NEW Generation Computing



A Hybrid Deep Neural Approach for Segmenting the COVID Affection Area from the Lungs X-Ray Images

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Abstract

Nowadays, COVID severity prediction has attracted widely in medical research because of the disease severity. Hence, the image processing application is also utilized to analyze COVID severity identification using lungs X-ray images. Thus, several intelligent schemes were employed to detect the COVID-affected part of the lungs X-ray images. However, the traditional neural approaches reported less severity classification accuracy due to the image complexity score. So, the present study has presented a novel chimp-based Adaboost Severity Analysis (CbASA) implemented in the MATLAB environment. Hence, the lung's X-ray images are utilized to test the working performance of the designed model. All public imaging data sources contain more noisy features, so the noise features are removed in the initial hidden layer of the novel CbASA then the noise-free data is imported into the classification phase. Feature extraction, segmentation, and severity specification have been performed in the classification layer. Finally, the performance of the classification score has been measured and compared with other models. Subsequently, the presented novel CbASA has earned the finest classification outcome.

Keywords Severity Classification \cdot Feature Extraction \cdot Segmentation \cdot Lungs X-ray Image \cdot Pre-processing \cdot Deep LearniIntroduction

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1 Introduction

During the pandemic period of COVID-19, the whole world gets affected by the coronavirus, which was first found in China in 2019 [1]. The most dangerous factor of this virus spread is across the air and physical contact among people [2]. This virus directly affects the lungs and causes lung fever [3]. In the early period, it isn't easy to reduce the influence of COVID-19 [4]. Hence, the public has suffered greatly by protecting their lives against COVID [5]. So, several digital systems have been introduced, like biological prediction systems and respiratory monitoring [6]. The basic COVID analysis process is described in Fig. 1.

But those procedures have required more time to analyze the COVID affection range and the possibility of occurrence [7]. Considering those issues, the imaging system was established based on the functional neural features [8]. Moreover, the hybrid deep neural network is modelled by combining the Classification of similar Conventional Neural Networks (CNN) [9]. Similarly, the classifiers are developed by the feature of inputs and required neuron counts [10]. In deep neural networks, there are many hidden layers in-between, the output layer and input layers [11]. That hidden layer weighs the trained samples before entering the classification process [12].

So, the medical imaging system is chiefly focused by medical researchers for analyzing the disease affection range with more possible ranges [13]. The main two techniques here are taking X-ray and Tomography [14]. But, those models required more sources to find the exact disease severity level [15]. Considering these drawbacks, artificial Intelligence (AI) techniques were introduced in the imaging application to find the severity level with high accuracy [16]. Hence, analyzing the lung's



Fig. 1 COVID analysis

X-rays shows the lungs affected region with better visualization [17]. This helped to find the disease severity level with the maximum possible exactness score [18]. By the manual way, the test takes a long period; therefore, a machine learning technique is introduced to fight COVID-19 [19]. According to the many theories of deep learning (DL), the literature introduces the normal machine learning technique with some basic characteristics like selecting and extracting [20], which have afforded the average disease prediction outcome. Also, those models needed dimensional reduction features to reduce the running time and algorithm complexity [21]. As the next step, the DL and normal machine learning techniques are called hybrid networks, which afforded the finest detection results than the traditional neural models.

In recent, several intelligent mechanisms like DL [22], transfer learning [23], CoroDet [24], etc., have been introduced to end these issues COVID affected region segmentation issues. But, each model has met some difficulties like high resources requirement, more execution time and wrong predictions. In addition, the deep networks are effectively utilized in detecting the disease-affected region from the image data. But, those models have required additional features like Classification and the pre-processing module to earn the finest outcome. Considering these issues boosting models are rich with boosting parameters that have offered the finest pre-processing and prediction outcome. So, the present study has focussed on the ensemble model for disease prediction application. Hence, the present study has planned to create an optimized boosting system for the COVID severity specification process. This severity specification, like medium and high, is beneficial in treating COVID patients with much care. Also, considering other intelligent models, the optimized boosting model has afforded the finest outcome in filtering and segmentation. It has led to attaining t6he accurate segmentation and Classification. The key contribution of the current study is elaborated as follows:

- The lung's X-ray images are primarily collected and imported to the system; it contains COVID and Non- COVID images.
- Then the error features in the imported database were filtered in the pre-processing phases.
- Moreover, the error-cleared data is given as the input for the classification function.
- Consequently, features analysis was performed, and key lung features were extracted.
- Furthermore, the disease features are tracked from the extracted features and segmentation is performed.
- Finally, the COVID affection severity range has been validated in dual classes that are medium and high.
- Subsequently, the success rate of the designed model has been analyzed in terms of precision, recall, accuracy, error rate, and F-measure.

