required, augmentation strategies are applied effectively based on data availability and quality. Our approach combines many strategies in order to support a large number of datasets for various situations, as follows:

- Rotation: the picture is rotated between two points. 10° and 10° are the temperatures.
- Zooming in or out on the picture will also increase the number of items in the collection.
- Shear: picture shearing may be done by rotating the image.The component of imitation in the third dimension
- Gaussian blur: high-frequency elements may be removed with a Gaussian filter, resulting in a blurred version of a picture.

The dataset was extended and utilised in the training phase using these approaches. Nonetheless, the testing set will not be expanded throughout the testing period. This would ensure the architecture's durability while avoiding over-fitting. Image Preparation.

Because the data is likely to originate from a variety of sources, a method to manage the complexity and accuracy is required. Image preprocessing reduces the complexity of data and improves the accuracy of the results. This approach standardises data in various phases in order to provide a clean dataset to the network. The following phases are used to do data preparation in this architecture:

• Image standardisation: Neural networks that deal with images need images with the same aspect ratio. As a result, the first step is to scale the photos to give them unique dimensions and a square form, which is the most common shape for neural networks.

• Normalization: every AI algorithm's input pixels must be normalised.

To improve the training phase's convergence, use a normalised data distribution. The operation of removing the mean of the distribution from each pixel and dividing by standard deviation is known as normalisation. Scaling normalised data is considered at the conclusion of this stage to produce positive results. Segmentation of Lesions.

The key factors are ground glass opacities (GGOs) and consolidation. identified traits in the case of COVID-19 patients, where 97.86% of patients develop such illnesses within 21 days after being infected with COVID-19 (Liang et al., 2020). As a result, we employed lesions segmentation to find out whether these illnesses were present and how much of the body was contaminated. Because different viral pneumonia may cause these diseases, this block will categorise an input picture as normal or abnormal. Normal ones are discharged as output, whereas abnormal ones are sent via the ResNet block to detect COVID-19 patients. The InfNet architecture is used in the segmentation procedure.

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Low-resolution features are recovered from preprocessed CT images using two convolutional layers. The high-level characteristics are then extracted by inserting these features into three convolutional layers. It was shown in the context of segmentation that Because edge information is useful, an edge attention unit is used to improve the depiction of areas of interest. The global map is created by collecting the high-level characteristics and segmenting the lung lesions using a parallel partial decoder. On the basis of the global map, the output and high-level features are combined with low-level features to be placed in cascaded reverse attention units. Finally, the data is fed into a Sigmoid activation function to estimate infection zones.(2020, Fan et al.)

This block creates a coloured depiction of the GGO and consolidation segment by segmenting the contaminated regions in a CT-scan picture. In the absence of such areas, the picture will be black and blank. Normal photos are those that are not filled with anything. The ResNet50 deep network model is given the remainder of the aberrant photos. These representations are also quantified so that the corona score can be calculated afterwards. Deep Network ResNet50

Transferring learning is a well-known approach for training convolutional neural networks, with a large body of research on the subject. The network is pre-trained using this way using ImageNet, a massive database. This stage leads to the initialization of the layers' weights, which reduces the vanishing gradient issue by loading such weights before deploying the network in the present design. This is a significant benefit of transfer learning, since it improves the convergence of the goal. Another benefit of this form of learning is the ability to extract key visual properties such as shape and edges. As a consequence, by restricting calculations to the last layers of the training phase, the computational time is minimised.

The surviving network ResNet is a cutting-edge deep learning technique that outperforms several other dense networks in terms of accuracy and computational complexity (He et al., 2016; Vatathanavaro et al., 2018). This is why, using transfer learning, we were able to identify the coronavirus and differentiate it from other viral pneumonia infections.

The pretrained model describes the final layers as classification layers in order to identify the dataset across several classes, and therefore the extracted features will be kept in the last convolutional layer to be translated into prediction values for each class. Except for the final layer, which will be trained to create estimates and lead the classification process for our new batch of photos, the initialization weights (the essential element of transfer learning techniques) remain unchanged. The pooling layer, dropout layer, flattening layer, and activation functions (rectified linear unit) are all included to this model.

