IJFANS INTERNATIONAL JOURNAL OF FOOD AND NUTRITIONAL SCIENCES
ISSN PRINT 2319 1775 Online 2320 7876
Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, 2022

Machine Learning Based Analysis and Classification of COVID-19 Chest Scan Images

Jaspreet Kaur[1], Khushboo Bansal[2]

[1] *Research Scholar, Desh Bhagat University, mandi Gobindgarh, Punjab*
[2] *Assistant Professor, Desh Bhagat University, Mandi Gobindgarh, Punjab*

Abstract - *Worldwide panic has been caused by the rapid spread of novel COVID-19 infection followed by millions of deaths and subsequently health threatening to the billions of human beings. Fast screening and isolation of the infected patients from the rest of the healthy population presented a great challenge to the health system. Clinical diagnosis techniques on admission of the patients are long time-consuming procedures. X-Ray and CT scan diagnosis requires highly expert medical manpower. This paper proposed ANN screening model using segmented chest CT-Images for fast screening of huge amount of data without much need of skilled medical manpower. Regionprops and GLCM techniques implemented for extraction of features and selection of features for training and testing purpose is accomplished by PSO Algorithm. The 60% of the grey images used for training and 40% for testing the proposed model. The results obtained in terms of sensitivity and specificity are highly favourable. The predicted classes of COVID infected and non-COVID images presented faithfully close agreement to the actual classes fed as input. Optimization of the screening is done by selecting the appropriate threshold limit. The false discovery rate is very much safe side. The technique need not highly expert team of doctors and results validated clinical reports.*

Keywords - *COVID -19, CT-Scan, Gray Level Coocurrence Matrix (GLCM), Lung Segmentation, PSO, Regionprops*

1. Introduction

Corona virus disease 2019 (COVID-19) is an infectious disease caused by severe acute respiratory syndrome corona virus 2 (SARS-COV-2) [1]. It was first identified in November 2019 in Wuhan, China, and has resulted in an ongoing pandemic spread [1][2]. More than 668047082 million cases have been traced over 190 countries, resulting in more than 6730566 deaths. However, about 661316516 million people have recovered [3].

The WHO has published several testing protocols for the disease [4]. The typical method of testing is real-time reverse transcription polymerase chain reaction (RT-PCR).The Clinical investigations of COVID -19 pneumonia carried out on specimens of oropharyngeal and nasopharyngeal swab of patient is time consuming procedure with promised outcome. Results are normally obtained within a few hours to two days [5]. On the other hand blood testing carried out requires two blood samples taken fourteen days apart, and the outcomes have little better prediction [6]. However, prolonged waiting clinical techniques presented epidemic spread platform for the disease.

The infection passes contagiously to thousands of people rapidly. Under such circumstances with limited clinical resources, large scale testing becomes challenging and generate the potential to explore another alternative technique for fast screening of the COVID infected and healthy persons. Recently screening of patients based on such imaging tests as ultra sound, X-Ray, and CT scanning becomes admirable techniques [7][8].

Benign and malicious image sorting using mammography based on GLCM feature extraction for the detection of breast cancer was presented 75% of screening [9]. The application of Gray Level Co-occurrence Matrix for extraction of second order statically texture features presented effective pattern recognition [10]. Haralick methodology based on novel FPGA for extraction of real time GLCM feature detection reflected authentic outcome [11]. Watershed technique of segmentation implementation on liver CT image segmentation to diagnose liver disease has average accuracy of 98.25% [12]. Similarly segmenting kidney CT image based upon crowdsourcing using convolutional neural network (CNN) has shown dice score of 0.885±0.112% [13]. Ultrasound, radiographs and CT scans comprehensive review presented motivation for the effective application of techniques in screening of COVID-19 pneumonia [14].Computed tomography scan, is a medical imaging technique that applies computer-processed combinations of many X-ray segments taken from various angles to crop cross-sectional images of specific potion of a scanned organ [7]. Recent development of computer assisted CT produces records that can be used in order to demonstrate various bodily structures based on their ability to absorb the X-ray beam. Advanced scanners able to assess volume of data to be reformatted in various planes or even as volumetric (3D) representations of structures. This technology is

ISSN PRINT 2319 1775 Online 2320 7876
 UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, 2022

successfully used in the screening of COVID-19 with considerable sensitivity and specificity [6].

However, these techniques require highly proficient team of doctors and supporting staff. Limited availability of high skilled medical manpower and the per day examining capability presented a great challenge for handling the situation when there occurred rapid escalation of the diseases. The screening has been sped up by implementation of deep learning technology on CT images [15]. In this paper, efforts have been made to speed up the screening using artificial neural network-based techniques.

In the wake of the COVID-19 pandemic, the global health infrastructure has been confronted with unprecedented challenges. One of the most pressing has been the rapid and accurate diagnosis of cases, a critical step in controlling the spread of the virus. The conventional methods of testing, while reliable, are hampered by their time-consuming nature and the scarcity of expert medical personnel required for interpretation [16]. As the virus continues to affect millions worldwide, the need for an expedited, reliable, and less labour-intensive method of screening is not just a medical necessity but a public health imperative [17]. This research paper introduces an innovative Artificial Neural Network (ANN) model that utilizes segmented chest CT images for the swift screening of COVID-19. By leveraging machine learning algorithms, specifically Region props and Gray Level Co-occurrence Matrix (GLCM) techniques for feature extraction, and Particle Swarm Optimization (PSO) for feature selection, our model presents a promising alternative to traditional diagnostic methods. This approach significantly reduces the reliance on highly skilled medical staff by automating the classification of COVID-19 from chest scan images with high sensitivity and specificity. The significance of this work lies in its potential to streamline the diagnostic process, allowing for the rapid isolation of infected individuals and more efficient allocation of medical resources. In a world where every second counts in the fight against a global pandemic, the implications of such a model are profound. It holds the promise of enhancing our diagnostic capabilities, thereby mitigating the spread of the virus, reducing mortality rates, and alleviating the burden on healthcare systems worldwide. This paper elucidates the development and validation of the ANN model, demonstrating its efficacy through a robust set of results. The findings suggest that the model not only meets but, in some respects, surpasses current diagnostic standards, offering a novel solution in the global effort to combat COVID-19. The adoption of this model could herald a new era in the management of infectious diseases, characterized by greater agility and resilience in the face of such global threats.