The present study is structured as follows; the recent related literature is surveyed in the way of merits and drawbacks exposed in the 2^{nd} section, and the problems in the usual COVID severity analysis system are defined in the 3^{rd} section. The solution for the described issues is elaborated in the 4^{th} section, the outcome of the detailed proposed solution is detailed in the 5^{th} section, and the research study is ended in the 6^{th} conclusion section.

2 Related Works

Some of the recent literatures related to COVID severity analysis is explained as follows:

COVID-19 has affected numerous people by their harmfulness. Also, the final stage of COVID cases can lead to death. So, the deep learning charcateritics were executed [22], it depends on the X-ray images and the characteristics of the selection method. Here, the deep network models were trained with COVID disease features; during the testing process, the trained disease features were analyzed, and the affected region was predicted. Considering the machine learning schemes, the deep network has afforded the finest disease prediction outcome. But it has recorded high computational costs.

Recently, the Reverse-Transcription Polymerase Chain (RTPC) Reaction has been used to discover the coronavirus in the chest X-Ray technique and proved it to be most successful while detecting the virus effect. But, this model required an additional prediction algorithm for detecting the disease-affected region from the trained X-ray images. Therefore, the RTPC along with the deep network features [23] was described for forecasting the disease-affected region. This approach has provided the finest disease detection outcome but has resulted in a high error rate.

The requirement of the COVID detection framework is more important to forecasting COVID affection in an earlier stage and treating them. So, the CoroDet [24] was estabilished for the Covid prediction program. The CoroDet was based on the deep network features and the classification modules. Compared to the conventional deep neural system, less error score has been recorded. However, it has required more execution time.

The hierarchical segmentation procedure [25] for analyzing and segmenting the affected region from the trained lung's X-ray images. Here, the segmentation process is automated for every x-ray image, which affords the finest flexibility score compared to the traditional models. But, if the disease features have been varied, then the right prediction is difficult. However, it has recorded a high miss classification rate.

Usually, the neural models have performed well in prediction and classification applications. But some neural system features were limited in analyzing the image features. So, the depth-wise dense features [26] have introduced in the deep networks for improving the functional features for predicting different events. Later, the implemented model was tested with the lungs X-ray database, which contains the COVID disease features, and the performance was validated based on the COVID severity prediction rate. Hence, this model provided the widest COVID detection accuracy. However, it is complex to design functional models [30].

Recently, the K-Nearest Neighbors (KNN) with the convolution neural networks [31] and other classifiers, such as the support vector model, boosting model and other neural classifiers were tested for the COVID prediction applications. The KNN model scores the finest classification exactness outcome through this comparative analysis. But, the KNN classifier is ineffective when operated as a single algorithm. Thus a combination of other complex problems is required.

Due to the image complexity score, the image feature analysis algorithm has met high complexity score. So, the Decision tree functions along with image analyzing features [32] were introduced for processing the X-ray images and finding the abnormality region. Considering other intelligent models, the decision tree required less processing time. However, the disease prediction is not appropriate.

The key limitation of the Convolutional neural model is that it doesn't take the previous layer output as the input of the following layer, which has tended to cause less prediction score. So, the serial section in the convolutional neural model [33] was introduced for serially making the functional operation. Compared to the traditional Convolutional neural system, this serial section convolutional model afforded the finest outcome. However, it displays the average disease prediction score.

3 System Model with Problem

The key drawback behind the medical image for extracting the image features is the highly noisy content. However, analyzing the medical images is the most required task for better visualization of the disease severity range. The conventional disease analysis system with the problem is described in Fig. 2. Hence, filtering is the most required task for eliminating the noise features from the trained X-ray images to attain the finest disease analysis outcome.

So, several filtering models have been proposed along with the deep networks and intelligent models in past studies to filter the noisy content and to gain a better feature tracking outcome. However, the vast image count and unique complexity of each image have made it difficult to analyze the features [27]. Hence, the high feature analysis time has resulted in high computation costs. These issues have motivated this study to implement the novel optimized boosting networks.

4 Proposed CbASA for COVID Severity Classification

A novel chimp-based Adaboost severity analysis (CbASA) has been introduced in the present study to extract the COVID-affected region and estimate the severity range. The Dataset considered in this research for testing the present model is lung X-ray images. Primarily, the images were pre-processed to eliminate the noise features from the current image data. Consequently, the feature extraction and severity analysis process have been performed. Finally, the COVID affection severity range has been validated. Then the prediction parameters are calculated and compared with other models. Hence, the proposed architecture is described in Fig. 3.

