Deep Convolution Neural Network with Gradient Boosting Tree for COVID-19 Diagnosis and Classification Model

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Abstract: ***Coronavirus is an epidemic that greatly distresses people all over the globe. The similarities amongst the COVID-19 and other lung diseases are highly equivalent and it makes it difficult to diagnose it. The currently presented deep learning (DL) models offer a method to identify the presence of COVID-19 from the radiological images. In this view, this paper presents a new deep convolutional neural network based AlexNet model with Gradient Boosting Tree (DCNNAN-GBT) model for COVID-19 diagnosis and classification. The presented DCNNAN-GBT model involves Gaussian filtering (GF) based preprocessing approach to remove the noise exists in the radiological images. In addition, AlexNet model is employed as a feature extractor to derive a useful set of feature vectors. Besides, GBT model is applied as a classification technique to allocate proper class labels to the input images. A wider experimental analysis was performed to highlight the effective COVID-19 diagnostic outcome. The experimental results pointed out that the DCNNAN-GBT model has resulted in a maximum average sensitivity of 94.32%, specificity of 93.10%, and accuracy of 94.13%.***

Keywords: COVID-19, Classification, Deep learning, Radiological images, GBT

1. INTRODUCTION:

In recent times, a deadly disease called corona has been spread over the world which is caused by the virus named Coronavirus belongs to a virus family and some of them are: Middle East Respiratory Syndrome (MERS) and Severe Acute Respiratory Syndrome (SARS) [1]. Recently, few models have been discovered for predicting COVID-19 for examining biotic material gained from the patients by using Polymerase Chain Reaction (PCR). One of the major challenges is that swab is performed for individuals affected with COVID, and existing some COVID patients have no symptoms unless examining in hospitals. Even though the prediction task is validated using PCR, COVID patients have defected with pneumonia can be found in chest X-rays as well as Computed Tomography (CT) images. Also, it is slightly examined by human eye when assured by the developers in [2]. The COVID-19 spreading rate depends upon the number of infected people with lower False Negatives (FN). Also, a minimum False Positives (FP) rate is highly required for developing a clinical system by isolating the patients. Using the applicable contamination controller, it is ensured that the earlier disease identification enables increased lifetime for COVID-19patients.

By the end of January 2020, various studies have been performed in clinical as well as paramedical facts of COVID-19 specifications in China. It is reported that the COVID cases have showcased a few anomalous behaviors in chest CT images. Based on the survey of World

Health Organization (WHO), COVID is caused due to the virus and millions of people were affected globally. Diagnosing process is carried out by implementing real-time reverse PCR (rRT-PCR) analysis on biotic samples of patients. The COVID-19 disorder can be predicted well by using radiological pictures, hence, the prospect for predicting COVID-19 is from clinical images and X-rays [23-24].

In general, Machine Learning (ML) relied on applications are utilized recently for automated disease diagnosing process in medical application [3]. Deep Learning (DL) is typical research in AI that enables to make better outcomes by using data gained from patients and perform feature extraction manually. Maximum awareness has been evolved for automatic prediction model according to the artificial intelligence (AI) scheme. Providing hospitals and medical facilities are highly difficult for millions of people with limited clinical services. Hence, modest, accurate, and robust AI methodologies are applicable to overcome the problems and support the patients appropriately [25-28].

[4] employed a Conventional Neural Network (CNN) for classifying COVID-19 patients from chest CT scan. [5] used 3- deep CNN (DCNN) mechanism for differentiating the respiratory artery veins from CT scans. [6] employed DCNN for classifying the interstitial lung infection from CT imaging. [7] classifies benign (non-cancerous) and malignant (cancerous) in pulmonary nodule. In [8], melanoma dermoscopy images have been applied for DL for gaining better accuracy. Then, [9] have deployed respiratory fissure in CT by using supervised discriminative learning environment. [10] employed multi-view CNN to predict the lung masses from CT imaging. [11] recommended Deep Adversarial Networks (DAN) for achieving segmentation of stomach CT imaging. [12] applied 3-DCNN for diagnosing the pulmonary lumps in chest CT images. [13] employed a classification approach for recurrent CNN for classification of Coronary Artery Plaque as well as Stenosis in Coronary CT.

[14] suggested a model for diagnosing alternate respiratory infection using DL approach. [15] utilized 3D block relied on residual DL framework for predicting severe tuberculosis state in CT lungs X-ray imaging. [16] developed Particle Swarm Optimization (PSO) based Adaptive Neuro-Fuzzy Inference System (ANFIS) to increase the classification rate. [17] projected gated bi-directional CNNs (GCNN) which have been used for COVID-19 patient classification. Hence, it is computed that the DL approach gains better simulation outcome for COVID-19 disease classification. However, the results are capable of enhancing feature models like variants of ResNet. Additionally, hypertuning of DL schemes are gained by using Transfer Learning (TL). Therefore, novel Deep TL (DTL) is relevant to COVID-19 patient classifying model.

This paper develops an efficient deep convolutional neural network based AlexNet model with Gradient Boosting Tree (DCNNAN-GBT) scheme for COVID-19 diagnosis as well as classification. The presented DCNNAN-GBT model comprises Gaussian filtering (GF) based preprocessing approach to eliminate the noise exist in the radiological images. Moreover, AlexNet model is employed as a feature extractor to derive a useful set of feature vectors. Besides, GBT model is applied as a classification technique to assign correct class labels to the input images. A widespread experimental analysis was performed to highlight the effective COVID-19 diagnostic outcome.

2. RESEARCH ELABORATIONS

The working process of the DCNNAN-GBT model is given here. The input images are primarily pre-processed using GF technique. Followed by, AlexNet model is executed to generate feature vectors which are then classified using GBT model.