2. Literature Review

The current literature on machine learning applications for COVID-19 diagnosis reflects a significant effort by researchers to address the pandemic's challenges. A synthesis of the work described in the abstracts provided is as follows: In [18], researchers acknowledge the dire need for rapid COVID-19 case identification due to its global health impact. They propose a deep transfer learning methodology, utilizing chest CT and CXR images for the classification of COVID-19 patients. Their study evaluated the performance of various pre-trained deep neural networks, with VGGNet-19 and an optimized version of Xception standing out for their high accuracy and other performance metrics, demonstrating the potential of deep learning in automating the analysis of chest scans. The study in [19] focuses on a computer-aided design system for classifying chest X-Rays into COVID-19, viral pneumonia, or healthy categories. Due to a limited dataset of COVID-19 images, the authors leveraged four pre-trained deep neural networks, with AlexNet achieving an impressive accuracy of 97.6%, thus highlighting the potential of such systems in speeding up diagnosis. In [20], the authors aim to reduce the spread of COVID-19 by shortening diagnostic times through the use of CT scans. Their approach involved extracting deep features with various deep learning models and using these for classification with traditional machine learning methods. The combination of ResNet-50 and SVM yielded the best performance, indicating the utility of such methods as decision support systems for radiologists. The work presented in [21] addresses the limitations of RT-PCR testing by applying deep learning algorithms to CT scans. The authors tested several CNN architectures, with VGG16 providing the best accuracy, suggesting that deep learning could serve as an effective alternative for COVID-19 diagnosis in the face of testing kit shortages. In [22], the authors tackled the challenge of low-performance models in early COVID-19 detection. By employing convolutional neural networks and Darknet on CT and X-ray images, they developed models that surpassed existing methods by approximately 10% in accuracy, underscoring the importance of machine learning in supporting healthcare systems. The extensive review in [23] of deep learning techniques for COVID-19 diagnosis underlines the importance of CNNs, reinforced by the use of medical images. The authors summarize the role of pre-processing, transfer learning, data augmentation, and pre-trained models, providing a guide for future research in early disease detection. [24] provides a comprehensive overview of over 160 ML-based approaches to combat COVID-19. The paper categorizes the approaches into supervised and deep learning-based methods, with a strong preference for the latter. It offers a statistical analysis of the state of the art, showing a predominance of CNN usage, which could inform future research directions. These summaries provide an insight into the current advancements and the effectiveness of machine learning and deep learning approaches in the detection and diagnosis of COVID-19, highlighting the potential of these technologies to aid in the global health crisis. In [25], the authors confront the issue of

IJFANS INTERNATIONAL JOURNAL OF FOOD AND NUTRITIONAL SCIENCES
ISSN PRINT 2319 1775 Online 2320 7876
Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, 2022

resource-intensive COVID-19 testing by exploring the use of routine blood tests combined with machine learning to detect indicators of SARS-CoV-2 infection. Their review focuses on developing predictive models that can discern COVID-19-specific features from standard blood test data, offering a more practical and cost-effective testing solution. The paper in [26] proposes an automatic detection system for COVID-19 using CT lung screening and a Computer-Aided Diagnosis (CAD) system, employing machine learning techniques such as Decision Tree, Support Vector Machine, and Radial Basis Function. They aim to provide an alternative diagnostic tool that can be more accurate and less expensive than RT-PCR tests, highlighted by a GUI application developed to assist doctors in interpreting results from clinical specimens. In [27], the researchers propose a deep learning approach using ResNet-50 for classifying chest X-ray images of COVID-19 patients. They emphasize the importance of image preprocessing and introduce a modified version of ResNet-50, which they validate against benchmark datasets. The proposed system showcases significant improvements over existing models, with accuracy and other performance metrics exceeding 99.63%. The study presented in [28] introduces a novel CNN model for the automatic identification of COVID-19 in chest X-ray images, aimed at assisting radiologists in expressing diagnostic uncertainty. They compare the performance of their model to pre-trained architectures like MobileNetv2 and ResNet50, with their model achieving a high accuracy of 96.71% and an F1-score of 91.89%, suggesting its potential as a reliable diagnostic tool. Lastly, [29] discusses the use of chest X-ray images for the detection of various pulmonary diseases, including COVID-19. The authors propose a deep learning model that is evaluated with a large dataset of CXR images and complement their findings with explainable AI techniques such as Grad-CAM, LIME, and SHAP. Their model not only provides high accuracy but also offers medical professionals transparent and understandable insights into the classification process, enhancing the trustworthiness of the computer-assisted diagnostics. These summaries reflect the rapid advancements in AI-driven diagnostics, underscoring the potential of these technologies to supplement traditional diagnostic methods and provide more efficient, accessible, and understandable tools for managing the COVID-19 pandemic.

