A Combined Image Segmentation and Classification Approach for COVID-19 Infected Lungs

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ABSTRACT

Lung infection or sickness is one of the most common acute ailments in humans. Pneumonia is one of the most common lung infections, and the annual global mortality rate from untreated pneumonia is increasing. Because of its rapid spread, pneumonia caused by the Coronavirus Disease (COVID-19) has emerged as a global danger as of December 2019. At the clinical level, the COVID-19 is frequently measured using a Computed Tomography Scan Slice (CTS) or a Chest X-ray. The goal of this study is to develop an image processing method for analysing COVID-19 infection in CT Scan patients. The images in this study were preprocessed using the Hybrid Swarm Intelligence and Fuzzy DPSO algorithms. According to extensive computer simulations, the persistent learning strategy for CT image segmentation using image enhancement is more efficient and adaptive than the Medical Image Segmentation (MIS) method. The findings suggest that the proposed method is more dependable, accurate, and simple than existing methods.

1. INTRODUCTION

The COVID-19 pandemic, according to the World Health Organization, is an infectious disease that has infected more than millions of people across worldwide and killed thousands of people since December 19, 2019 [1]. Because of the pandemic's widespread impact, COVID-19 offers a significant challenge to medical professionals. COVID-19 preparation and response must include rapid diagnosis and contact tracing in order to prevent the virus from spreading further [2]. As the number of new cases increases, particularly those requiring critical care, healthcare providers can use disease monitoring to make important treatment decisions. COVID-19 is a widespread disease that claims the lives of thousands of individuals every day [3]. Early detection of this issue has proven to be one of the most effective strategies for infected tree cutting [4].

The rising number of COVID-19 patients is putting a strain on many countries' health-care systems. As a result, having a reliable automated approach for identifying and measuring infected lung regions would be invaluable [5]. The creation of a system for linguistically segmenting medical lung scans of COVID-19 patients would help with the quantification of anomalies and research in this area [6]. It would aid front-line responders in better managing the situation of overwhelmed hospitals during the pandemic. While CT is a viable approach for diagnosing COVID-19, it has some disadvantages that make it impractical to utilize on a daily basis: CT scans are not widely available, take a long time to complete, and require patients to be transferred from their unit [7]. It's logistically challenging to use CT technology safely during a pandemic, and it can deplete available resources [8]. Even when adequately cleaned, CT scanners can be a source of infection for other patients who require imaging. CT scans are used in healthcare facilities to speed up the image acquisition and categorization process [9]. However, a professional medical practitioner is required to verify the final results, which adds to the computation time. On the other hand, supervised learning models can be used to classify patients from CT images [10].

On average, classification algorithms based on Machine Learning (ML) produce the highest reported accuracy rates. Machine learning models require a lot of processing power and high specifications to run because of their high categorization accuracy rates [11]. Large hospitals in first-world countries may be able to afford this high-cost processing method, while hospitals in impoverished countries and rural areas may not. To reduce the computational cost, a machine learning model that consumes fewer resources is necessary [12].

Machine learning researchers are seeking to battle the pandemic by putting together databases and developing algorithms that learn from them. A vast number of research studies have been launched to try to improve diagnosis and predict the virus's propagation, number of fatalities, and genetic evolution [13]. This could aid officials in determining how the virus spreads and the locations of quarantine zones. For COVID-19 lung infections, a thoracic CT scan is used as a diagnostic technique in hospitals [14]. By creating methods for CT image processing, the current hot study hopes to contribute to the automatic detection of the corona virus [15]. According to the researchers, algorithms that were used to identify lung cancer and lung collapse using X-ray images may also be useful for finding abnormal cases in COVID-19 patients [16]. As a result, stronger algorithms are still required.

Section II reviews the related work, Section III explains the system model. Section IV describes the results and discussion followed by conclusion in Section V.

2. RELATED WORK

In the medical profession, machine learning technologies are gaining traction for diagnostics, predictive analytics, and general research. For the diagnosis of COVID-19, four distinct deep CNN architectures were built and tested on chest X-ray images. These models require fewer large training sets because the weights have already been pre-trained on the ImageNet database [17].

