Journal of Advanced Zoology

ISSN: 0253-7214

Volume ***44*** *Issue* ***I-3 Year 2023*** *Page* ***746****:****755***

A FUSION OF IMAGE PROCESSING AND DEEP LEARNING FOR COVID19 DETECTION USING 2D ITERATIVE CONVOLUTIONAL NEURAL NETWORK

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Article History

Received: 08July2023

Revised: 29 Aug 2023

Accepted: 07 Oct 2023

ABSTRACT:

Covid-19 still continues to be cataclysmic danger to humankind even after the discovery of vaccines because of passing of similar mutants which leads to creation of new variants. Image processing techniques are fused with a deep learning model to bring out the detection of covid19. A Raw Low Dose CT database Images (RLD-CTDI) are used along with the CAD approach to bring out a novel automatic framework. Raw Ct images in general have some clamors such as Gaussian, pepper & salt; speckle noises etc or might even be affected by shaky voltage disturbance. To remove these clamors and disturbances 2D Improved Anisotropic Diffusion Bilateral Filter (2D IADBF) is used which restores the image. The image is further pre-processed by using 2D Edge Preservation Efficient Histogram Processing to preserve the edges. After the pre-processing steps a clear noise-free image is obtained for further processing like clustering and thresholding. Clustering is done using 2D Hybrid-Fuzzy C-Means Algorithm (2D HFCM) to obtain disease clusters and thresholding is done using 2D Adaptive OTSU Thresholding to extract the Region of Interest (ROI). Using the ROI, Feature extraction is applied using Gray-Level Co-Occurrence Matrix Histogram Of Gradient (GLCM HOG) calculation to obtain features. These features are fed as input to the deep learning model.2D Iterative Convolutional Neural Network is used for classification of the image which categorizes the CT image into covid affected / Non-covid affected image.

Keywords -Covid19, Pre-processing, Segmentation, Feature extraction, Classification.

INTRODUCTION

CAD of lung CT Images is a revolutionary step in early diagnosis and detection of lung diseases. The utmost priority step in CAD is to obtain Region of Interest (ROI). Therefore to obtain ROI, there are 3 steps involved 1) Pre-processing 2) Clustering and 3) Thresholding. Pre-processing is further divided into Restoration and Enhancement. Clustering & Thresholding are the succeeding steps to obtain Region of Interest (ROI).Here clustering (Segmentation) must be done accurately which can help radiologists to detect them in an early stage. But nowadays segmentation for detection (manual) is not just required for detection but also a clear idea of the patient's report is required to diagnose at an early stage. Hence an advanced novel approach called Iterative Convolutional Neural Network ICNN is utilized to classify the image as covid/non-covid affected image. Neural Networks in general require some input to be fed as input into the network. The input might be features obtained using Gray-Level Co-Occurrence Matrix Histogram Of Gradient (GLCM HOG) calculation .The features obtained are stasticstatical in nature and are fed into the network as input to ICNN.This model is an iterative deep learning model which uses small sets of sub-sets as input and classifies the accuracy based on the enhancement made. The main aim of using ICNN is to remove large computational deep neural network models and construct them into small iterative learning models. This learning model combines the results of the previous iteration and comes out with new results, thus reducing computational cost, time with an efficient impact on performance.