3. Materials and Methods

In this paper, MATLAB R2016a have been used for the examination of 527 pairs of CT-Scan chest images of COVID and Non-COVID persons as shown in figure 1 and figure 2 respectively.

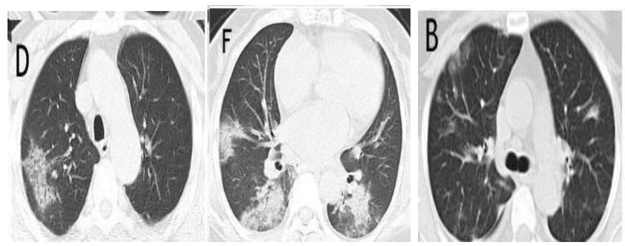

Fig. 1 COVID Chest CT-Scans Images

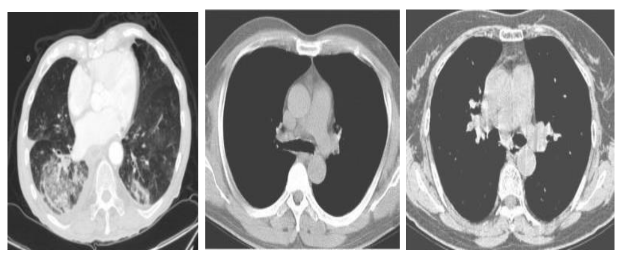

Fig. 2 Non-COVID Chest CT-Scans Images

The texture features are extracted from both the lungs in each image of all 1054 chest CT images. The requisite data has been duly retrieved from Github [30]. The total 19 features have been extracted using feature extraction methods. The detailed methodology is shown in the flowchart in figure 3. The selection of appropriate features is accomplished by using PSO algorithm.

ISSN PRINT 2319 1775 Online 2320 7876
Research paper © 2012 IJFANS. All Rights Reserved, UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, 2022

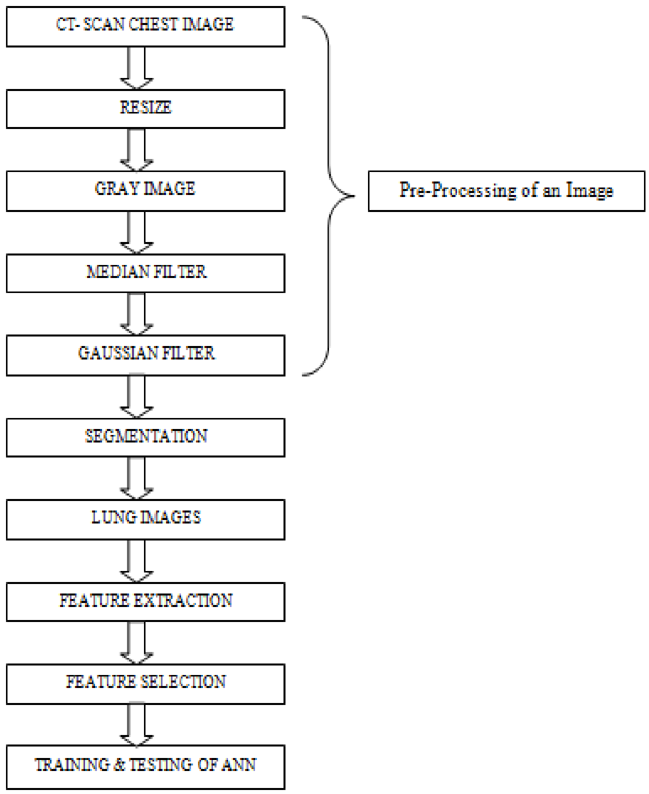

Fig. 3 Methodology Flow Chart

2.1. Pre-processing

Initially the input CT Image is converted into gray image using conversion function of MATLAB toolbox. Image enhancement is achieved by implementation of Median Filter and Gaussian Filter.

2.2 Feature Extraction and Selection

The resized CT image is cropped and finally segmented image of both lungs are obtained as shown in figure 4. After completing the segmentation process, the resultant image is converted into binary image to evaluate desired characteristic features. The shape features have been extracted using regionprops methodology and the texture features extracted using GLCM method.

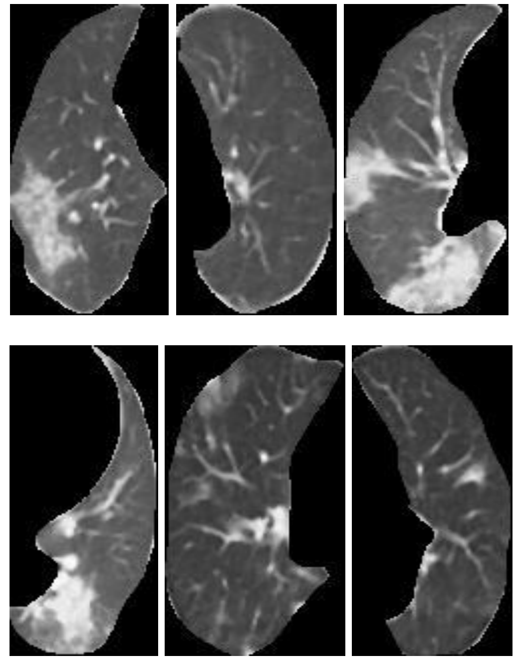

Fig. 4 Cropped Images of Lungs

2.2.1 Gray Level Co-occurrence Matrix

GLCM is statistical method used to examine texture feature of the image. Gray Matrix function is used and the spatial relationship of occurrence of a pixel with intensity (gray level) value i into the relationship to pixel with value j and in the final resultant GLCM, element (ij) indicates the total number of spatial relationship reoccurrence of pixel i with pixel j as shown in figure 5. Using this method, four texture features of gray image have been extracted used for screening the COVID-19 infected patients from the others.

