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A Novel Optimized Artificial Intelligence Based Deep Learning for Predicting the Infectious Disease Using Computed Tomography

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Abstract: The coronavirus disease from 2019 (COVID-19) spread over the world in 2020 and caused several health problems. Additionally, because it frequently affects the lungs, automatic detection is particularly crucial for protecting people from death. Using Computed Tomography (CT) images, the Artificial Vulture-based Anamorphic Depth Convolutional (AVbADC) Model is suggested in this study to segment the COVID-19 lungs affected region and categorize COVID-19 cases. Using CT scans of the lungs, the Modified AVbADC model separates COVID-19 infection from other pneumonia cases and normal pneumonia. The suggested architecture is built utilizing two parallel levels with various kernel sizes to capture the local and global properties of the inputs. It is based on the convolutional neural network. The outcomes of the experiment show that our AVbADC. On a short dataset, these results show a promising segmentation and classification performance; more improvements can be made with more training data. All things considered, the updated AVbADC model may be a useful tool for radiologists to aid in the diagnosis and early identification of COVID-19 cases. Finally, the proposed framework's results are contrasted with those of other methods currently in use in terms of sensitivity, accuracy, specificity, F-measure, and other factors.

Keywords*: COVID-19, Lungs, Computer Tomography, Infected Region, Tracking, Vulture Optimization, Convolutional Neural Network.*

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1. Introduction

Early in 2020, COVID-19 spread over the planet, causing numerous health problems [1]. Since the lungs are mostly affected, automatic detection of lung infections utilizing Computed Tomography (CT) images is particularly crucial to improving the healthcare strategy. However, there are certain difficulties when segmenting the damaged area in the lungs from the CT images, such as low contrast and considerable variance [2, 3]. Additionally, the most widely used method for diagnosing lung illness is CT imaging. Additionally, segmentation with different lesions and organs provides a clinician with crucial information for classifying and diagnosing lung disease [4, 5]. Additionally, the newly discovered COVID-19 is transmitted to human life in December 2019 and has significant short- and long-term societal and economic effects [6]. Figure 1 depicts the biological behavior of quantified abnormal lungs.

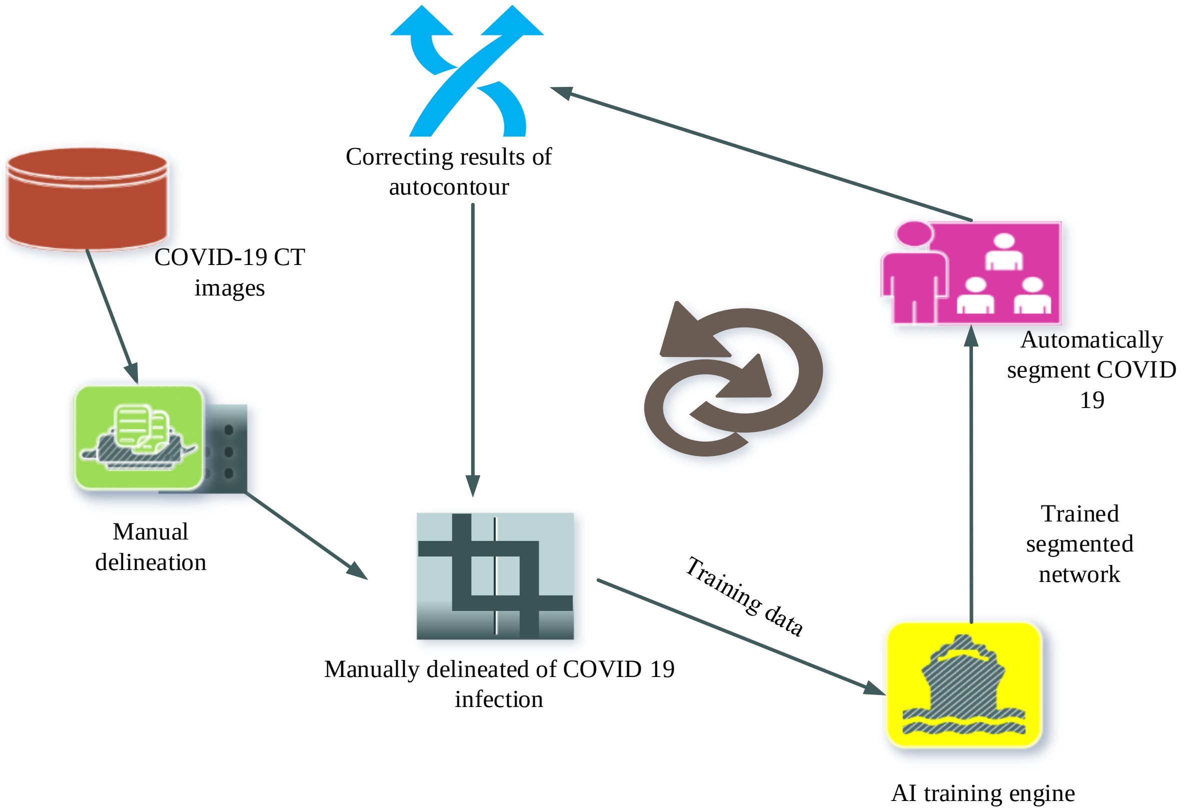


Fig.1 Abnormal lungs quantification using lungs images

Additionally, COVID-19 has an impact on a variety of organs, including the kidneys, brain, heart, lungs, blood vessels, and stomach [7]. As a result, the virus enters the body through the angiotensin-producing cells, which can be found using a CT scan, a useful and promising auxiliary as well as alternative tool for managing and identifying COVID-19 disease [8, 9]. Therefore, dry cough and fever are COVID-19's most prevalent symptoms, but breathing problems can also result from the dangerous condition [10]. In general, COVID-19 propagated swiftly when it was passed from person to person; hence early discovery and patient isolation play a vital role in containing the threat [11]. In recent years, the use of neural networks in healthcare has been advocated for clinical judgment and disease detection. The coronavirus continues to be the main killer on the planet [12, 13].

Due to the daily increase in cases, emergency clinics only have a certain amount of COVID-19 test units available [14]. To prevent COVID-19 from spreading among people, it is crucial to implement an automatic detection as a quick elective finding option [15]. Among the most promising fields of research is medical image processing, which offers tools for diagnosing and making judgments about a variety of illnesses, including the Coronavirus [16, 17]. In response to this issue, scientists, engineers, and experts in artificial intelligence (AI) have pushed for the creation of a Deep Learning (DL) model to assist healthcare [18] professionals in quickly and cheaply detecting COVID-19 from lungs X-ray images and determining the severity of the infection [19]. Numerous methods have been developed to improve COVID-19's effectiveness in the detection and segmentation of the lung infection region, but these methods still suffer from high error rates, time-consuming processing, and poor segmentation accuracy. Thus, a unique optimization-based neural network was constructed to improve the segmentation of lung infections in COVID-19.

The paper is organized as follows: Session 2 discusses the literature review for this study. In Session 3, the examined issue and the system model are further developed. In Session 4, the created innovative technique is explained. The final session, Session 5, discusses the outcomes and comparative analyses. Session 6 goes into further depth about the work's conclusion.

2. Related Works

Some recent literature surveys related to infectious disease prediction are followed below,

A unique Inf-Net framework was created by Deng Ping et al. [21] for autonomously classifying and segmenting COVID-19 lungs infection. The goal of employing a parallel encoder is to generate a global map that collects high features. Additionally, semi-supervised algorithms improve learning capacity and achieve good performance, although COVID-19 segmentation and identification take a lot of time.

Better specificity and sensitivity for the detection of COVID-19 are produced by the new invention of employing CT scans to detect radiographic patterns. Using CT scans, Athanasios et al. [22] created an efficient DL framework for a semantic slice of an affected area. Additionally, U-Net and Fully convolution systems are employed for precise segmentation, and the method is a promising one for future research, however improper detection due to data complexity.

An AI-based automatic detection approach was put forth by Zhang Li et al. [23] for identifying COVID-19-infected lung areas. Additionally, the segmentation of the lungs' abnormality using two imaging biomarkers automatically and manually is compared. As a result, the created method achieves 0.97 percent in Area under Curve (AUC), although the erroneous prediction rate is significant.

The COVID-19 virus, which is transmitted throughout the world, typically results in death. The virus incubates in the human body for five days before symptoms appear. Maheshwar et al. [24] created the two-dimensional DL technique-based U-Net to accomplish segmentation jobs more effectively that were executed using the Kaggle dataset and observed depending on the variation of the hyperparameter. As a result, when compared to other existing methodologies, the design achieves superior performance in the F-measure but lower segmentation accuracy.