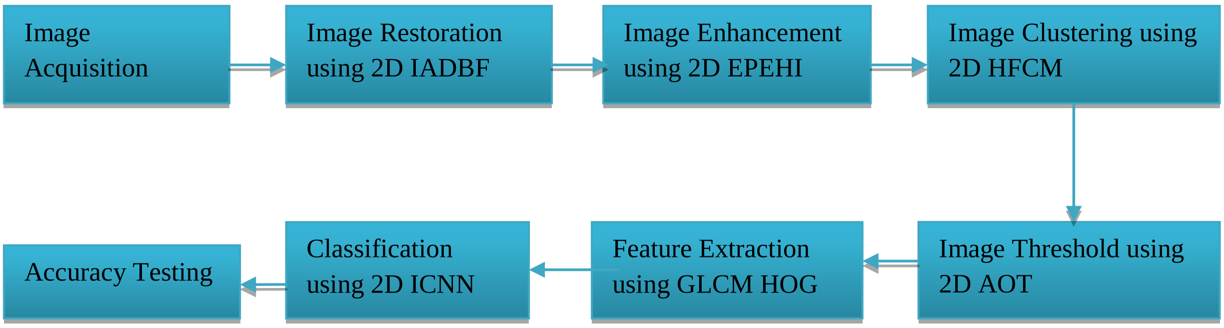


Figure1 Architecture diagram of Classification and detection of covid19 on lung CT image

OBJECTIVES

The main objective of the work is to detect Covid19 at an early stage so as to reduce the mortality risk of the patients.For this fully automated and efficient method, to classify COVID-19 infections using lungCT images.To show the efficiency of the proposed algorithms using a few standard parameters .This automated approach detects the disease from CT images based on deep models for faster examination .Themodule used for segmentation is based on pixels regions for clustering .This module increases the ability of the model without information loss. To make the work independent and novel from the existing frameworks.

METHODOLOGIES

This paper presents automatic, rigid and a robust method using ICNN to detect covid19 infection. There are 6 methodologies included to bring out the detect are divided into 3phaseswith each phase consisting of 2 sub-stages

Phase 1: Image Pre-processing

i) Image Restoration using 2D Improved Anisotropic Bilateral Filter (2D IADBF)

ii) Image Enhancement using 2D Edge Preservation Efficient Histogram Processing (2D EPEHI)

Phase 2: Extraction of Region of Interest (ROI)

i) Image Clustering using 2D Hybrid Fuzzy C-Means

ii) Image thresholding using 2D Adaptive OTSU Thresholding (2D AOT)

Phase 3: Classification and Detection

i) Feature Extraction using Gray-Level Co-Occurance Matrix Histogram Of Gradient GLCM HOG

ii) Classification using 2D Iterative Convolutional Neural Network

Phase 1: Image Pre-processing

i) Image Restoration using 2D Improved Anisotropic Bilateral Filter (2D IADBF)

CT Images in general contains impulse noises, speckle noises etc. These Noises can be removed by using 2D Improved Anisotropic Bilateral Filter (2D IADBF) .It is a combination of spatial domain and frequency domain filters making it a Spacio-frequency domain algorithm. Anisotropic algorithms are used to remove any kind of noise and preserves gradient information. Bilateral Algorithms are used to remove impulse noise, speckle noise and also removes outliers without reducing the sharpness of the image

ii) Image Enhancement using 2D Edge Preservation Efficient Histogram Processing (2D EPEHI)

Under Image Enhancement techniques, usually histograms are cut out at some threshold and then eqalizilation is applied but here edges are preservation and histograms are obtained efficiently by improving the overall contrast of the image on small area called tiles rather than the entire image.

Phase 2: Extraction of Region of Interest (ROI)

i) Image Clustering using 2D Hybrid Fuzzy C-Means

This clustering algorithm clusters the enhanced CT Image into Diseased and Non diseased regions. The algorithm is mainly uses Orthogonal Matching Pursuit Algorithm for creating dictionaries of Diseased and Non diseased ROI regions by matching them with the original input image and the clustered image. The algorithm splits these regions as non-overlapping blocks and creates 2 dictionaries Dr-ROI region dictionary DN-Non-ROI region dictionary and D is the original dictionary used in the OMP algorithm. The 2D HFCM Algorithm is actually a fuzzified version Fuzzy C-means algorithm.

ii) Image thresholding using 2D Adaptive OTSU Thresholding (2D AOT)

Once after clustering ,the inner structure of the lungs like nodules, bronchi and blood vessels are taken into consideration which are separated from the parenchyma region. OTSU Thresholding is applied which emphasizes through all conceivable edge esteems and also measures even the smallest inner pixel levels on any ROI region i.e. it gives both the foreground and background view segmented pixels. These separated inner structures appear as bright spots (black and white) due to the differentiable intensity levels between the different inner lung parts.2D AOT separates these inner pixel spots from rest of the region. The separation occurs mainly on the shape factor i.e. for example nodules appear as spherical in shape and bronchioles appear as cylindrical shape. For detecting these shapes Near-round Shape algorithm and Region-Growing algorithm is used for extracting these shapes. To bring out a small difference from existing methods a special principle called **Superimposed Segmentation principle** is used which traces out the exact location of the infection. It is a combination of the enhanced output image and segmented ROI image.