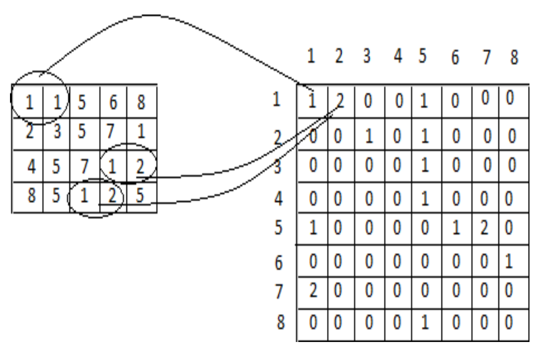

Fig. 5 Spatial relationship of occurrence of a pixel with intensity value i into the relationship to pixel with value

The mathematical equations governing these features and related terms used are introduced in this section.

The Governing Equations

Energy: The energy of the CT image measures angular second moment(ASM), that presented the global homogeneity of the image Mathematically the energy is given by the sum of the squared entries in the GLCM. The relation is given by the equation (1) [31].

$$\text{Energy} = \sum_{i,j=0}^{N-1} (P_{ij})^2 \quad (1)$$

Here P_{ij} is the element ij of the normalized symmetrical GLCMand N is number of gray levels in the image as specified by Number of levels in under Quantization on the GLCM texture page of the variable properties dialog box. Higher the value of P_{ij} higher will be the energy of the image [31].

Contrast: This feature is used to enhance the visibility of internal structures on the basis of local intensity variation in the CT image. The infected portions in the Lung image is heighted by favour influences of the function P_{ij} with element $i \neq j$ using the contrast feature and the relation used is given by (2) [31].

$$\text{Contrast} = \sum_{i,j=0}^{N-1} P_{ij}(i-j)^2 \quad (2)$$

Homogeneity: This is the inverse difference moment (IDM) and presented the local homogeneity of the pixels of specific portion of the CT image. The equation used to evaluate homogeneity is given by (3) [31].

$$\text{Homogeneity} = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \quad (3)$$

Due to the weighting factor $(1+(i-j)^2)^{-1}$ homogeneity contributes to small extent from inhomogeneous portion $i \neq j$ therefore outcome of IDM for inhomogeneous segments is low and high for that homogeneous segments.

Correlation: The relationship between two adjacent pixels of linearity dependency of gray image is known as correlation. The governing equation for the linearity dependency is given by the equation (4)[31].

$$\text{Correlation} = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \quad (4)$$

Here, μ is the GLCM mean (being an estimate of the intensity of all pixels in the relationships that contributed to the GLCM) and σ^2 is the variance of the intensities of all reference pixels in the relationships that contributed to the GLCM.

2.2.2 Regionprops

Extent: Ratio of pixels in the region to pixels in the total bounding box, returned as a scalar. Computed as the Area divided by the area of the bounding box [32].

Orientation: Angle between the x-axis and the major axis of the ellipse that has the same second-moments as the region, returned as a scalar. The value is in degrees, ranging from -90 degrees to 90 degrees. This figure illustrates the axes and orientation of the ellipse.

The left side of the figure shows an image region and its corresponding ellipse. The right side shows the same ellipse with the solid blue lines representing the axes. The red dots are the foci. The orientation is the angle between the horizontal dotted line and the major axis as shown in figure 6 [32].

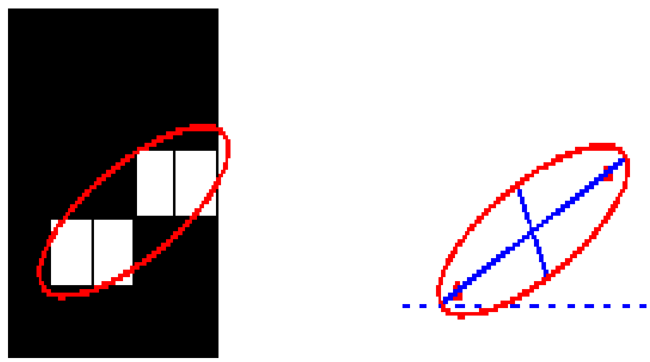

Fig. 6 Orientation of the image

Solidity: Proportion of the pixels in the convex hull that are also in the region, returned as a scalar. Computed as Area/Convex Area [32].

2.2.3 Particle Swarm Optimization

The PSO algorithm is most appropriate algorithm used by the researchers in the recent past for the selection of features of CT scan images. In particle swarm optimization, simple software agents, called particles, move in the search space of an optimization problem. The position of a particle represents a candidate solution to the optimization problem at hand. Each particle searches for better positions in the search space by changing its velocity according to rules originally inspired by behavioral models of bird flocking. Particle swarm optimization belongs to the class of swarm intelligence techniques that are used to solve optimization problems [33]. The tabular form data was obtained at the end of PSO algorithm execution which includes 7 best suitable features used for the investigation and analysis. 4

IJFANS INTERNATIONAL JOURNAL OF FOOD AND NUTRITIONAL SCIENCES
ISSN PRINT 2319 1775 Online 2320 7876
Research paper UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, 2022

texture features contrast, energy, homogeneity, correlation and three shape function features orientation, extent and solidity selected by PSO have been used to train and test the network.