ResNet50 (Vatathanavaro et al., 2018), a deep network that takes the learning rate as an evaluation in the stage to change the weights of the layers, is the residual network utilised in this design. The weights are changed in each iteration depending on the loss computed from the input and predicted values. The modified weights' formula is as follows:

$$w_{i+1} = w_i - \alpha \frac{zL(w)}{zw_i}, \qquad (1)$$

where w denotes the weight, I is the process iteration, L denotes the loss function, and is the learning rate. Metrics for Evaluation

In addition to our novel metric, the corona score, the performance of the proposed design is assessed using many statistical indicators.

Accuracy

Accuracy is a statistic that measures a method's ability to define the right expected cases:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \qquad (2)$$

• TP: the number of correctly predicted positive instances is equal to the number of true positives.

• FP: false positive is the amount of false positives anticipated incorrectly.

• TN: the number of correctly predicted negative situations is equal to the number of genuine negatives.

• FN: the number of inaccurate is equal to the number of false negatives. situations that were expected to be negative

Recall

The sensitivity of a procedure is defined by its recall:

$$Recall = \frac{TP}{TP +} \qquad (3)$$

Precision

Precision is the ratio of the unnecessary positive case to the totalnumber of positives:

$$Precision = \frac{TP}{TP + FP}. \quad (4)$$

Specificity

Specificity is the ratio of correct predicted negatives over negative

observations:

$$Specificity = \frac{TN}{TN + FP}. \quad (5)$$

F1-Score

F1-Score is the measure of the quality of detection:

$$F1 - Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}. \quad (6)$$

Corona Score

The corona score is a novel metric for assessing the severity of a virus's infection in the lungs. It is determined by the lungs' volume and the volume of the infected region as determined by the segmentation block. The following formula is used to compute this metric:

The volume of the lung is first measured using a lung CT picture.

• The alveolar area, also known as parenchyma, accounts for 90% of the lung's overall capacity (Knudsen and Ochs, 2018).

• Radiologists classify the severity of coronavirus infections depending on their appearance. minimum (10 percent of lung parenchyma), moderate (10–25 percent), intermediate (25–50 percent), severe (50–75 percent), and critical (greater than 75 percent of lung parenchyma) GGOs and consolidation in lung CT images (Guillo et al., 2020).

$$CoronaScore = \frac{InfectedVolume}{0.9 \cdot (LungVolume)}. \quad (7)$$

Calibration Metrics

Depending on the test findings and the job at hand, this architecture combines several calibration procedures. In this part, we'll go through the many approaches that our platform takes into consideration.

Speed of Learning When it comes to updating the weights formula, this rate is crucial. Its ideal value is sometimes out of reach. Learning rates that are either low or too high cause a variety of issues. Low values slow down the training process, causing the whole operation to be delayed. High values, on the other hand, accelerate convergence and lower set weights, ensuring that no suboptimal weight is obtained. In this model, we utilised Smith's recommended rate as the best option (2017). To improve classification accuracy, the authors adjusted the learning rates cyclically in a realistic interval. Another.The SGD optimizer may be used to define this rate by initialising it and updating it.

$$LearningRate = \frac{InitialLearningRate}{1 + decay \cdot iterations}, \quad (8)$$

where iterations denote epoch steps and decay is a decaying parameter suggested by the optimizer. Function of Loss.

The loss function is a method of calculating the algorithm's performance after it has been trained with the dataset. It calculates how far the forecasts are off the mark. This factor is subsequently utilised to optimise the method by reducing the loss suffered. In reality, the loss function indicates whether or not a certain tuning of the algorithm is beneficial. Loss functions are divided into three categories: regression, binary classification, and multi-class classification. Because the output of both blocks, segmentation and ResNet50, produces binary classification (normal, abnormal; COVID, non-COVID), binary classification loss functions are more likely to be employed in the present investigation. There are three types of loss functions in this category: binary cross entropy, hinge loss, and squared hinge loss. For the segmentation and ResNet50 blocks in this design, we employed binary cross entropy as a loss function.