Phase 3: Classification and Detection

i) Feature Extraction using Gray-Level Co-Occurance Matrix Histogram Of Gradient GLCM HOG

Gray Level Co-Occurance Matrix GLCM is a spatial relationship among pixels .It is well known to give the spatial dependency matrix used for classification. Both the methods are truly stasticstatical measures of feature of an image. In addition to GLCM, Histogram of Gradient n is used to extract the visual characteristics

$$\varepsilon^2 A = \frac{1}{n}\sum_{k=1}^{n}(y_k - \vartheta A)^2 + \gamma \hat{x}_k$$

Where $\varepsilon^2 A$-Feature Extraction

n-Histogram Of Gradient ;yc_k-ROI ; visual- ϑA,

Texture- $\hat{x}_k$, Intensityand geometric moment features -γ.

The following are the 21 GLCM HOG features that are extracted in this research work: Autocorrelation, Amplitude ,Correlation ,Cluster prominence, cluster shade, Dissimilarity, Energy, Entropy , Homogeneity , Maximum Probability, Sum of squares, Sum Average, Sum variance, Sum Entropy ,Difference Variance ,Difference Entropy , Information measures of correlation (1) ,information measures of correlation (2),Maximal correlation co-Efficient ,Inverse Difference Normalized ,Inverse Difference ,Moment Normalized. These features are arranged as a matrix and stored in the database.

ii) Classification using 2D Iterative Convolutional Neural Network

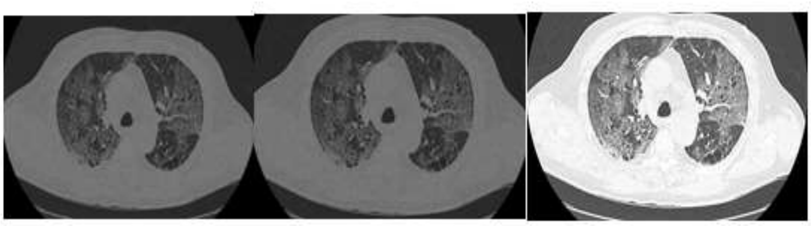
Neural networks are generally composed of 3 layers; input layer , hidden layer and output layer .Since this work is based on an iterative model ,the blocks may be divide into input layer, hidden layer, iterative layer and output layer. The network is trained using epochs, iteration and batches. Epochs mean training neural network with all training data for one cycle i.e. inputs are forwarded and back warded once/one pass through the network where as an iteration means training the network for one time processing of a single training data. Batch is the number of training examples in one forward and backward pass. Higher the batch size more the memory space is required. The aim of 2D ICNN is to avoid memory issues, reducing the size of the network and construct them into iterative learning models. ICNN process small sets of sub-sets of input and classifies the accuracy based on the enhancement made. The model combines the results of the previous iteration and comes out with a new set of results thus reducing computational cost and consumption time as well as gives a good impact on results.

There are few graphs represented as a result of the feature extraction and classification process such as Segmentation accuracy graph, Sensitivity graph, Specificity graph, Confusion matrix, false positive rate graph, Classification time graph, F1 Score Analysis graph, Precision Analysis graph , Correlation Fitness Factor graph and Differentiation % for correlation factor.

RESULTS &DISCUSSION

A Raw Low Dose CT Image Database (RLD-CTD) of 100 covid19 patient Images taken from GITHUB and EIBIR are used for the work. The implementation IS DONE USING Matlab software.