2.3 Radial Basis Neural Network

This is a three layered network potential used for medical image diagnosis and analysis. Researchers in the recent past significantly used to detect to cancerous signs in lung images [34]. In this paper the ANN model proposed to investigate the COVID-19 infection in the lungs. The proposed model is shown in figure 7.

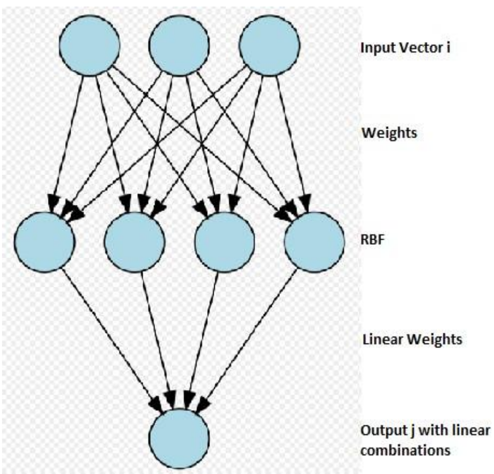

Fig. 7 Radial Basis Function

A radial basis function network is an artificial neural network that uses radial basis functions as activation functions. The output of the network is a linear combination of radial basis functions of the inputs and neuron parameter. RBF trains faster than a MLP. Its hidden layer is easier to interpret than the hidden layer in an MLP. Although the RBF is quick to train, when training is finished and it is being used it is slower than a MLP, so where speed is a factor a MLP may be more appropriate.
The network is configured with following properties:

The architecture of network has an input layer, a hidden layer and an output layer. The input layer takes 7 inputs variables including contrast, energy, homogeneity, correlation orientation, extent and solidity. The output layer provides 2 outputs either 0 or 1. The hidden layer holds 20 neurons. The input layer and hidden layer used log sigmoid transfer function and linear transfer function respectively. Moreover, to train the network, Scaled conjugate gradient back propagation training function and Mean squared error performance function is used. Furthermore, Maximum performance gradient 0.00000001 with maximum 1000 number of epochs and Learning rate 0.1 is used. Maximum 20 validation failures are set.

2.3.1 Training of ANN

The radial basis artificial ANN is used to train the network by giving input of 60% COVID and 60 % Non-COVID features of CT Images. Initially the training of ANN is done without signing the threshold values of the features. The results of the trained ANN obtained used for testing the accuracy level of the system. During the training phase, set of 392 COVID-19 infected CT image and 240 non-COVID CT images used. Each image used was resized to fixed number of pixels. The over fitting of the model on the training data set has been overcome by randomly cropping the patches after resizing and lung image and 100% zooming with large data set. The ANN was trained for seven suitable CT images selected by PSO algorithm without applying the conditions of threshold. The system was successfully trained with 632 CT images.

2.3.2 Testing of ANN

The trained network was tested by applying input sample of 422 CT images that includes 160 non-COVID and 262 COVID-19 infected images in two sets. All images selected are of same age group ranges 40-60 year of age.
The sensitivity, specificity and area under curve have been evaluated for classification of images. The accurate identification of proportion of true positive (TP) and true negative (TN) given by sensitivity and specificity depend upon the threshold limit set during testing work. This has alleviated the imbalance between two classes. The AUC used to measure the overall outcome of the system.

4. Results and Discussion

Two data sets of same size containing 160 images of Non-COVID class marked as set "0" and 262 images of COVID -19 infected patients indicated by "1" have been targeted for testing the ANN. The final output was obtained on the basis of averaging the two splits. The trade-off between true positive rate (TPR) and true negative rate (TNR) controlled by taking threshold 0.1 to 0.5 in steps of 0.1 incremental values. Confusion matrix of the total 5 threshold values obtained presenting classification, TPR, TNR PPV, FDR, FOR and accuracy as shown in the figure 8 (a and b). Predictive accuracy of the system is 90.2% against the actual 94.39% value of COVID-19 infection. The overall accuracy rate is recorded 90.2%.

The results obtained from the confusion matrix of tested data of ANN given in table 1. The graphical variation of sensitivity and FNR have been shown in figure 9.

Table 1

Threshold	Sensitivity(%)	FNR
0.1	79.4	20.6

ISSN PRINT 2319 1775 Online 2320 7876
 UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, 2022

0.2	87.4	12.6
0.3	94.3	5.7
0.4	91.9	8.1
0.5	75.6	24.4

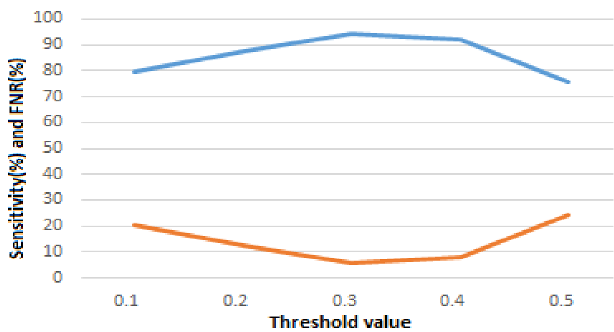

Fig. 9 Sensitivity and FNR vs. Threshold

The true identification rate for both positive and negative classes presented the improvement with increase in threshold. The maximum TPR and FNR recorded as 94.3% and 5.7% corresponding to the threshold 0.3 and on either side of this value of threshold both positive and negative rate fall.