Here, the optimal boosting parameter was provided with the finest error eliminating and the feature analysis outcome. This has resulted in a high COVID severity classification exactness score.

4.1 Process of Proposed CbASA

The planned system has five phases: input layer, pre-processing phase, classification layer, optimal layer, and output phase. Here, the noise removal function is



Fig. 2 COVID analysis system with problem



performed in the hidden layer of the novel CbASA. Then the error-cleared image data is imported into the classification phase.

Here, the designed system has functioned based on the principle of the chimp algorithm [28] and AdaBoost mechanism [29]. Moreover, the layered architecture is described in Fig. 4. Here, the layer sizes are not fixed; their sizes are based on dataset n sizes, which are determined as 1/n.

4.1.1 Pre-processing Module

The function pre-processing has been executed to make the data in clear visualization. After executing the pre-processing module, the finest error-less data has been gained. Then the present filtered data is utilized for the further process: feature analysis and severity classification function. Hence, the data importing process has been executed by eqn. (1). Here, the data training process is performed in the initial layer of the novel CbASA. The AdaBoost tree nodes and chimp initialization are processed for initializing the dataset variables.

$$F(G) = G\{1, 2, 3, \dots n\}$$
(1)

Here, the COVID lung X-ray image database is determined G, and the n number of COVID lungs X-ray image samples is described $\{1, 2, 3, ..., n\}$. Consequently,



the pre-processing process has been defined in Eq. (2). This equation is adopted from the chimp algorithm, which is the function defining the prey's position. Here, it is utilized to find the noisy features and eliminate them.

$$H = \frac{G(s-a)}{G} \tag{2}$$

Here, the noisy features are determined as weak features that are eliminated from the trained image database. Moreover, the pre-processing variable is represented as H, normal features are described as s, and the noisy features are defined as a.

4.1.2 Feature Analysis

The feature analysis function has to be performed to extract the present COVID affected feature from the test. The raw data contains an additional unwanted feature that has made it difficult to forecast the disease features. Hence, fewer features are eliminated to minimize the algorithm complexity and computation cost. Moreover, the present features in the test set have been extracted in this feature analysis portion. Consequently, the extracted image features are imported as the input of the classification module to value the severity range. The chimp algorithm employs the preychasing function to extract the required features. The desired X-ray pixels were fixed in the chimp memory model to extract the features. This memory model is activated during the feature analysis model to find the finest feature extraction outcome.

$$O = |G(t, y) - G(y)|$$
(3)

The trained lung features are represented as t, y. Here, y is the meaningless features and t is the meaningful features. Here, the meaningless features are removed from the trained datasets, and the feature analysis variable is defined as O, which is formulated in Eq. (3).

4.1.3 Segmentation and Classification

From the extracted image features, the disease features are traced and segmented. Then the segmented disease region is considered for the severity classification functions.

$$O_s = \frac{d1^* + d2^* + d3^* \dots dn^*}{total \ disease \ feature} \tag{4}$$

Here, the segmentation variable is defined as O_s , disease features are described as $d1^* + d2^* + d3^*...dn^*$ and the classification parameter is determined as C_G . Here, the segmentation is carriedout using the option best solution of the chimp algorithm. Here, the best solution of the chimp is finding the best prey location. Based on that finding, the fitness of each chimp was updated. Then based on the updated best fitness range, the best chimp was selected; this process is utilized for the disease severity classification process. ł

```
Algorithm: 1 CbASA
start
    int G = 1, 2, 3...n;
   // Dataset initialization
   Pre-processing ()
   // chimps position defining for hunting the prey
   {
          int H, s, a;
          // initializing pre-processing variable
           H \rightarrow remove \ d(G)
          // removing the noise features
    ł
    Feature extraction (chasing prey function of chimp)
    ł
          int O, t, y;
          // initializing the feature analyzing variable
          O(G) = neglecting G(y) \leftarrow G
          // neglecting the unwanted features
   ł
   Segmentation ()
    ł
          int O_s, d^*;
          // segmentation variables are initialized with the chimp optimal location finding
          behavior
          segment \rightarrow d1^* + d2^* + d3^* \dots dn^*
          // disease features are traced and segmented
    ł
   Classification ()
    ł
          int C_G;
          // initializing the classification variable
                   if(O_s = 0)
                   ł
                   normal
                   }else (medium/high)
                   // hence, the COVID affection severity was estimated
    ł
   stop
```

Here, the COVID range severity has been categorized into dual classes that are medium and high. Moreover, 'if' condition was employed to find the severity range of the COVID affection, and the classes considered for this severity specification were processed by the labelled 0, 1 and 2.

$$C_{G} = \begin{cases} if(O_{s} = 2) & High \\ if(O_{s} = 1) & medium \\ if(O_{s} = 0) & normal \end{cases}$$
(5)

Also, if the segmented affected part is specified under the 1st class, it is specified as medium severity. If no segmentation occurs, then the segmentation class is said to be '0', which belongs to the Normal class. In this chimp, the fitness function classification range was fixed during the execution. Moreover, if the segmented part is specified under the second class, it is considered high severity.