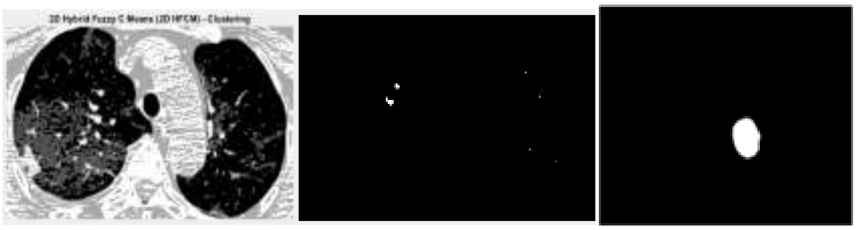
Initially a CT image is selected from the database and restored using 2D IADBF algorithm and the parameters used are Peak-Signal to Noise Ratio (PSNR),Mean Square Error(MSE) .More the PSNR value more the restoration is done and less the MSE means there is almost no error in the image. Figure 3 shows the images obtained using various restoration algorithms. The restored image is enhances using 2D EPEHI to get a clear image for further processing and the parameters are Structural Similarity Index Mean (SSIM) and Average Mean Brightness Error (AMBE).



(a) (b) (c)

Figure 3 Covid-19 CT lung input image filtered using (a) Noisy input (b) 2D IADBF (c) 2D EPEHI

The enhanced output image is clustered using 2D HFCM where either ROI /Non-ROI cluster is obtained. The parameters used are Gradient clusters and intensity pixels. The obtained cluster is thresholded to get the inner edges of the lung image using 2D AOT .true and false segmented pixel values are obtained. Further Superimposed segmentation Principle is used to get the exact location of the infection. Figure 4(a) the clustered image using 2D Hybrid Fuzzy C Means Algorithm, (b) shows the thresholded image using 2D Adaptive OTSU Thresholding Algorithm, (c) shows enhanced image using ROI image which contains the diseased portion, (d) shows the final superimposed principle



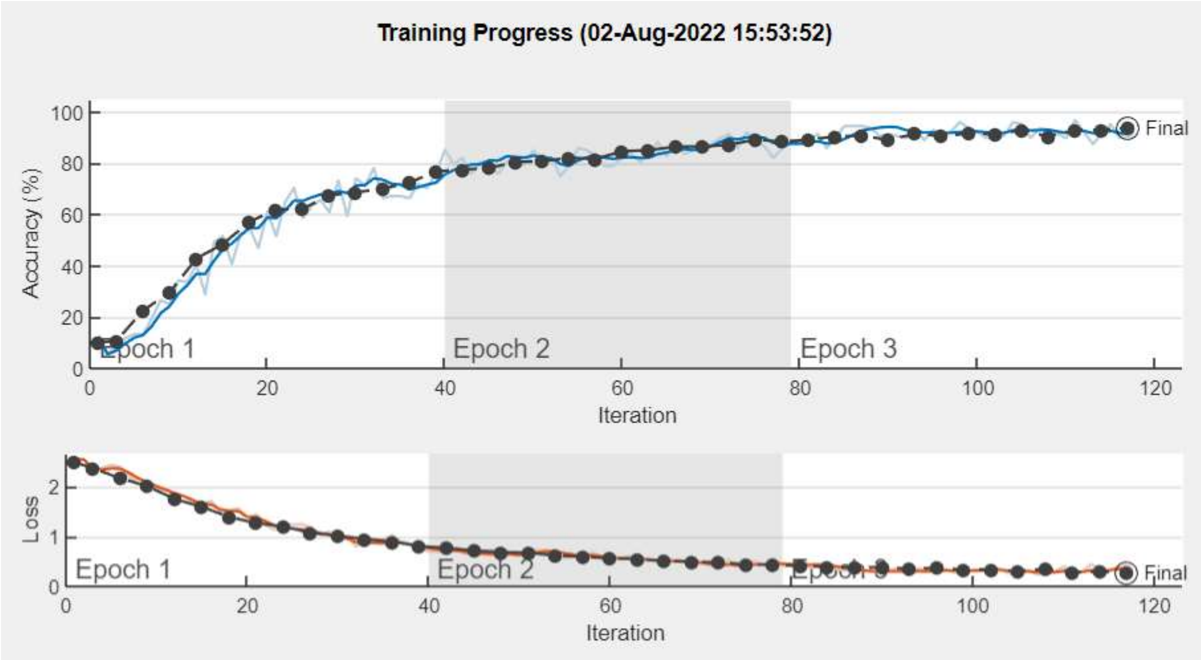
(a) **(b)** **(c)**

Figure 4 (a) Clustered image using 2D HFCM, 3 (b) Thresholding image using 2D AOT, (c) Segmented ROI