The BCE equation is as follows:

$$L = \frac{1}{M} \sum_{i=1}^{M} y_i * \log \hat{y}_i + (1 - y_i) * \log\left(1 - \hat{y}_i\right), \quad (9)$$

The output size is M, the output scalar value is yi, and the goal value is yi.

Regularization

Overfitting is one of the most common difficulties in AI algorithms that may be avoided by explicitly submitting the algorithm's design to the training set. Regardless of the input, the network's output is limited to the specific output generated earlier by the training set. Regularization is a technique for adjusting the mapping and preventing over-fitting. Data augmentation is known to be used to increase the training dataset and hence reduce over-fitting, although the method's high memory cost might be a major drawback. Regardless of the size of the training dataset, regularisation techniques may be applied. The most well-known regularisation methods are dropout and drop-

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connect. Dropout techniques based on the probability distributions of connections in each tier are often used in fully linked networks. As a consequence of this procedure, connections are discarded and nodes are dropped. Fast dropout, adaptive dropout, evolution dropout, spatial dropout, nested dropout, and max pooling dropout are some of the several types of dropout that are used depending on the situation.

RESULTS OF MODEL SIMULATION

With the help of many AI and image processing tools that boost training efficiency, the suggested architecture was developed in Python v3.6 using PyCharm in a Windows 10 environment.

FIGURE 2 | CT chest scans of normal, COVID-19 pneumonia, and common pneumonia (A) and (B) respectively.

to improve one's performance Fastai, numpy, scipy, and openCV libraries were used in our testing setup, which was accelerated by an NVIDIA GeForce RTX 2070 super GPU with 8 GB dedicated RAM. We are evaluating our models using genuine datasets used in the literature, and the simulation is built on Linux and Python scripting that is compatible with most hardware.

The testing procedures for both blocks, lesion segmentation and ResNet50 deep network, will be discussed individually in this section. Based on the projected output, each block will have its own assessment metrics. The whole system will then be put through a complete test to assess its performance. The platform test results are shown in the tables and figures below. Dataset

The China National Center for Bio-information provided the CT chest imaging dataset that we utilised in our investigation. There are three types of pneumonia in these images: coronavirus pneumonia, common pneumonia, and normal pneumonia. These statistics were made accessible by the China National Center to aid researchers in their fight against the epidemic. The dataset includes 617,775 CT slices from 6,752 CT scans from 4,154 individuals, spread between 999 COVID-19 patients, 1,687 normal pneumonia patients, and 1,468 common pneumonia patients (Zhang et al., 2020). The various classes studied in this research are shown in Figure 2: a) normal, b) COVID-19 pneumonia, and c) common pneumonia. In our research, we randomly selected 450 photos from each class. The selected dataset was supplemented with 150 more photographs, 50 from each class, for a total of 1,500 images. Block for Lesion Segmentation

Our suggested model was trained to assess CT-scan chest pictures in order to distinguish between abnormal (infected lungs) and normal (healthy lungs) (healthy lungs).

The segmentation block was given a big dataset with augmentation to assess and identify the presence of GGOs and consolidation in patients' lungs, as well as to quantify their size and location. The presence of any or both of these illnesses served as a criteria for distinguishing between normal and atypical patients. There were 1,500 CT chest pictures as a consequence of enhanced data and genuine data: 500 normal, 500 COVID-19, and 500 different pneumonia disorders. As previously stated, 80 percent (1,200 pictures) of these photographs were employed as a training set. As illustrated in Figure 3, the output representation of this block is either blank, indicating the lack of infection, or a segmented version of the picture, displaying GGO and consolidation in blue and green, respectively. The corona score is computed and supplied as an output with the positive COVID-19 prediction in the later block if an anomaly is discovered.

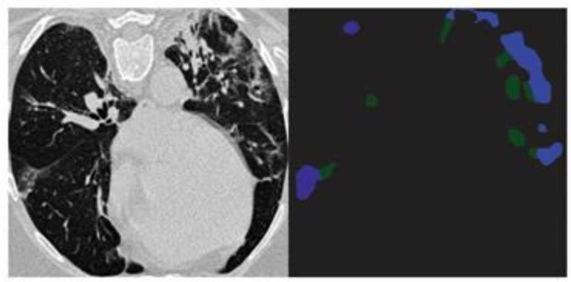

FIGURE 3 | Segmentation of COVID-19 CT image; GGOs in blue andconsolidation in green.