The beauty of the model lies in positive predictive value (PPV) and false discovery rate(FDR). The PPV recorded as 90.5% and FDR as 9.5% corresponding to threshold 0.3. Since PPV of system indicates the classification of COVID-19 infected as COVID class and FDR presented the non-COVID into COVID category, therefore high value of PPV places the COVID -19 suffering patients in class "1" whereas high value of FDR places non- COVID patients in class "1" that is declares patient suffering other type pneumonia into COVID -19 category. This will significantly avoid the epidemic spread of the disease. Though the problematic values can be clinically screened easily as the number of patients required to be examined are not in bulk.

Fig. 8a Confusion matrix for Threshold 0.1 to 0.3

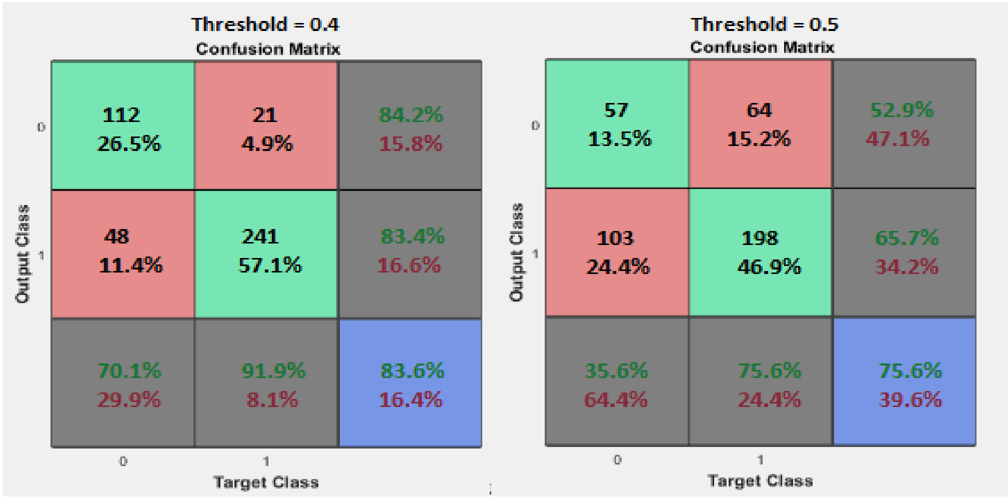

Fig. 8b Confusion matrix for Threshold 0.4 to 0.5

3.1 Accuracy Curve

The variation of TPR with threshold is shown in the accuracy curve in figure 9. The graph is useful for the selection of optimum value of threshold to obtain highly précised results. The maximum overall system efficiency is recorded as 94.3% at threshold value 0.3. The variation of True positive rate with threshold value is shown in the figure10.

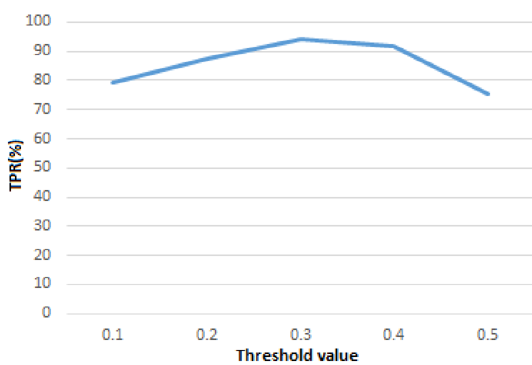

Fig. 10 TPR Vs Threshold value

5. Comparative Analysis

This section will do a comparative analysis between the recent work and our work. The analysis is recorded in table 2.

Table 2. Comparative Analysis between proposed work and related works.

Work Done	Methodology	Data Set Size	Metrics	Accuracy	Notable Findings
[18]	Deep transfer learning with four pre-trained networks	422 CT & CXR images	Precision, Recall, F1-score, Accuracy	CT: 87%, CXR: 98%	VGGNet-19 best for CT, Xception best for CXR
[19]	Four pre-trained DNNs on chest X-Rays	2905 images	Accuracy, Precision, Recall, F1-score	97.6%	AlexNet shows high accuracy
[20]	Deep features with deep learning models and ML classifiers	1345 CT images	Accuracy, F1-score, AUC	96.296%	ResNet-50 and SVM showed best performance
[21]	CNN architectures on CT scans	3873 CT images	Accuracy	VGG16: 97.68%	VGG16 provides best accuracy
[22]	CNN and Darknet on CT scans and X-ray images	-	Accuracy	+10% improvement	Outperformed state-of-the-art by ~10%
[27]	Deep learning using ResNet-50 on chest X-ray images	2 datasets	Accuracy, Precision, Recall, F1-score, AUC	>99.63%	Outperforms VGG, Densnet

ISSN PRINT 2319 1775 Online 2320 7876
 UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, 2022

[28]	Novel CNN model using chest X-ray images	13,824 X-ray images	Accuracy, F1-score	96.71%	Outperforms other advanced algorithms
[29]	Deep learning model with XAI on CXR images	7132 CXR images	Accuracy	94.31% (CV)	Provides interpretable results for clinicians
Your Work	ANN using segmented chest CT-Images with Regionprops, GLCM, and PSO	422 images (160 Non-COVID, 262 COVID)	Accuracy, TPR, FDR	90.2%	High PPV and TPR at threshold 0.3