Proposed Algorithm	Parameter	Value
2D IADBF	PSNR	44.57
	MSE	0.68
2D EPEHI	SSIM	0.44
	AMBE	4.72
2D HFCM	Intensity Pixel	0.71
	Gradient clusters	4
2D AOT	True segmented pixels	256
	False segmented pixels	128

Table 1 Proposed Algorithms with standard parameter values

The output of the ROI image is used for feature extraction using GLCM HOG calculation which will be used as input for the neural network and decimal pair values ranging from 0.01 to 25.40 is obtained based on the feature extracted. The 21 Features of GLCM HOG calculation is fed as input to the 2D ICNN. For example Epochs =3; Batches =39 i.e. Iteration=Epochs* batches (3*39=117).Once after classification the image is categorized into 2 classes class1 Covid affected and class2 non-Covid affected image.



Graph 2 2D Iterative Convolutional neural network training progress with accuracy and loss

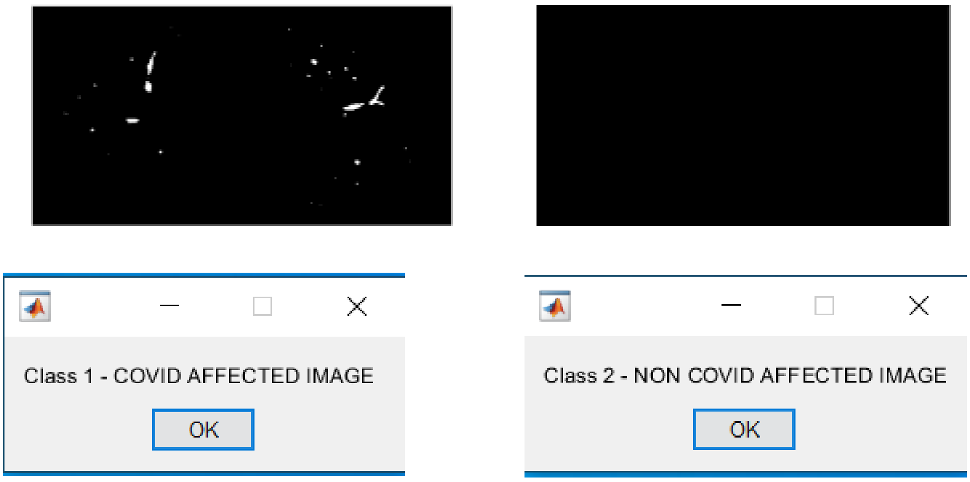
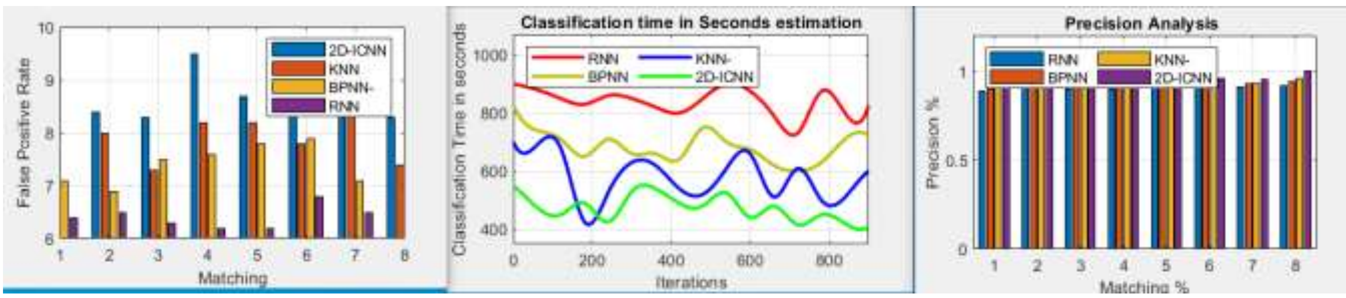
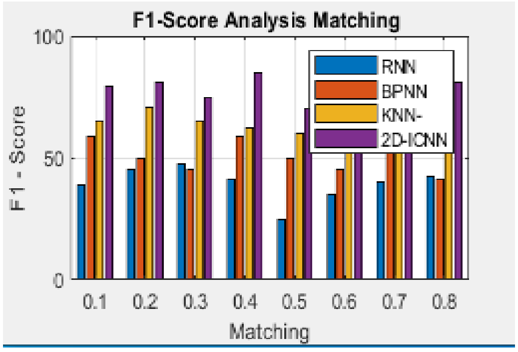