TABLE 1 | Testing results of lesions' segmentation block.

	True normal	True abnormal
Predicted normal	97	11
Predicted abnormal	3	189
Overall true	100	200
Accuracy	95.54%	
Precision	98.44%	
Sensitivity	94.5%	
Specificity	97%	
F1-score	0.964	

The CT picture given to the system is 352 352 pixels in size. In order to generalise the module, images are resampled. The learning rate in this module is set to 0.0001 by Adam optimizer. Based on 200 epochs, the training component uses bogus values that reach convergence in around 8 hours. As noted in the calibration metrics section, the loss function employed is BCE. This function takes into account the ground truth map as well as the convolutional layer's edge map. A rapid dropout is then used to regularise the training data.

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The trained InfNet model has a 95.54% accuracy rate. Some of the aberrant photos were misclassified because they were taken during the early stages of pneumonia, when the lungs were not severely injured and infections were not yet apparent. The findings of the testing dataset are summarised in Table 1. The suggested model demonstrated that the sensitivity and specificity of aberrant photos are equivalent to 189 out of 200 (94.5%) and 97 out of 100 for normal images, respectively, with a f1–score of 0.964 and 98.44 percent for accuracy.

TABLE2 | Evaluation metrics of different methods used in segmentation.

Methods	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1-score
InfNet	95.54	96.04	94.5	97	0.953
UNet	91.63	90.15	91.16	92.53	0.907
UNet++	94.71	94.35	92.3	95.14	0.933
Attention-UNet	93.42	94.03	91.67	94.48	0.928
Dense-UNet	94.26	92.94	91.75	93.89	0.923

TABLE3 | Testing results of ResNet50 block.

	True COVID	True Non-COVID
Predicted COVID	97	4
Predicted non-COVID	3	96
Overall true	100	100
Accuracy	96.5%	
Precision	96.04%	
Sensitivity	97%	
Specificity	96%	
F1-score	0.965	

Different segmentation techniques were examined and compared to these findings to ensure that Infnet is the optimum option for deployment in this architecture.

All of the approaches listed in Table 2 were tried for detecting contaminated areas (regions of interest). As a result, the classification has been completed, and the evaluation metrics have been calculated. Deep Network Block ResNet50

The model of deep networks ResNet50 has been trained to identify the kind of pneumonia in pictures by discriminating between COVID and non-COVID pneumonia. The backpropagation of errors between layers is crucial in this AI model. Simultaneously, weights are adjusted based on the learning that has been determined to be suboptimal. 0.001 percent (Smith, 2017). There are 23 million parameters in this method, which are fine-tuned using a variety of optimization approaches. The loss function is one of these parameters. We employed the binary cross entropy loss function in our existing system. The augmented dataset is provided to this block in the same way as it is fed to the segmentation block, with the exception of normal cases. The algorithm is trained with 800 photos and validated with 200 images. The validation method is based on the loss function value, which is determined by the difference between the predicted and real value as well as the class probability.

In testing mode, the network concentrates on each class's probability score in order to produce a prediction. The class is predicted using the least loss value. By reducing the size of the area of interest, segmented pictures sped up model convergence. Furthermore, greater understanding is gained via the process of infection location, since COVID-19 is known to infect the lungs' margins bilaterally (Ding et al., 2020). The accuracy of the trained deep network was 96.5 percent. The findings of the testing phase are summarised in Table 3. The suggested model correctly predicted the presence of COVID-19 in 97 of 100 cases and its absence in 96 of 100 cases, where these values correspond to the model's sensitivity and specificity, respectively. In addition, it

Precision was 96.04 percent, with a f1–score of 0.965.

Different classification algorithms were evaluated and compared to these findings to ensure that ResNet50 is the optimum option for deployment in this architecture.

To discriminate between COVID infection and other pneumonia infections, the techniques in Table 4 were evaluated. As a consequence, the classification has been completed, and the evaluation metrics have been calculated. Model in its entirety.