Because data is frequently unlabeled or difficult to obtain, unsupervised learning networks are critical in the medical business. Unsupervised networks like Self-Organizing Feature Maps (SOFM) can be used to train unlabeled data. With a mean Euclidean distance of 1.1 between the first and second winning neurons in the testing set, the SOFM network was utilized to classify COVID-19 patients' chest x-ray photos and identified a strong differential between sick and healthy patients [18]. It can also show which properties in the input space influenced the classification the most, which can be used to evaluate the significance of features in an unsupervised network. As proven in this paper, unsupervised learning can extract features from medical data, such as COVID-19 patients' chest x-rays, while also successfully recognizing the image [19].

The technique is given, which uses strong 2D and 3D deep learning models to adapt and alter current Artificial Intelligence (AI) models while incorporating clinical expertise. A 3D volume review and a Corona score are utilized to evaluate the system's efficacy in recognizing suspected COVID-19 thoracic CT characteristics and monitoring disease development in each patient over time. The classification findings for Coronavirus versus Non-coronavirus infections per thoracic CT examination were 0.996 AUC on datasets of Chinese control and infected patients [20, 21].

This study presents a poorly supervised deep learning strategy for detecting and classifying COVID-19 infection from CT scans. Infection detection and discrimination between COVID-19 and non-COVID-19 patients is accurate, and manual CT image labelling is no longer required. Based on the positive qualitative and quantitative outcomes obtained, it envisioned a wide deployment of our established methodology in large-scale clinical research [22].

The use of artificial intelligence to analyze Chest X-Ray (CXR) photos for COVID-19 identification and clinical triage is becoming increasingly relevant in the aftermath of the global COVID-19 epidemic [23]. Due to the pandemic's dynamic nature, systematic CXR data collecting for deep neural network training is problematic. For COVID-19 detection, a patch-based convolutional neural network technique with a small number of trainable parameters has been developed. Our statistical analysis of the possible imaging indications of CXR radiographs inspired the proposed technique.

This study focused primarily on the CT for the evaluation since it provides more clear information and more judgement accuracy than a chest X-ray. Because current methods for detecting the virus need the presence of a skilled radiologist, automating detection would be necessary to save radiologists' assessment time [24]. Machine Learning (ML) and Deep Learning (DL) algorithms have lately made major advancements in autonomously diagnosing diseases, lowering the cost and increasing the accessibility of diagnostics [25]. This study focused primarily on the CT for the evaluation since it provides more clear information and more judgement accuracy than a chest X-ray. Because current methods for detecting the virus need the presence of a skilled radiologist, automating detection would be necessary to save radiologists' assessment time [26]. Machine Learning (ML) and Deep Learning (DL) algorithms have lately made major advancements in autonomously diagnosing diseases, lowering the cost and increasing the accessibility of diagnostics [27].

3. SYSTEM MODEL

Image segmentation is a critical step in the image analysis process. The purpose of developing a Convolutional Neural Network for segmentation is to use more meaningful information to improve lung segmentation [28]. The promise of better performance in general automatic lung segmentation systems, which are crucial for a variety of medical and scientific applications, has encouraged this.

Lung abnormalities are now only diagnosed by imaging after the development of neurological symptoms. The CT scans are interpreted by doctors to see whether there are any anomalies [29]. In other circumstances, however, discrimination, decision-making, and diagnosis are extremely difficult for clinicians. Misdiagnosis and incorrect treatment approaches place a significant financial burden on the patient, diminish patient comfort, and result in conditions that are irreversible. As a result, we're going to show you how to use Dropout CNN classification for automatic COVID-19 prediction [30].

The main contribution of this work is

● CNN-based segmentation is proposed with the goal of employing more meaningful information to improve lung segmentation. This is prompted by the possibility of improved performance in general automatic lung segmentation systems, which are critical for a variety of medical and scientific applications.

● A new approach called Dropout CNN classification is applied to detect lung abnormalities automatically, which can improve the prediction accuracy of COVID-19.