For assessing, monitoring, and identifying the progression of associated pneumonia COVID-19 using CT scan, Jiantao Pu et al. [25] presented a program of test computer. Automated vascular and lung border segmentation, registration, identification, and assessment are some of the four processes it contains. Heat maps are produced using a large number of registered scans, although the spatial intensity is only moderate.

- Initially, the COVID-19 lungs CT image dataset is utilized for training the system.
- Subsequently, a novel AVbADC was developed to detect the positive and negative cases of COVID-19.
- The vulture fitness module works in the Anamorphic Depth Convolutional Model (ADCM) pooling layer that is used to segment and predicts the COVID-19 cases.
- Hence, the developed AVbADC tracks and predict the positive and negative with high performance.
- Moreover, the developed approach is validated using recent prevailing approaches in terms of detection accuracy, specificity, sensitivity, precision, F-measure, and AUC.

3. Problem Statement And System Model

The COVID-19 disease is anticipated to cause more than 5,411,759 deaths by December 29th, 2021, as a result of significant long- and short-term societal and economic impacts. Additionally, COVID-19 typically infects the portions of the human body's lungs that result in pneumonia and Acute Respiratory Distress Syndrome, which both cause death (ARDS). As a result, it draws scientists and researchers that want to spread knowledge about COVID-19 and identify the impacted area.

Additionally, it is very difficult and in some cases impossible to anticipate COVID-19 at an earlier stage. Additionally, early-stage segmentation and detection of the COVID-19 lung afflicted areas are more challenging. The damaged areas of the lungs were detected and segmented using a variety of methods, including machine learning and naive Bayes. Figure 2 illustrates the fundamental system concept for identifying and classifying COVID-19 lung afflicted areas.

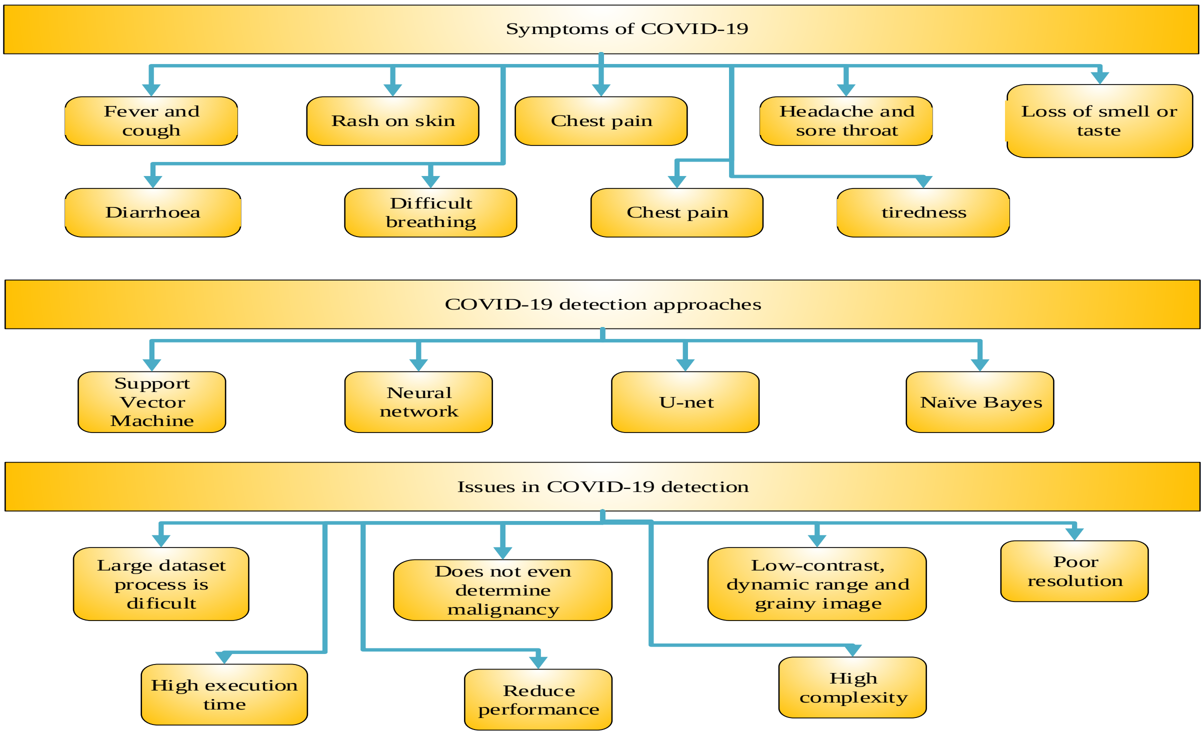


Fig.2. System model for detecting COVID-19

These methods haven't, however, improved to the point where they can segment and predict the damaged sections of the lung. The COVID-19 symptoms, classifiers for recognizing them, and the issues encountered are described in fig. 2. Additionally, X-ray and computer tomography are used to obtain COVID-19 (CT). However, a diagnostic tool like an X-ray must be processed manually, which leads to inaccurate results and mistakes. Additionally, mammograms are far less sensitive to detecting abnormalities than COVID-19. As a result, this research creates a novel DL strategy to identify and segment the lung area that is damaged. Additionally, this technique processed CT scans since they are more sensitive than other diagnostic techniques.

4. Proposed Methodology

The findings from research on the COVID-19 disease show that a CT abnormality occurs before the onset of clinical symptoms, and that asymptomatic persons typically have defective lungs that cause viral pneumonia. Identification and classification of the COVID-19 afflicted lung tissue are hence more crucial. To accurately separate the COVID-19 lung-affected region, create an Artificial Vulture-based Anamorphic Depth Convolutional (AVbADC) framework. Preprocessing, feature extraction, affected region tracking, segmentation, and classification are some of the five steps that are involved. The first step in preprocessing is the removal of error and noise from the dataset of CT images. The abnormality of the lungs is then extracted from a captured dataset during the feature extraction step. Fig. 3 provides specifics on the proposed architecture.