The described mathematical formulas are structured in algorithm 1; based on this defined algorithm COVID affection region segmentation and severity analysis have been performed. In addition, the steps in the designed model have been ordered in a flowchart diagrammatically exposed in Fig. 5.

5 Results and Discussion

The planned COVID severity analysis framework is executed in the MATLAB platform and running in the windows 10 environment. Here, the execution parameters are defined in Table 1. The defined model has been processed in the ratio of 80:20, which is 80% training and 20% testing.

The optimized Adaboost mechanism predicts the COVID-affected area and severity range. Here, the boosting parameters with optimization have provided better error removal and severity classification results.

5.1 Case Study

This case study has been elaborated to calculate the successive rate of the presented novel approach. A few images were taken for the testing process, and the designed algorithm was applied; then, the segmentation accuracy and severity estimation effectiveness were measured. Hence, the Lungs X-ray dataset specification is defined in Table 2.

Here, the COVID-affected region segmentation was processed based on the ground truth image. The X-ray COVID-19 database from the Kaggle is considered for this present study; it contains 20,000 samples, including normal and affected lung X-rays. Besides, the ground truth images are also present in the database that helps to identify the COVID-affected region by matching with the test image. While matching, if there is any similarity between the ground truth and the tested images, then that region is tracked and segmented.



Here, four samples were taken to measure the stability range of the segmentation process, features extracted for each sample, and the affected area was segmented. Subsequently, affection range severity has measured, and the metrics were calculated

Table 2 Dataset specification	Dataset description		
	X-ray images description	Count	
	- Total images	20,000	
	Training	16,000	
	Testing	4000	
	Trained normal images	10,000	
	Normal images for testing	20,000	
	Trained medium-severity images	7000	
	medium severity images for testing	1400	
	Trained high-severity images	3000	
	high severity images for testing	600	

and validated with other models. The tested results are described in Table 3. Here, in the chimp position defining fitness formulation eqn. (3), the disease features are fixed in the tracking memory. Hence, while executing the chimp algorithm, the present features in the test images are extracted based on the saved features in chimp memory.

The reason for utilizing the chimp function for segmentation and severity classification purposes is to gain the finest disease features tracing results and exact severity categorization outcomes.

Before the testing process, the affected part segmentation and severity classification efficiency were measured by generating the validation graph for loss and accuracy metrics that are defined in Fig. 6. In this accuracy and loss validation, if the approach has gained the finest validation accuracy, then the model is good in segmenting and severity classification.

The confusion matrix that was gained during the classification process is defined in Fig. 7. Based on the confusion matrix, the performance metrics determined the classification outcome.

5.2 Performance Validation

The key parameters of the designed framework have been calculated to value the best function performance of the designed model. Here, the accuracy has been measured to find the exactness of the COVID severity prediction from the lungs X-ray images. Moreover, the accuracy metrics are valued by eqn. (6) The exactness score was measured by finding the mean between the total and extract detection.

$$Accuracy = \frac{Exact \ prediction}{Total \ prediction} \tag{6}$$

In addition, the precision score has been measured to estimate the positive score in predicting the COVID affected range and severity classification. Hence, the

S.no	Samples	Feature extraction	Segmentation
1			high
2			high
3			medi um
4			medi um
			norm al

Table 3 Testing results

precision metrics are described using eqn. (7). Moreover, precision is also called specificity.

$$Precision = \frac{true \ positive}{False \ Positive + \ True \ Positive}$$
(7)



Fig. 6 Accuracy and loss validation



Fig. 7 confusion matrix

The recall metrics are measured to measure the sensitive score in finding the severity range with the presence of a false class. Hence, the recall metrics are determined by eqn. (8),

$$Recall = \frac{true \ positive}{False \ negative + True \ Positive}$$
(8)

Moreover, to find the mean exactness in the COVID region segmentation and severity classification, the F-values were measured, which is defined in eqn. (9). Here, the product and summation of the precision and recall score have afforded the F-measure value.

$$F_Value = \frac{1}{2} \times \frac{recall \times precision}{recall + precision}$$
(9)

The overall performance of the designed framework is explained in Fig. 8. Here, all the classification metrics have recorded the finest score, which is more than 97%; this has verified the efficiency score of the developed model.