● To improve the PSNR ratio and SSIM index, a Lee filter with equalisation is utilised to enhance the pictures in order to reduce noise.

3.1 Preprocessing

Due to preprocessing, automated COVID-19 lungs pollute area segmentation and measuring systems can better understand what's going on in the images. Bright areas in the original CT-scan images are used to introduce a lot of visible data [31]. Some places, however, are overly bright, while others are overly black. To get a more exact segmentation, it is required to improve local contrast before classifying details. Positive local contrast is seen in COVID-19 targets, indicating that the lesion areas are lighter in all directions than the surrounding backdrop. The proper brightness level is controlled using an exponential and logarithmic function.

3.2 Hybrid swarm intelligence and fuzzy DPSO

Some of the assumptions in Discrete Particle Swarm

Optimization (DPSO) are spawning a swarm, favourable adaptation, and negative adaptation. Simple ideas are executed in a way that resembles natural selection. When a swarm is exposed to a longer time of survival, it has a higher chance of producing progeny. The swarm's life span will be prolonged if it finds a more suitable state, such as favourable adaptation, but it will be reduced if it fails to find a suitable state, such as unfavourable adaptation. The fuzzy c-means clustering algorithm is effective, however the random selection of centre points reduces the iterative process to the local best answer. Researchers have proposed numerous changes to the FCM in order to improve its convergence during the previous few years. The ideas of Fuzzy and DPSO are combined to create Fuzzy DPSO which is illustrated in Figure 1. The algorithm's junction rate is managed using fractional calculus, and swarms of Fuzzy DPSOs compete using Darwin's survival-of-the-fittest principles. By applying these concepts, the particles are spared the challenge of local minima. At the same time, several PSO algorithms are run.
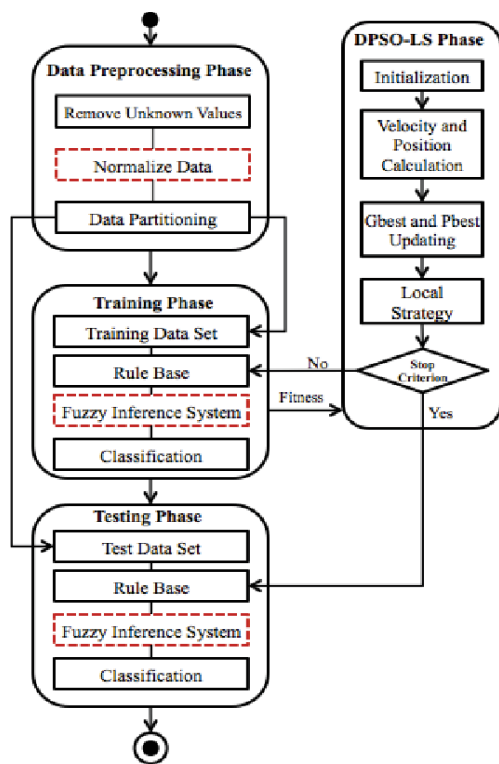

Figure 1. Fuzzy DPSO process

Swarm Intelligence Algorithm
1. Initialize particle array (PA) and velocities (V_i).
2. Allow the particle to traverse at $V_i=Vmax$.
3. Find new global fitness.
4. Check
a. If μ_{min} decreases, the neuron is deleted. $\mu_{min} <m<=\mu_{max}$
b. if the maximum critical threshold Ct exceeds, a particle is detected from the input at scheduled time.
5. Input collection is maintained.

Fuzzy DPSO Procedure
- In the beginning, a local optimum is sought in a certain area.
- If it can't be found, it's simply ignored, and local optima in other places are sought.
- Swarms that pass all of the tests for locating local optima sites have a longer life span, while particles that fail have a shorter one.