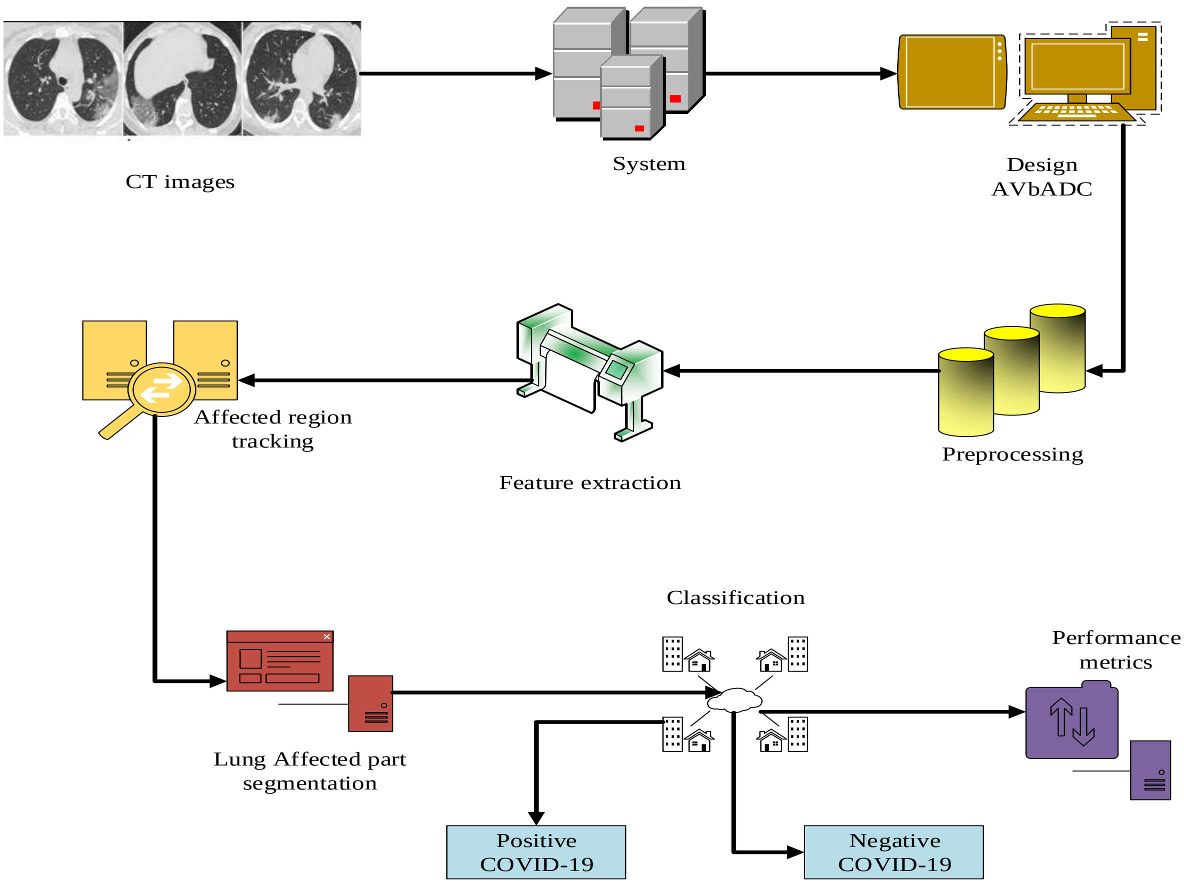


Fig.3 Proposed methodology

Next, follow the COVID-19 afflicted region according to the label and segment the area of the lung impacted by COVID-19 on the CT scans. Finally, update the fitness of vulture in a fully connected layer to predict infectious diseases. As a result, the established framework achieves superior outcomes and performs better when it comes to segmenting lung-affected regions and predicting COVID-19 cases. The developed framework is built with some parameters for the necessary reduction of annotated data during training, and the computation time for testing and training lung-affected part segmentation is low. Offer a quick first evaluation of COVID-19 lung abnormalities as well.

4.1 Design of AVbADC

The created AVbADC primary goal is the precise segmentation of the lung afflicted region caused by COVID-19 and classifies positive and negative COVID-19 cases. To remove unnecessary errors and noise, preprocessing is carried out. Feature extraction is then employed to extract the abnormalities of the COVID-19 lung afflicted areas utilizing radiological features. Additionally, the fully connected layer updates the vulture's fitness to track the afflicted regions of the lungs; accurate prediction and segmentation are then carried out to identify the affected regions in the lungs. The main reason for adopting vulture fitness is that Egyptian vultures are capable of throwing pebbles to destroy eggs. Broken eggs are used to locate weak or crack points, and rolling twigs are used to move an object to determine its location. By accurately segmenting the COVID-19-affected lung region and predicting COVID-19 cases using the established framework, the performance of the results is improved. Preprocessing, feature extraction, affected region tracking, segmentation, and classification are the five procedures that are involved.

- **Dataset description**

  The COVID-19 CT image dataset is initially gathered from the radiopaedia, and each image is scanned using CT according to the dimensions of pixels that are then labelled, confirmed, segmented, and classified by radiologist specialists. The dataset consists of 746 CT scans in total, 349 CT scan images are labelled as positive COVID-19 and 397 CT scan images are labelled as negative COVID-19, and it is segmented using a created framework. There are both positive and negative examples in the dataset. More than 80% of the datasets are used in the training phase, while 20% of the CT images are used in the validation phase.

- **Preprocessing**

  Typically, the system is tested and trained on the gathered datasets before updating the trained dataset to the convolution layer for preprocessing. Preprocessing is used to remove undesired mistakes and noise from datasets, which also improves the image quality of CT images. As a result, Eqn. (1) is used to derive the preprocessing.

$$K_r(l_e) = O_e(l_e; \theta d_e) + l_e \qquad (1)$$

  Let, l_e is denoted as input CT images and d_e is considered as training flaws, errors, and noises. Moreover, O_e is represented as depth squeezing and depth stressing. Then, the filtering of CT images performs the feature extraction process for extracting the relevant features from the dataset.

- **Feature extraction**

  In the convolutional layer, feature extraction is performed to extract the aspect terms of CT images which is helpful to minimize the quantity of dataset and the minimization leads to enhancing the performance of the developed framework which is mainly used for segmentation. The feature extraction has happened over the image patch and each pixel is denoted as features values they are extracted typically, locally, and in a small area. Furthermore, feature extraction measurement used through the convolutional layer is obtained by Eqn. (2).

$$F_e(A_1, A_2) = l_e(A_1, A_2)^2 \qquad (2)$$

  Where, F_e is denoted as feature extraction of collected CT datasets and A_1 is represented as redundant information of the CT image. Moreover, A_2 is represented as relevant information on abnormality in CT images.

- **Affected region tracking**

  The COVID-19 afflicted region in the lungs is frequently located and tracked using the extracted features that have been processed through the Maxpooling layer. The created framework uses mask pictures to identify and track the location of the damaged areas. By taking into account entropy, energy, and correlation properties, this method works well for tracking the damaged lung area. The segmentation of the impacted area is also carried out based on pixel variation. The following equation (Eqn. 3) is used to track the area that is affected:

$$FT_p = \begin{Bmatrix} -\alpha(1-k)^{\beta} a \ln(k) & a=1 \\ -(1-\alpha)k^{\beta}(1-a)\ln(1-k) & a=0 \end{Bmatrix}$$

(3)

  Where, T_p is denoted as loss function of cross-entropy, a is represented as real category label, and k is represented as probability value of prediction labels. Moreover, FT_p is denoted as focal loss function, α is represented as the balanced contribution of negative and positive samples. β is represented as the balanced contribution of easy and hard samples.

- **Segmentation**

  The COVID-19-affected region of the lungs is segmented in the Maxpooling layer by examining the pixel variation in each CT picture and making use of the tracking data. In order to guarantee precise segmentation of the COVID-19 lung-affected region, this layer updates the vulture's fitness functions. The weighting of problematic pixels is improved by the segmentation procedure, which includes both pixel-level and global-level supervision. Using the following equation (Eqn. 4), segmentation is carried out:

$$T_{seg} = T_{seg}(l_e, F_e)T_p + T_{edge} + \sum_{a=3}^{a=5} T_{seg}(l_e, F_e) JS(v) \quad (4)$$

Where, T_{seg} is denoted as the segmentation parts of COVID-19 lung region and T_p is mentioned as tracking results of the affected region and $JS(v)$ is represented as the fitness of vulture. The lung-affected region can be precisely segmented using the AVbADC method. The COVID-19 lung-affected region segmentation algorithm is given in Algorithm 1:

Algorithm:1 AVbADC for predicting COVID-19-affected cases

Start

Input: COVID-19 CT image dataset

Output: Predict COVID-19 affected patient

{

Initialization

{

Update the dataset ***// input layer***

// CT image dataset

}

Pre-processing ***// convolution layer***

// clean error and noise in the dataset

{

For all $\boldsymbol{d_e = 1}$ ***to all*** $\boldsymbol{l_e}$

{

Remove errors and noise // l_e - input CT images

// d_e -training flaws, errors and noises

End for

}

}

Feature extraction ***// convolution layer***

{

For all $\boldsymbol{A_1}$ ***and*** $\boldsymbol{A_2 = n^2}$

$F_e \rightarrow A_1, A_2$ // F_e - feature extraction of CT image

// A_1 - redundant information of CT image

// A_2 - relevant information of abnormality in CT images

End for

}

Affected region tracking ***//Maxpooling layer***

// track the position of lung-affected region

{

$T_p, FT_p \rightarrow \alpha, \beta, k$ // FT_p - focal loss function

// T_p - loss function of cross entropy,

// k - probability value of prediction labels

// α - balance contribution of negative and positive samples

// β - balance contribution of easy and hard samples.

```
    }
        Segmentation                                            // Maxpooling layer
        {
        Update vulture fitness
        // enhance the segmentation of lung affected parts
        Mask images
        // detect variation among pixels in the segmented region
            if (T_seg ≤ 100)
            {
            segment affected parts                          // real value
            }
                    if (T_seg ≤ 250)
                    {
                    Not segment                             // non-real value
                    }
                    End if
        }
        Classification                                          //Fully connected layer
        {
        classify the COVID-19 cases based on labels
            if (Cl_p = 1)
            {
            Positive COVID-19
            }
            end if
                else if (Cl_p = 0)
                {
                Negative COVID-19
                }
                End if
        }
      Predict COVID-19 cases                                    // output layer
      Finest output solutions
      }
End
```

- **Prediction**

  Thus the developed framework segments the position of the COVID-19 lung-affected region by variation of pixel value from the sample dataset. Finally, classify the positive and negative cases of COVID-19 in the fully connected layer. Consequently, the developed model classifies the COVID-19 cases with less execution time. Thus the classification is processed using Eqn. (5).

$$Cl_p = \begin{cases} -a\ln(k) & a=1 \\ -(1-a)\ln(1-k) & a=0 \end{cases} \quad (5)$$

The COVID-19 instances are then classified using the segmented results. The value of 0 in this classification procedure denotes non-real values, whereas the value of 1 denotes a real value, indicating the presence of COVID-19. Furthermore, a flowchart of designed AVbADC for segmenting COVID-19 lung-affected region and classifying COVID-19 cases are shown in fig.4.