The comparative analysis table encapsulates a variety of approaches to COVID-19 detection using machine learning and deep learning techniques across several studies, revealing a trend towards the use of convolutional neural networks (CNN) and deep transfer learning to interpret chest CT and X-ray images. Methodologies span from the application of pre-trained deep neural networks to novel CNN models and the utilization of deep learning coupled with explainable AI (XAI) frameworks for better interpretability by clinicians. Data set sizes vary, with some studies such as [21] and [28] using thousands of images, while others like [18] and your work use a more modest sample size, yet still derive significant insights. Accuracy across the studies is high, often surpassing 90%, with some, like in [27], achieving greater than 99.63%. This indicates a strong potential for these models to complement or even substitute traditional diagnostic procedures, especially in resource-constrained environments. Notably, our work, while presenting a slightly lower accuracy of 90.2%, offers a high positive predictive value (PPV) at an optimized threshold, which is crucial for reliable COVID-19 detection and minimizing the risk of false positives—a significant advantage in preventing unnecessary isolation or treatment. our model's strength lies in its strategic combination of Region props and GLCM for feature extraction and PSO for feature optimization, which facilitates the processing of image data without extensive reliance on skilled medical manpower. This approach not only aligns with the current needs of the healthcare system to streamline and expedite the diagnosis process but also demonstrates the robustness of ANN in medical image analysis, particularly in scenarios where rapid and accurate screening is essential. In summary, while the comparative analysis showcases a range of effective techniques with high accuracies, our work stands out for its practical application in fast screening, requiring less skilled personnel without compromising on predictive accuracy—an advantageous proposition for healthcare systems worldwide grappling with the pandemic's demands.

6. Conclusion

The ANN-based screening model introduced in our study has demonstrated a promising accuracy of 90.2%, providing a significant advancement in the rapid and reliable screening of COVID-19 infection. This level of accuracy is particularly noteworthy when contrasted with existing deep learning techniques, which have reported a maximum accuracy of up to 72% at a threshold of 0.15. The model's low false discovery rate (FDR) is a testament to its efficacy in quickly identifying COVID-positive cases, minimizing the risk of an epidemic spread within the community.

Furthermore, the system's precision ensures that for every one thousand patients screened, only about one hundred require further clinical examination. This is a substantial reduction in the healthcare system's burden, particularly in terms of the required number of expert medical staff. Traditional clinical diagnostic methods are much more time-consuming and labor-intensive by comparison. Our ANN model streamlines the diagnostic process, thereby enabling faster decision-making and potentially reducing the need for a large number of specialist consultations.

The current model's performance is an encouraging development in the fight against COVID-19, yet there is room for further refinement. By integrating additional patient data, such as immune response indicators, physical condition, and age, we anticipate that the accuracy and reliability of the model could be further optimized. Incorporating these features could enable a more nuanced understanding of the disease's manifestation across diverse patient profiles, ultimately enhancing the model's diagnostic precision. In summary, the ANN model we have developed is not only a robust tool for the current pandemic but also a blueprint for future rapid diagnostic strategies. Its ability to deliver high accuracy with a low false discovery rate paves the way for its use as a frontline diagnostic tool, offering a scalable and efficient solution to healthcare challenges during such critical times.

Conflicts of Interest

"There is no conflict of interest regarding the publication of this paper."

References

[1] Hui DS, Azhar EI, Madani TA, Ntoumi F, Kock R, Dar O, Ippolito G, Mchugh TD, Memish ZA, Drosten and Zumla A. "The continuing 2019-nCoV epidemic threat of novel coronaviruses to global health—The latest 2019 novel coronavirus outbreak in Wuhan, China." *International journal of infectious diseases*, vol. 91, pp. 264-266, 2020.

[2] Ma J. Coronavirus: China's first confirmed Covid-19 case traced back to November 17. South China Morning Post, 13, 2020.

[3] The worldometers website, 2019. [Online]. Available: http://www. worldometers.info/.

[4] The cdc website, 2019. [Online]. Available: https://www.cdc.gov/.

[5] The mayoclinic website, 2019. [Online]. Available: https://www.mayoclinic.org/.

[6] The who website, 2019. [Online]. Available: https://www.who.int/.

[7] The acr website, 2019. [Online]. Available: https://www.acr.org/.

[8] Salehi S, Abedi A, Balakrishnan S and Gholamrezanezhad A. "Coronavirus disease 2019 (COVID-19): a systematic review of imaging findings in 919 patients", *Ajr Am J Roentgenol*, vol. 1, 215, pp.87-93, 2020.

[9] Vasantha M, Bharathi VS and Dhamodharan R." Medical image feature, extraction, selection and classification" *International Journal of Engineering Science and Technology*, vol. 2, 6, pp. 2071-2076, 2010.

[10] Mohanaiah P, Sathyanarayana P and GuruKumar L, "Image texture feature extraction using GLCM approach", *International journal of scientific and research publications*, vol. 3, 5, pp. 1-5, 2013.

[11] Rao SV and Vardhan MH, "GLCM architecture for image extraction", *International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE)*, Vol. 3, 2014.

[12] Himmah F, Sigit R and Harsono T, "Segmentation of Liver using Abdominal CT Scan to Detection Liver Desease Area", In IEEE *International Electronics Symposium on Knowledge Creation and Intelligent Computing (IES-KCIC)*, pp. 225-228, 2018.

[13] Mehta P, Sandfort V, Gheysens D, Braeckevelt GJ, Berte J and Summers RM, "Segmenting The Kidney On CT Scans Via Crowdsourcing*", In IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019)* , pp. 829-832, 2019.

[14] Lomoro P, Verde F, Zerboni F, Simonetti I, Borghi C, Fachinetti C, Natalizi A and Martegani A, COVID-19 pneumonia manifestations at the admission on chest ultrasound, radiographs, and CT: single-center study and comprehensive radiologic literature review, *European journal of radiology open 7*, pp. 100231, 2020.