3.3 Dropout CNN classifier

To segment lung images, the Dropout CNN classifier is employed, and the CLAHE algorithm is used to improve the lung picture. The CLAHE approach separates an original image into non-overlapping contextual sub-images, tiles, or blocks. Block Size (BS) and Clip Limit (CL) are the two most important elements of the CLAHE (CL). These two properties are significantly responsible for the improvement in image quality [32]. Increased CL brightens the image and flattens the histogram because the input image has a low intensity. The image is of dynamic range, as well as its contrast, increases as the BS increases [33]. The two parameters determined at the location with the biggest entropy curvature, using the image's entropy, produce subjectively good image quality.

Procedure
1. Create non-overlapping contextual zones using the original intensity image.
2. Calculating the histogram of each contextual zone using the grey levels in the array image.
3. The CL value is used to calculate the contextual region's contrast limited histogram.
4. Re-distribute the remaining pixels till they're evenly distributed.
5. The Rayleigh transform is used to improve the intensity values in each zone.
6. Taking steps to mitigate the impact of an unexpected change.
7. The new grey level assignment of pixels within a sub-matrix contextual region is produced using a bi-linear interpolation between four alternative mappings to eliminate border artefacts.

The CT image is converted from RGB to YIQ colour space via linear transformation, and subsequently to HSI colour space via nonlinear transformation in this method. In the YIQ and HSI colour spaces, chromatic and brightness information are independent. Second, the brightness information is used to improve contrast while Rayleigh CLAHE is used to keep the chromatic information. Dropout is implemented per layer in a neural network. It works with a variety of layers, including dense fully connected layers, convolutional layers, and recurrent layers like the long short-term memory network layer. Dropout can be utilized on the visible or input layer, as well as any or all of the network's hidden layers. It isn't used on the output layer. The likelihood of the layer's outputs being dropped out or maintained is controlled by a new hyper parameter. We trained dropout neural networks for classification challenges on data sets from a variety of domains. We discovered that using dropout improved generalization p when compared to neural networks that did not use it.

4. RESULTS AND DISCUSSION

The Kaggle dataset was provided by the Radiological Society of North America (RSNA). Hundreds of pictures of healthy and pneumonia-infected people remain in this collection, which are useful for this study. To generate a training dataset, images from those two datasets must first be downloaded. The desired photographs are then picked and saved to the appropriate location. Images are then loaded and preprocessed before being sent into the training process by being turned into numpy arrays of the necessary size. It is vital

to set up the study's working environment before collecting data. Colab (Google Colaboratory) is a free cloud-based Jupyter notebook environment that requires no installation. Colaboratory allows users to build and execute code as well as access advanced computational resources directly from their browser. Colab, in particular, generously provides GPU, which significantly accelerates the computationally intensive training process. For these reasons, Colab has become highly popular among Deep Learning and Data Science enthusiasts who may not have access to a PC with expensive GPUs. To begin, we show that our method works on a COVID-CT-Dataset, which contains COVID-19-positive CT scans as well as ground-truth lesions that a radiology specialist manually recognizes. Figure 2 depicts the sample Covid-19 lung images. Second, we examined newly released CT images from a nearby hospital that contained individuals who had tested positive for the coronavirus. Finally, the COVID-19 lesion and its repercussions over patient's lungs are depicted in three dimensions. The performance metrics compared in Table 1.

To analyze and find out the result of the recommended segmentation approach, the segmented COVID-19 lesion statistical values are matched to the results of the Medical Image Segmentation (MIS) Methodology as shown in Table 2 and Figure 3. The performance of the provided algorithms was evaluated using generally established assessment scores. One of our work's primary characteristics is the capacity to assess the COVID-19 lesion, show the polluted region, and to trace disease changes in real time. Furthermore, the proposed method may detect aberrant regions despite the low-intensity contrast among healthy tissues and lesions. Even if our suggestions were effective, there are still disadvantages to be aware of. We also want to improve the algorithms so that lesions like ground-glass opacity, crazy paving, and consolidation can be identified. To improve COVID-19 detection, diagnosis, and assessment, we want to merge imaging data with clinical markers and laboratory testing results. COVID-19 continues to spread over the world in an uncontrollable and unpredictable manner.