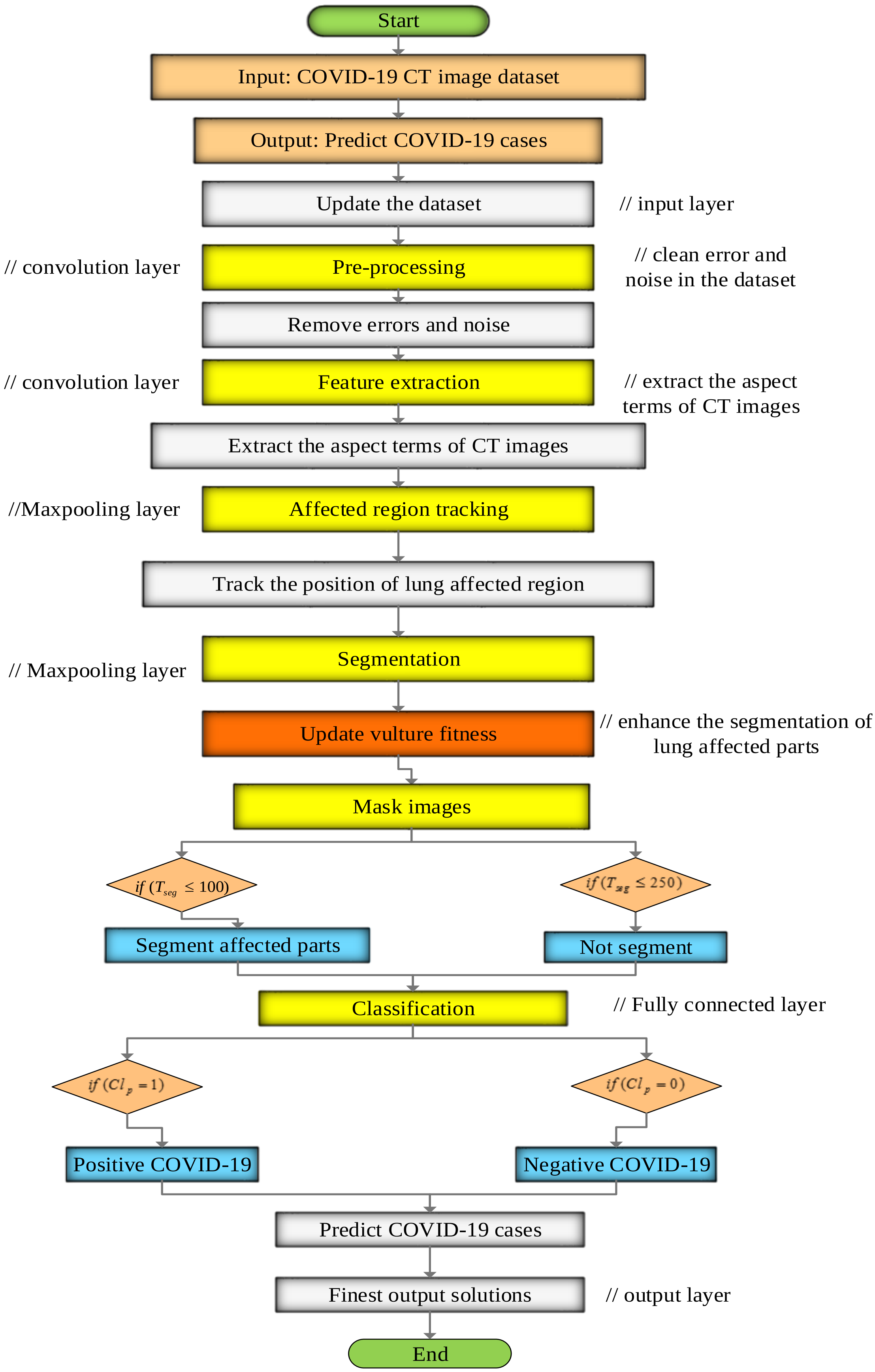


Fig.4 Flowchart of proposed AVbADC

5. Results And Discussion

By comparing the generated AVbADC model's accuracy, sensitivity, F-measure, precision, and recall to those of existing techniques, its performance is assessed using MATLAB. This strategy relies on using CT imaging to separate the COVID-19 lung afflicted areas. When predicting COVID-19 patients from CT images and segmenting lung-affected areas, the proposed AVbADC technique produces superior results. As a result, the generated model performs well in tasks requiring segmentation and classification. Figure 5 depicts the model's training loss and training accuracy.

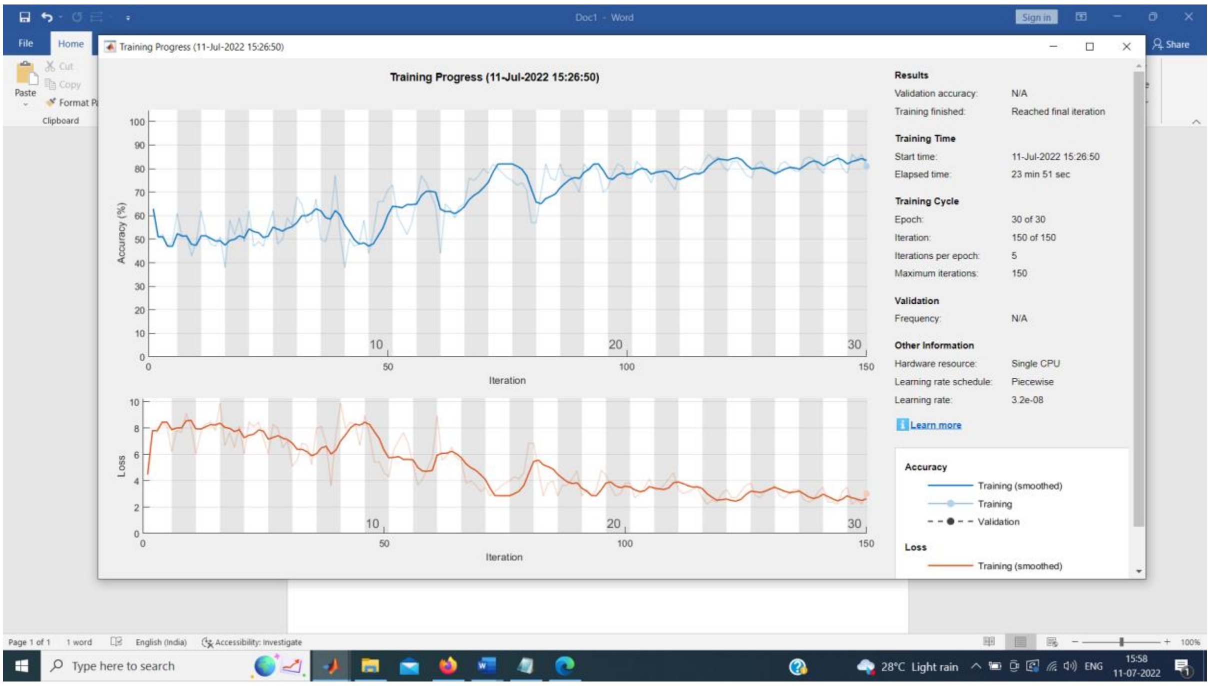


Fig.5 Training accuracy and training loss

5.1 Case study

The disease COVID-19, which affects people of all ages, is universally acknowledged as being extremely deadly. In order to save lives, early detection is essential, and the precise segmentation of COVID-19 lung-affected regions is necessary. The suggested AVbADC model is trained in this study utilising a dataset of lung CT images. The dataset is then segmented using the model to determine which parts of the lung are damaged. Sample CT input pictures for four patients are displayed as examples in Figure 6. The dataset is pre-processed and filter extraction is performed before segmentation in order to remove unnecessary mistakes and improve the image quality.