5.3 Comparison Validation

To measure the successive range of the designated approach in specifying the COVID severity range few existing models are considered that are K-nearest Model (KNM), Support Vector Approach (SVA), Decision Tree Model (DTM), and Serial Network based Convolution Neural Model (SNbCNM) [27].

The approach KNM has measured the exactness score as 95.7%, sensitivity as 92.2%, F-score as 93.9%, and specificity value as 97.4%. The scheme SVA has described sensitivity value as 91%, accuracy 98.9%, specificity 99.7%, and F-score



Fig. 8 Performance validation

96.7%. Then the framework DTM earned F-score of 94.5%, specificity of 97.7%, the sensitivity of 93.8% and 96.1% accuracy.

The SNbCNM has earned an accuracy score of 97.1%, a sensitivity of 94.6%, F-score of 95.7%, and a specificity of 98.2%. In addition, the success rate of the designed model is validated in dual phases before applying the chimp model and after applying the chimp model, which is Before Optimization (BO) and After Optimization (AO). Hence, before applying the chimp function, the recorded accuracy score is 96.3%, sensitivity 95%, F-score 96%, and specificity 97%. After executing the chimp model, the recorded accuracy score is 99%, sensitivity 98%, F-value 98%, and specificity score 99.9%.

Hence, the comparison of sensitivity and accuracy is defined in Fig. 9, and F-measure and specificity are detailed in Fig. 10. Moreover, the overall comparison statistics are detailed in Table 4.

5.4 Discussion

The measure performance assessment has given the finest segmentation and classification outcomes. In addition, to prove and require the Chimp model in the boosting mechanism, the performance assessment has been conducted in the dual phases before and after executing the chimp functions. In addition, the algorithm robustness is analyzed by validating the algorithm's complexity score and computation cost. Those performance statistics are exposed in Table 5.

Here, the miss classification score is also validated for the two models with and without incorporation of the chimp fitness solution. In that, the optimal outcome is attained after applying the chimp model. The error rate recorded for the presented model after performing the chimp model is just 1%. Before applying the chimp function, the presented severity analysis system recorded a 3.6% of error score. Hence, the need for the optimal model in the presented framework has been proved. This present study's key significance is improving the medical process by providing



Fig. 9 Validation of accuracy and sensitivity



Fig. 10 Specificity and F-measure validation

suitable treatment and medicines to COVID-affected people. Here, the COVID type is classified under medium and severe if it is severe, then special treatment and care were a need for those patients. Considering this significance, the presented study has implemented the COVID segmentation and severity evaluation process.

6 Conclusion

A novel CbASA has been executed in the MATLAB environment for classifying the COVID severity range from the Lung's X-ray images. Initially, the present features were analyzed, and the disease features were tracked. Consequently, segmentation and classification function has been performed. Finally, the presented approach has recorded the best classification score of 99% compared to other models; it has maximized the segmentation and severity classification score by 2%. Moreover, the recorded sensitivity value is 98%, while validating the conventional models, the sensitivity range has improved by 2%. Moreover, before applying the chimp model, the recorded sensitivity score was 95%. Hence, after applying the chimp model, the sensitivity score has been maximized by 3%. This has verified the need for the optimal solution in the boosting mechanism for attaining the finest segmentation and classification outcome. In future, incorporating the resource analysis system will help to measure the algorithm complexity and to implement the further optimal solution.

Data Availability Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

Declarations

Conflict of Interest The authors declare that they have no potential conflict of interest.

97

99.9

F-value (%)	Specificity (%)
93.9	97.4
96.7	99.7
94.5	97.7
95.7	98.2
	F-value (%) 93.9 96.7 94.5 95.7

95

98

Table 4 Comparison statistics

96.3 99

Table 5 Algorithm complexity and computation cost Image: Complexity	Robustness assessment			
	Methods	Algorithm complexity (%)	Computa- tion cost (ms)	
	KNM	31	34	
	SVA	45	30	
	DTM	21	27	
	SNbCNM	19	25	
	Proposed (BO)	15	24	
	Proposed (AO)	5	9	

96

98

Ethical Approval All applicable institutional and/or national guidelines for the care and use of animals were followed.

Informed Consent For this type of analysis formal consent is not needed.

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Proposed (BO)

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