[15] Zhang J, Xie Y, Pang G, Liao Z, Verjans J, Li W, Sun Z, He J, Li Y, Shen C and Xia Y. Viral, pneumonia screening on chest X-rays using confidence-aware anomaly detection, *IEEE transactions on medical imaging*, vol. 3, 40, pp.879-90, 2020.

[16] Jha, N., Prashar, D., Rashid, M., Shafiq, M., Khan, R., Pruncu, C. I., ... & Saravana Kumar, M. (2021). Deep learning approach for discovery of in silico drugs for combating COVID-19. Journal of healthcare engineering, 2021, 1-13.

[17] Jha, N., & Prashar, D. (2021). Rapid Forecasting of Pandemic Outbreak Using Machine Learning: The Case of COVID-19. Enabling Healthcare 4.0 for Pandemics: A Roadmap Using AI, Machine Learning, IoT and Cognitive Technologies, 75-90.

[18] Chouat, I., Echtioui, A., Khemakhem, R., Zouch, W., Ghorbel, M., & Hamida, A. B. (2022). COVID-19 detection in CT and CXR images using deep learning models. *Biogerontology*, *23*(1), 65-84.

[19] Gupta, V., Jain, N., Sachdeva, J., Gupta, M., Mohan, S., Bajuri, M. Y., & Ahmadian, A. (2022). Improved COVID-19 detection with chest x-ray images using deep learning. *Multimedia Tools and Applications*, *81*(26), 37657-37680.

[20] Oğuz, Ç., & Yağanoğlu, M. (2022). Detection of COVID-19 using deep learning techniques and classification methods. *Information Processing & Management*, *59*(5), 103025.

[21] Kogilavani, S. V., Prabhu, J., Sandhiya, R., Kumar, M. S., Subramaniam, U., Karthick, A., ... & Imam, S. B. S. (2022). COVID-19 detection based on lung CT scan using deep learning techniques. *Computational and Mathematical Methods in Medicine*, *2022*.

[22] Al Shehri, W., Almalki, J., Mehmood, R., Alsaif, K., Alshahrani, S. M., Jannah, N., & Alangari, S. (2022). A Novel COVID-19 Detection Technique Using Deep Learning Based Approaches. *Sustainability*, *14*(19), 12222.

[23] Shyni, H. M., & Chitra, E. (2022). A comparative study of X-ray and CT images in COVID-19 detection using image processing and deep learning techniques. *Computer Methods and Programs in Biomedicine Update*, *2*, 100054.

[24] Meraihi, Y., Gabis, A. B., Mirjalili, S., Ramdane-Cherif, A., & Alsaadi, F. E. (2022). Machine learning-based research for covid-19 detection, diagnosis, and prediction: A survey. *SN computer science*, *3*(4), 286.

[25] Kistenev, Y. V., Vrazhnov, D. A., Shnaider, E. E., & Zuhayri, H. (2022). Predictive models for COVID-19 detection using routine blood tests and machine learning. *Heliyon*.

[26] Shahin, O. R., Alshammari, H. H., Taloba, A. I., & Abd El-Aziz, R. M. (2022). Machine learning approach for autonomous detection and classification of COVID-19 virus. *Computers and Electrical Engineering*, *101*, 108055.
[27] Sahin, M. E. (2022). Deep learning-based approach for detecting COVID-19 in chest X-rays. *Biomedical Signal Processing and Control*, *78*, 103977.
[28] Bhandari, M., Shahi, T. B., Siku, B., & Neupane, A. (2022). Explanatory classification of CXR images into COVID-19, Pneumonia and Tuberculosis using deep learning and XAI. *Computers in Biology and Medicine*, *150*, 106156.
[29] Ullah, N., Khan, J. A., Almakdi, S., Khan, M. S., Alshehri, M., Alboaneen, D., & Raza, A. (2022). A novel CovidDetNet deep learning model for effective COVID-19 infection detection using chest radiograph images. *Applied Sciences*, *12*(12), 6269.
[30] The github website, [Online]. Available: https://github.com.
[31] Albregtsen F, Statistical texture measures computed from gray level coocurrence matrices, Image processing laboratory, department of informatics, university of oslo. pp. 5, 5, 2008.
[32] The mathworks website, [Online]. Available: https://in.mathworks.com.
[33] The radial basis network website, [Online]. Available: https://en.wikipedia.org.
[34] The Particle swarm optimization website, [Online]. Available: http://www.scholarpedia.org.
[35] Siddhu AK, Kumar A and Kundu S, Review Paper for Detection of COVID-19 from Medical Images and/or Symptoms of Patient using Machine Learning Approaches. *In IEEE 9th International Conference System Modeling and Advancement in Research Trends (SMART)*, pp. 39-44, 2020.
[36] Punia R, Kumar L, Mujahid M and Rohilla R, Computer vision and radiology for COVID-19 detection, *In IEEE International Conference for Emerging Technology (INCET)*, pp. 1-5, 2000.
[37] Wang L, Shen H, Enfield K and Rheuban K, Covid-19 infection detection using machine learning. *In IEEE International Conference on Big Data (Big Data)*, pp. 4780-4789, 2021.
[38] Turabieh H and Karaa WB, Predicting the existence of COVID-19 using machine learning based on laboratory findings. *In IEEE International Conference of Women in Data Science at Taif University (WiDSTaif)*, pp. 1-7, 2021.
[39] Sevi M and Aydin İ, COVID-19 detection using deep learning methods, *In IEEE International conference on data analytics for business and industry: way towards a sustainable economy (ICDABI*, pp. 1-6, 2020.