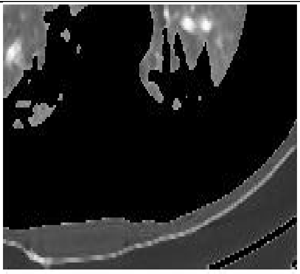
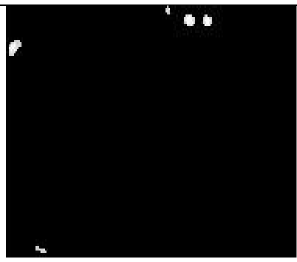
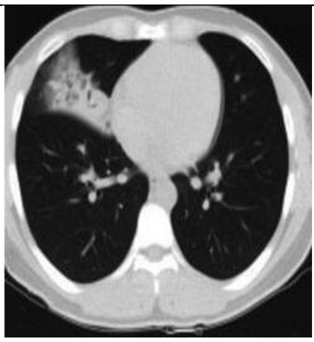
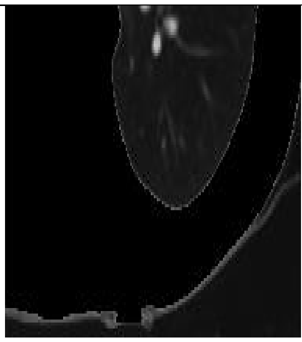
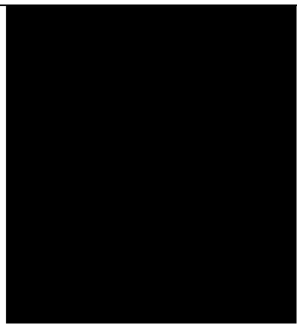
Input images	Segment part	Segment image	Predicted results
			Covid
			Non-Covid
			Covid
			Non-Covid

Table.6 Segmented and predicted results

The convolution layer of the proposed model performs a filtering operation on the input images to eliminate undesirable errors. The process of feature extraction comes next, during which pertinent features are extracted. The afflicted portion of the lung is subsequently divided using the Maxpooling layer. The suggested model uses the fitness function of the vulture optimisation strategy to increase segmentation accuracy. The COVID-19 and non-COVID-19 cases can be predicted in the fully connected layer thanks to the AVbADC approach's successful segmentation of the lung's damaged area. By segmenting the lung-affected region, the created approach enhances the segmentation outcomes and accurately forecasts COVID-19 instances.

5.2 Performance metrics

MATLAB was used to carry out the implementation of the developed AVbADC method. To assess the effectiveness of the approach, a number of measures including accuracy, sensitivity, recall, specificity, F1-measure, and precision were calculated. DL based Quantitative Analysis (DLQA) [23], AI Aiding in Diagnosing (AIAD) [24], Automated Quantification of COVID-19 (AQ) [25], Anamorphic Depth Embedding Convolutional (ADEC) model [26], and DL approach to Characterise COVID-19 Pneumonia (DLCP) [27] were all used to compare the effectiveness of the developed approach.

5.2.1 Accuracy

The effectiveness of the proposed model's performance is assessed using its accuracy. It is determined as the ratio of observations that were successfully predicted to all observations. Equation (6) uses mathematics to express this.

$$A = \frac{T_{po} + T_{ne}}{T_{po} + T_{ne} + F_{po} + F_{ne}} \qquad (6)$$

Where, T_{po} is denoted as precise prediction and correct segmentation, T_{ne} is denoted as precise prediction and incorrect segmentation, F_{po} is considered as imprecise prediction and correct segmentation and F_{ne} is denoted as imprecise prediction and incorrect segmentation of COVID-19 lungs affected parts. Moreover, the accuracy compared with the existing technique is detailed in fig.7.

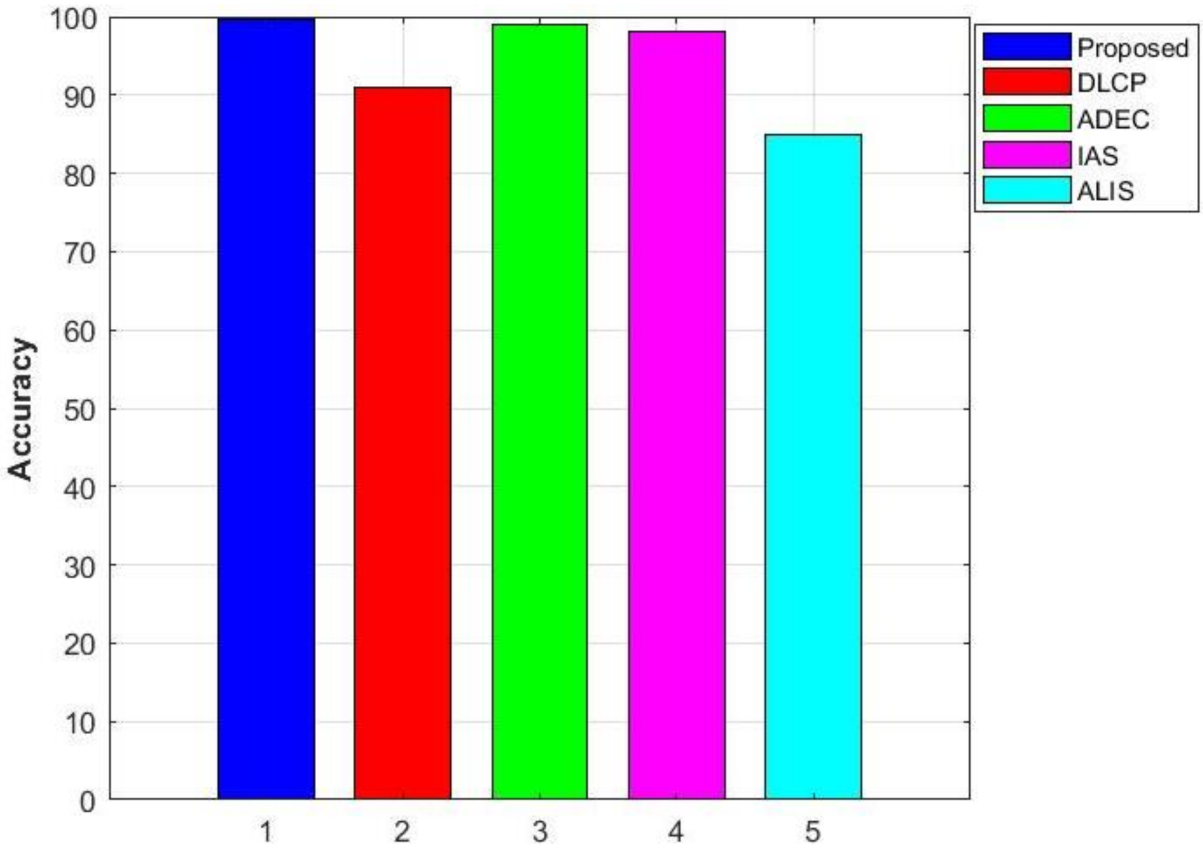


Fig.7 Comparison of accuracy

The new technique's accuracy rate is contrasted with that of other approaches already in use, such as ALIS, IAS, ADEC, and DLCP. The accuracy rate for the ALIS replica was 85%, while the accuracy rate for the IAS method was 98%. Additionally, accuracy rates of 99 percent and 91 percent, respectively, were reached by the DLCP and ADEC approaches. In contrast, the created AVbADC technique outperformed other methods, achieving an accuracy rate of 99.57 percent in accurately segmenting COVID-19 lung-affected areas.

5.2.2 Sensitivity

Sensitivity, also referred to as the true positive rate, is a metric used to determine how many true positives were accurately predicted. It measures how well a model can identify the specific lung regions that are impacted. Using Eqn. (7), which considers the ratio of the number of true positive predictions to the total number of real positive cases, the likelihood of segmenting the damaged lung regions is assessed.

$$S_{en} = \frac{T_{po}}{T_{po} + T_{ne}} \qquad (7)$$

The suggested AVbADC model's sensitivity is assessed and contrasted with that of other approaches, including OS, CN, RCNN, FST, and CCA approaches. The created technique's realised sensitivity rate is also contrasted with those of ALIS, IAS, DLCP, and ADEC approaches. The IAS technique got a sensitivity rate of 93.67 percent compared to the ALIS technique's 87 percent. The sensitivity rate for the ADEC method was 95.9%. These comparisons show how well the suggested AVbADC model performs in terms of sensitivity.