**Table 1.** Performance metrics comparison

Performance metrics	MIS method	Proposed method
Accuracy	0.843	0.99
Specificity	0.967	1
Sensitivity	0.854	0.99
Fmeasure	0.812	0.12
Precision	0.914	1
MCC	0.917	0.97
DICE	0.923	0.981
JACCARD	0.891	0.960

Table 2. Summary of quantitative segmentation statistics

Lung (Vx)	In (cm)	Lesion	In(cm)	Ratio
109530	2897	75149	1988.3	68.61
240827	6371.8	43752	1157.6	18.167
94919	2511.3	10578	279.87	11.14
38726	1024.6	20734	548.58	53.54
37637	995.8	30477	806.3	80.97
231634	6128.6	42215	1116.9	18.22
38372	1015.2	8920	236	23.24
151116	3998.2	7632	201.9	5.05
232166	6142.7	36725	971.6	15.81
44204	1169.5	7892	208.8	17.85
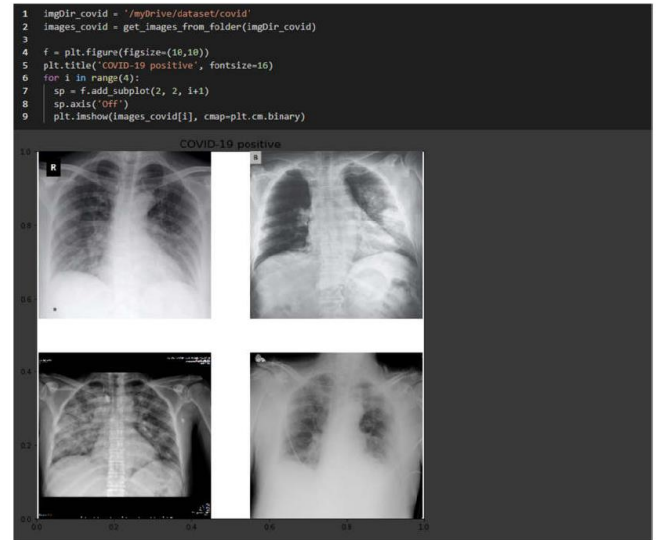
Figure 2. COVID-19 chest X-ray images
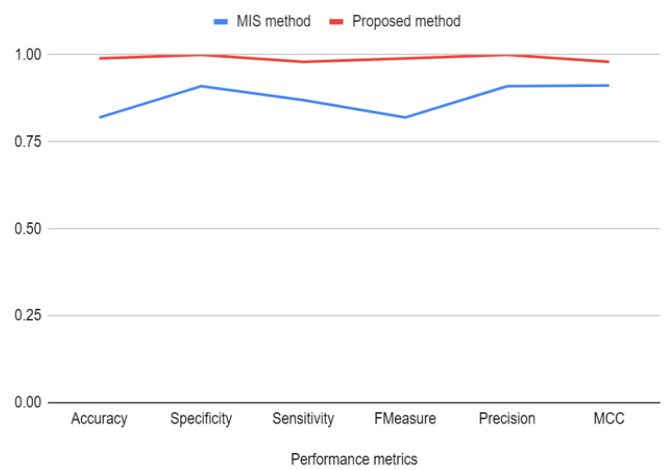
Figure 3. MIS Vs HFDPSO method

5. CONCLUSIONS

Until date, CT-scan imaging has been a widely used, low-cost, comprehensive screening method that efficiently aids in the visualization and rapid assessment of COVID-19 lesion severity. We assessed the efficacy of an automated technique for COVID-19 lung infection segmentation and quantification using chest CT data. The goal of this project is to build and analyze automated COVID-19 Lung Infection segmentation and quantification using Hybrid Swarm Intelligence and Fuzzy DPSO for chest CT images. According to extensive computer simulations, our persistent learning strategy for CT image segmentation using image enhancement is more efficient and adaptive than the Medical Image Segmentation (MIS) method. In future, the enormous dataset can be considered to approve our proposed model on it. Such strategies may be sought for further research to demonstrate their real case implementation.

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