Each block was put to the test on its own to ensure that it was effective. For convergence purposes, the latter block takes use of the fact that it is tested with segmented pictures. To assess the overall performance, a comprehensive system test was run with the dataset as input. In this scenario, the ResNet block gets a sample of incorrectly classified normal pictures from the previous block, which is put through a more realistic test environment. The whole system test was found to be 95 percent accurate. Table 5 shows all of the classifications and metrics, each with its own accuracy and sensitivity. Corona Rating

For all positive COVID-19 scans, a corona score was calculated at the output, and the cases were divided into four groups as previously stated. We verified the validity of the severity classifications by comparing to the ground truth segmentation figures and confirmed that the severity of all instances was accurately classified. Figure 3 has a corona score of 0.1323, indicating a moderate severity class. Efficiency in Computing

The overall system attributes show improved computing performance. performance using a variety of metrics

• Ternary problem partitioning: by separating the aim into two binary classification blocks, block partitioning resulted in greater computing efficiency.

• Time efficiency is one of the key advantages of such an arrangement.

When compared to comparable systems, architecture is the efficiency of detection in terms of time, resulting in a faster convergence time.

The prediction complexity in neural networks is around O(p(nl1 nl1*nl2)), where p is the number of features. nl is the number of neurons per layer retrieved. In the ternary system,

Because there is a requirement for high precision in order to identify three classes in a classification task, p would be significantly larger than in the binary situation. This significantly increases the algorithm's complexity. On the input of the latter block, ResNet50, the inserted images are heat maps of the lesions extracted by the segmentation block, so there is no complex CT scan anymore, which leads to a minimal number of

TABLE 4 | Evaluation metrics of different methods used in pneumonia classification.

Methods	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	F1-score
ResNet50	96.5	96.04	97	96	0.965
CoroNet	93.5	93.63	90	92.53	0.9177
DenseNet	96.4	96	96	96	0.96
CNN	91.21	90.47	90.52	91.58	0.905
VGG16	95	95.5	90	97	0.927

TABLE 5 | Testing results of the whole architecture.

	Normal	COVID-19	Other pneumonia	Precision (%)
Predicted normal	97	4	1	95.1
Predicted COVID-19	2	93	4	93.94
Predicted other pneumonia	1	3	95	95.96
Overal true	100	100	100	
Sensitivity	97%	93%	95%	
Overal accuracy	95%			

to be extracted characteristics p. As a result, the prediction complexity in this design reaches a suboptimal value.

The setting of this ternary issue was meant to confirm our assumptions. Except for the segmentation block, the same design applies. The classification block for the whole system is now ResNet50. After being supplemented, preprocessed, and separated into training and testing sets, this block gets the whole dataset. In the testing phase, the computing time was reduced by 36%, and in the training phase, it was reduced by 28%.

WORK IN THE FUTURE

This article is part of a larger study. The purpose of the paper was to compare AI-based segmentation algorithms. Our findings will be compared to conventional and non–AI based segmentation approaches in the future. Our overarching goal is to create a complete medical centre that can identify and analyse a variety of medical disorders. This medical centre would not be restricted to COVID-19 detection, but would also include the identification of other diseases and the severity of their diagnoses. Furthermore, our staff makes it a priority to maintain the system up to date, taking use of new methodologies and published research. Finally, we're adding and testing a new layer of validation as well as improving our calibration processes to reduce false positives and mistakes.

CONCLUSION

We suggested an advanced medical hub design with an AI system in this research, which comprises of two phases: segmentation and the ResNet deep network. The first phase is in charge of identifying anomalies in CT scans in order to distinguish between normal and abnormal patients. The second is in charge of identifying COVID-19 instances from other types of pneumonia. Both stages showed encouraging results. The segmentation accuracy was excellent.

The ResNet50 block scored 95.54 and 96.5 percent. The total accuracy was found to be 95%. Because of the inclusion of the segmentation block, the whole model proved to be trustworthy and required much less computing time. In addition, our research created a severity index for COVID-19 instances (corona score). Even little severity may be recognised, prompting an immediate quarantine decision to prevent the virus from spreading. In the present research, this platform was utilised to identify COVID-19, but it may also be deployed and used for medical imaging analysis of other disorders.

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