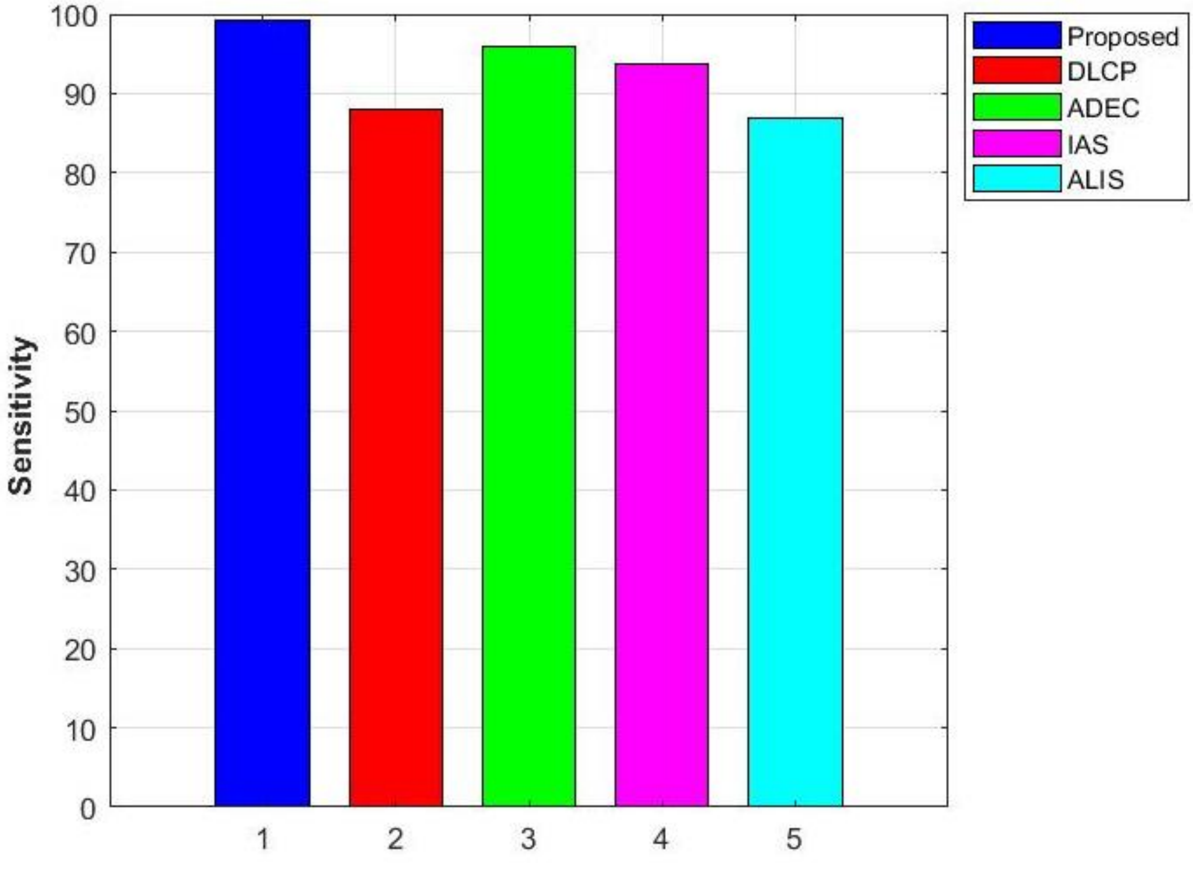


Fig.8 Comparison of sensitivity

When compared to existing methods, which only managed to obtain sensitivity levels of about 96 percent, the DLCP technique demonstrated a notable improvement, raising it by 88 percent. In contrast, the proposed AVbADC method outperformed existing approaches with a higher sensitivity of 99.12%. This illustrates how well the created model works. Fig. 8 also shows a graphic comparison of sensitivity.

5.2.3 Specificity

Specificity is a metric used to assess how accurately true negatives are identified. Additionally, it is used to evaluate how well afflicted lung regions can be separated using mask pictures. Eqn. (8), which offers the mathematical expression for this measure, is used to calculate specificity.

$$S_{pe} = \frac{T_{ne}}{T_{po} + T_{ne}} \quad (8)$$

The new technique's specificity rate is contrasted with those of other approaches already in use, such as ALIS, IAS, DLCP, and ADEC. For instance, when evaluated on a COVID-19 dataset with 100 samples, the ALIS technique had a specificity rate of 97.4%. Furthermore, the specificity rate of DLQA technique is 88.05 percent, respectively. Furthermore, the ADEC and DLCP methods achieve 99.7 percent and 95 percent, respectively. When compared to other techniques for segmenting affected parts of the lungs, the developed AVbADC achieved a high specificity of 99.56 percent. Figure 9 depicts a comparison of specificity.

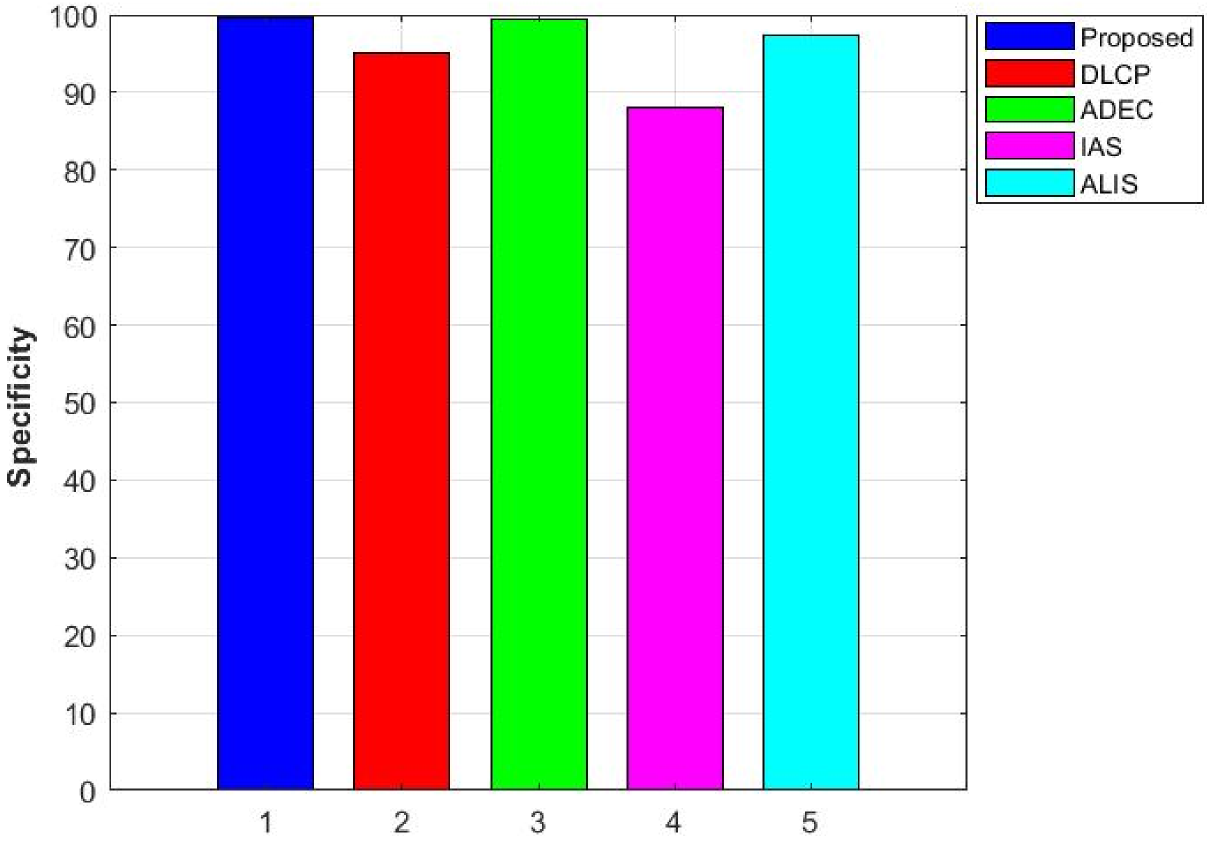


Fig.9 Comparison of Specificity

5.2.4 Precision

This process was used to assess how many correctly identified positive instances there were relative to all positive cases. Equation (9) illustrates how precision is calculated as the ratio of the appropriately segmented COVID-19 lungs impacted sections to the overall positive estimates.