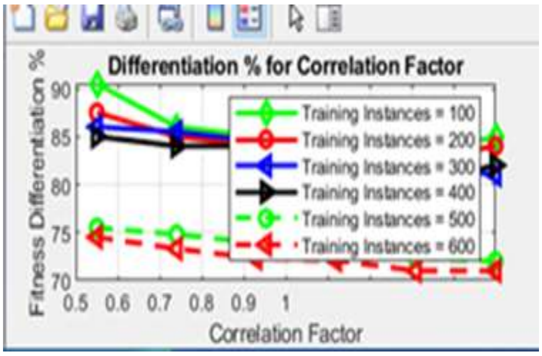
Figure 6 Classification (a) Class 1: Covid affected (b) Class2: Non-Covid affected

Once after classification process a few graphs represented as a result of the process such as Confusion matrix, false positive rate graph, Classification time graph, F1 Score Analysis graph, Precision Analysis graph, Correlation Fitness Factor graph and Differentiation % for correlation factor are obtained as shown below

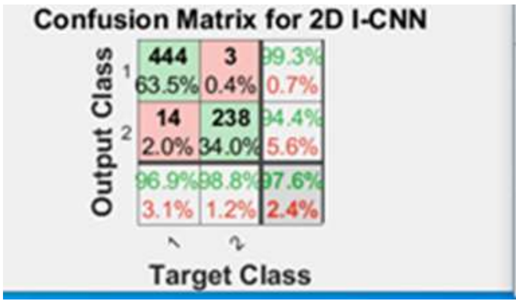


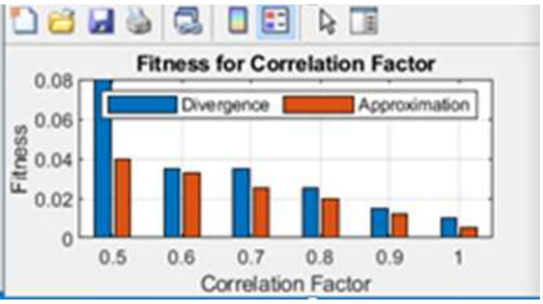
Graph 2 (a) False-positive reduction (b) Classification time (c) Precision Analysis





Graph 2 (d) F1-Score Analysis (e) Differenciation % for Correlation factor





Graph 2 (f) Confusion Matrix (g) Correlation Fitness

CONCLUSION

Thus a novel, automated CAD approach was utilized in the detection of covid19 infection using CT images. The aim of the paper was not only to bring out the presence of covid19 infection but also to show the efficiency of the proposed 2D ICNN algorithm using factor analysis graphs. The pre-processing techniques processed the image clearly and with good efficiency at the very first point thus making segmentation, thresholding easy. The work also showed the exact location of the infection using the special superimposed segmentation principle. Finally the network was well trained and tested by using the 21 GLCM HOG features iteratively to classify the infection. These proposed frameworks make the work even more efficient and independent of any other existing works. The future work would be based on double check analysis with blood sample images under microscope as well as CT scan image comparisons.

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