$$P = \frac{T_{po}}{T_{po} + F_{po}} \quad (9)$$

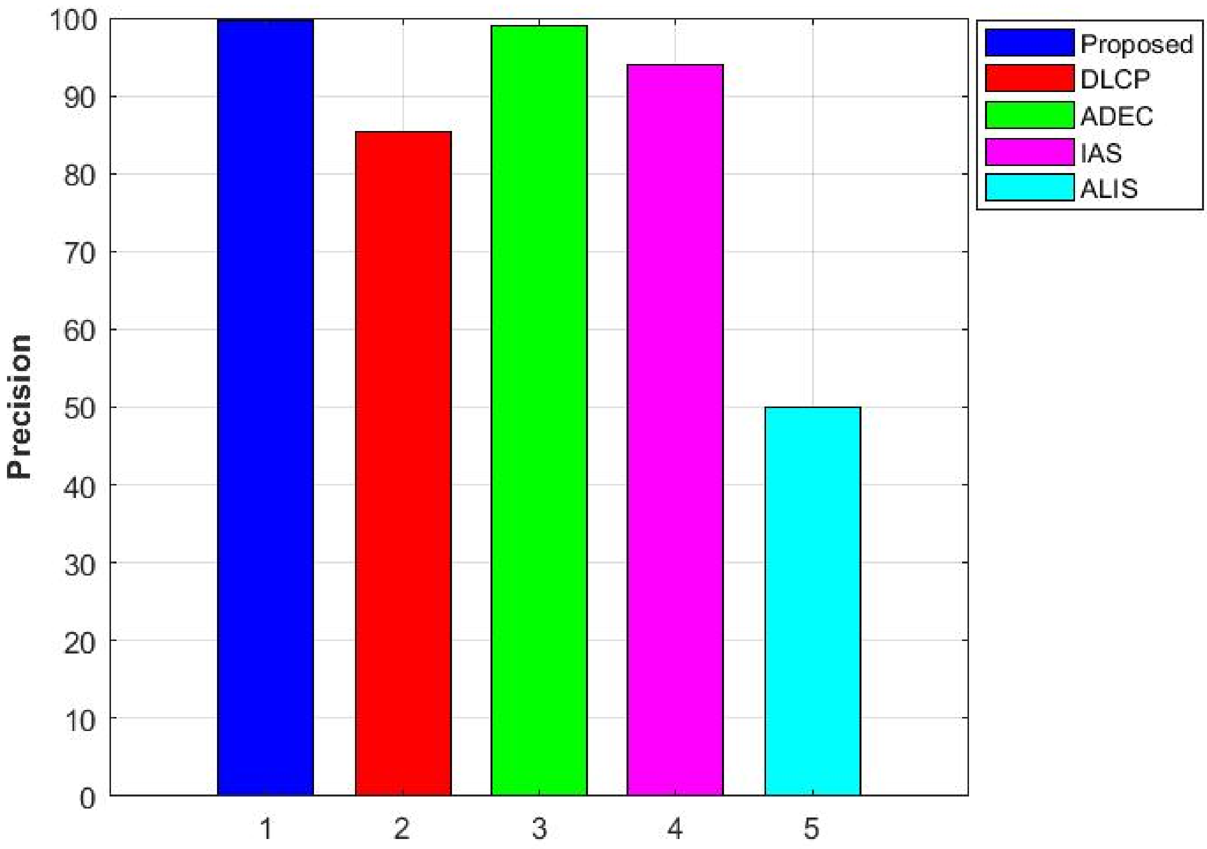


Fig.10 Comparison of Precision

The suggested AVbADC model's precision is evaluated and contrasted with well-known techniques as the ALIS, IAS, ADEC, and DLCP approaches. Using a dataset of 100 samples, the IAS replica improved its precision rate by 94% while the ALIS approach exhibited a 50% improvement. Additionally, the accuracy rates for the DLCP and ADEC approaches were 99% and 85.4%, respectively. The created AVbADC method, in contrast, managed to attain a precision rate of 99.57%. Figure 10 shows a comparison of the precision rate.

5.2.5 F-measure

Equation (10 is used to calculate precision and recall metrics, which are used to assess the effectiveness of segmenting and tracking COVID-19 lungs-affected areas.

$$F - measure = 2\left(\frac{P * R}{P + R}\right) \quad (10)$$

Let R stand in for the calculated recall value, and let P represent the determined accuracy value. The suggested AVbADC model's F1-score is calculated and contrasted with current approaches like ALIS, IAS, ADEC, and DLCP approaches. Figure 11 shows how the F-measures are compared.

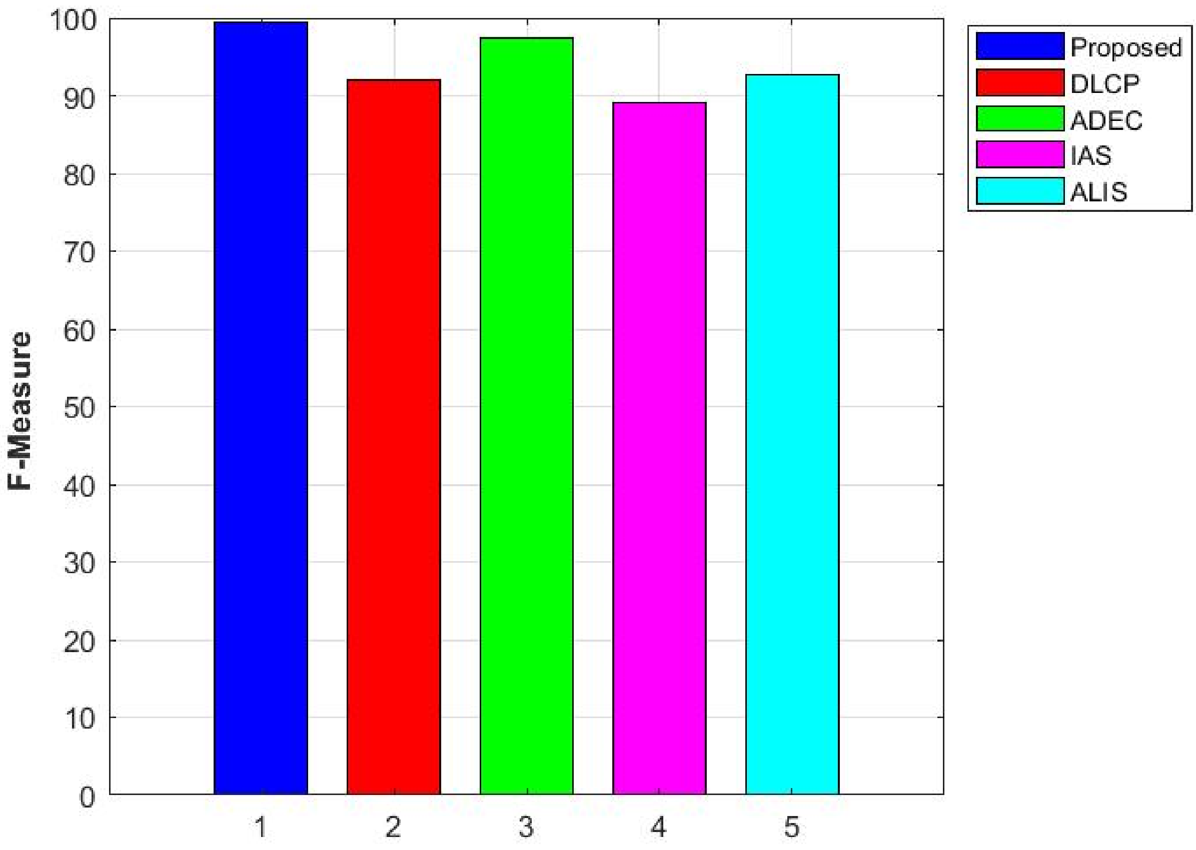


Fig.11 Comparison of F-measure

Initially, the IAS technique achieved an F-measure of 89 percent, the ADEC replica achieved a precision of 97.31 percent, ALIS model gained 92.7 percent for a 100-sample dataset, and the DLCP methods achieved an F-measure of 92 percent. The duplicate of our method that has been produced gets a high f-measure of 99 percent when compared to other methods already in use.

5.2.6 Area under Curve (AUC)

The AUC between two points is calculated by performing a perfect integration between two points. Furthermore, the identification of the under the curve is calculated by integrating through the given limits. It is a measure of quantitative diagnostic test accuracy, as well as the average possible value of specificity and sensitivity. Figure 12 depicts the obtained AUC results with other existing replicas.

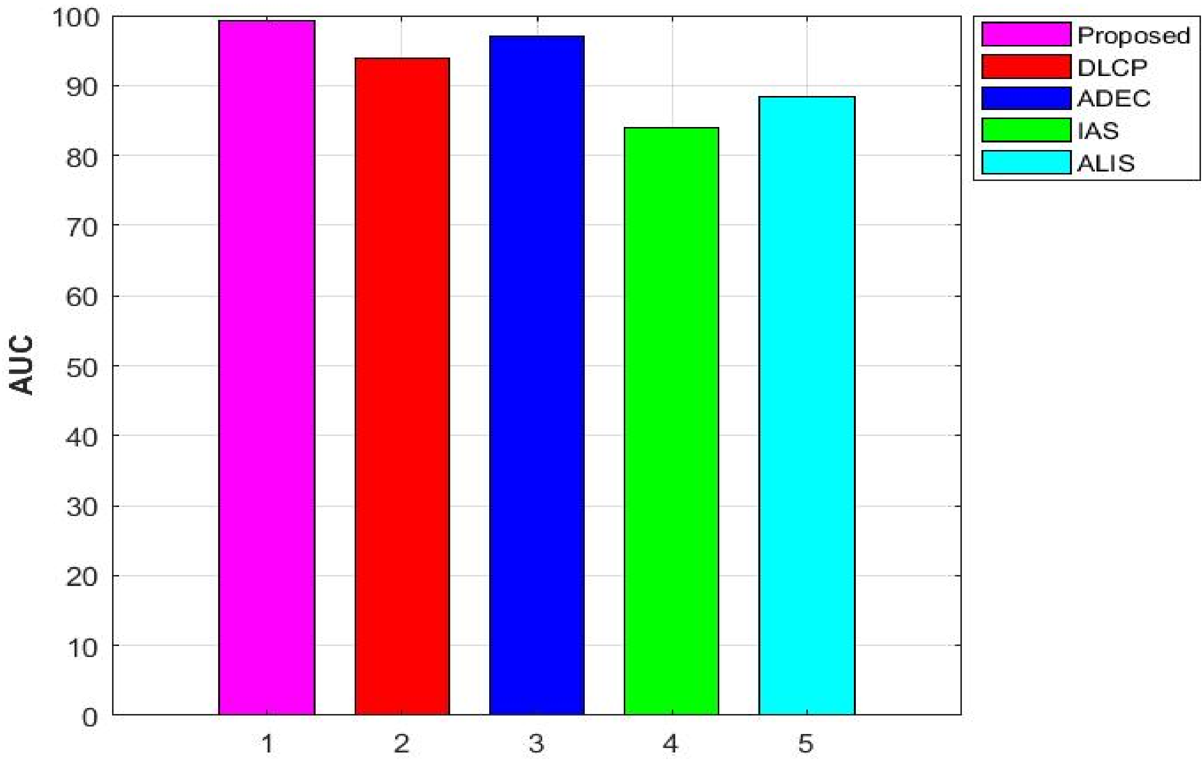


Fig.12 Comparison of AUC

The AUC result is compared to other existing approaches such as ALIS, IAS, ADEC and DLCP approaches. Furthermore, ALIS and IAS techniques achieved an AUC of 88.4 percent and 84 percent, while ADEC and DLCP models achieved an AUC of 97 percent and 94 percent. Finally, the developed AVbADC technique achieved 99.2 percent accuracy in segmenting COVID-19-affected lungs.

5.3 Discussion

In comparison to existing models, the suggested AVbADC model outperformed them in terms of accuracy, sensitivity, specificity, F-measure, precision, and AUC. The suggested technique enhanced segmentation outcomes by eliminating training faults and retrieving pertinent characteristics from COVID-19 lung-affected regions. The segmentation of COVID-19-infected lungs utilising mask pictures was done using the classification layer to improve the performance of the AVbADC approach.

Table.1 Measures for overall performance

Methods	Performance evaluation using important metrics		
	Sensitivity	**Accuracy**	**specificity**
ALIS	87	85	97.4
ADEC	95.9	99	99.7
DLCP	88	91	95
Proposed	99.12	99.57	99.56

The outstanding performance measures comparisons are computed in table.1, and the proposed AVbADC has obtained the best results in all parameter validation. Furthermore, they achieved 99.12 percent sensitivity, 99.56 percent specificity, and 99.57 percent segmented accuracy. The suggested AVbADC method's robustness has been confirmed, demonstrating that it can precisely segment the lung-affected regions brought on by COVID-19.

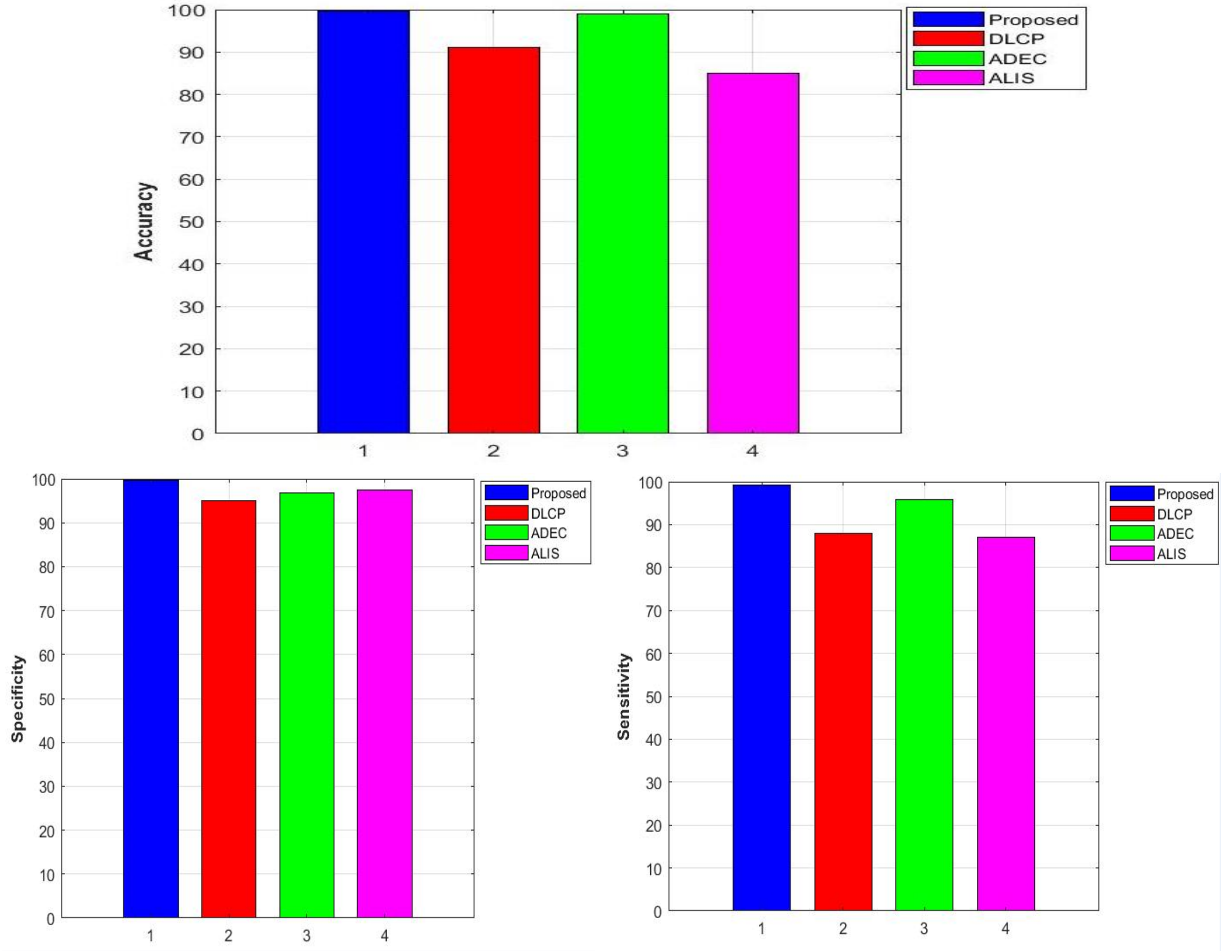


Fig.13 Overall performance

6. Conclusions

This study introduces a brand-new AVbADC method for segmenting the lung-affected areas in COVID-19 patients. Using CT scans as its training data, the system goes through a number of processes, including pre-processing, feature extraction, affected region tracking, and segmentation. The afflicted lungs are then segmented using the created AVbADC model on a dataset of CT images. To determine which areas of the lungs are affected by COVID-19, the segmented images are further examined. When compared to existing models, the suggested model performs better in terms of accuracy, sensitivity, specificity, precision, and AUC. Notably, the model segments the lung-affected areas with a high accuracy of 99.57 percent. This work offers a useful way for precisely segmenting the lung-affected areas brought on by COVID-19 using CT scans and the AVbADC approach. The suggested model's increased performance demonstrates its potential to help doctors diagnose and plan treatments for COVID-19 patients.

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