A. GF based Pre-processing

The implementation of 2D Gaussian filter is applied widely for the purpose of smoothing and noise elimination. Some of the classical operators are Gaussian operators and Gaussian smoothing which are used to perform convolution tasks. Therefore, Gaussian operator in 1-D is expressed in the following:

$$G_{1D}(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\left(\frac{x^2}{2\sigma^2}\right)}. \tag{1}$$

Best smoothing filter of images are localized for spatial frequency domains in which the uncertainty is depicted as:

$$\Delta x \Delta \omega \geq \frac{1}{2}. \tag{2}$$

The Gaussian operator in 2D is illustrated by:

$$G_{2D}(x, y) = \frac{1}{2\pi\sigma^2} e^{-\left(\frac{x^2+y^2}{2\sigma^2}\right)}, \tag{3}$$

where σ (Sigma) defines the standard deviation (SD) of Gaussian process. (x, y) defines the Cartesian coordinates of an image which implies the dimensions of window.

B. Feature Extraction

In this stage, the feature extraction process takes place using a CNN based AlexNet model. Generally, CNN is a supervised learning mechanism where CNNs is highly beneficial with limited parameters and effective training when compared with deep Artificial Neural Network (ANN). The image segmentation, prediction, and classification are described as some of the benefits involved in this approach. Hence, feature map of first layer has been accomplished using convolving input, and convolution kernels [18]. Therefore, size of a feature map can be derived from given function:

$$n_f = \frac{n_i + 2p - f}{s} \tag{4}$$

where n_f implies the size of feature map; n_i denotes the input size; p signifies the padding value; f represents the kernel size and s shows stride value. Hence, the convolution process is expressed by:

$$a^l = \delta(W^l a^{l-1} + b^l) \tag{5}$$

where a^l indicates the resultant value of lth convolution layer; W^l denotes the kernel of lth convolution layer; a^{l-1} means the final outcome of $l - 1$ th convolution layer; b^l signifies the bias of lth conv. layer; δ defines an activation function of lth conv. layer.

In case of subsampling, pooling operation is selected. The size of a pooling kernel is 2×2 and stride is 2. There are 3 pooling models namely max -pooling, mean-pooling, and stochastic pooling. As a result, features obtained using conv. layer and forward to the Fully Connected (FC) layer at final layer for image classification.

Basically, AlexNet is a well-known and reputed model. The image classification is highly supreme when compared with traditional approaches. But, DL method was effective until developing AlexNet approach. Also, AlexNet is a huge scale structure with numerous variables and neurons. The brief survey is identified in training the parameters, Krizhevsky [19] have made drastic enhancements. Fig. 1 demonstrates the structure of AlexNet.

Initially, activation function was established which is assumed to be the first enhancement. Then, activation function applied in NN is to offer the nonlinearity. Hence, classical activation functions are logistic function, tanh function, arctan function, and so on. However, in deep methods, the above defined function intends to implement the gradient diminishing issues, since the gradient is huge mechanism when the input is ranged from 0. This problem is solved using activation function called rectified linear unit (ReLU) which is expressed by,

$$ReLU(x) = \max(x, 0) \tag{6}$$

Mostly, if the input value is higher than 0, then gradient of ReLU is 1. Consequently, deep networks with ReLU has gained rapid convergence when compared with tanh.

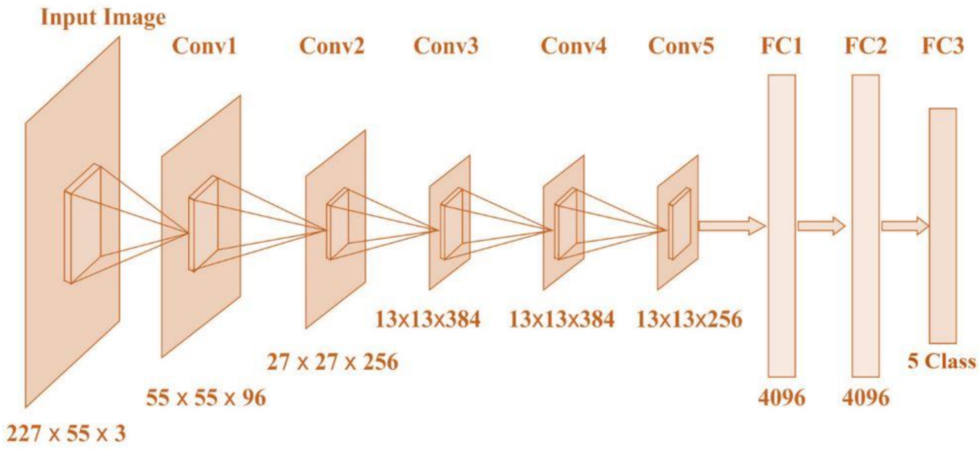

Fig. 1 Structure of AlexNet

Followed by, dropout is applied for the purpose of eliminating overfitting issues [20]. Generally, it is employed in FC layers. In case of dropout, a portion of neurons is trained for all iterations. Dropout promotes a neuron to collaborate with each other and limits the combined application between neurons and enhance the generalization. The final outcome of complete system is average of sub-network and dropout has enhanced the efficiency of model performance.

Convolution and pooling were employed for automated feature extraction and reduction. Convolution is used for signal analysis. The image M in size of (m, n), and convolution is described as

$$C(m,n) = (M * w)(m,n) = \sum_{k}\sum_{l} M\,(m-k, n-l)w(k,l) \tag{7}$$

Where w denotes the convolution kernel from the size of (k, l). Convolution provides a solution to learn features from images and the parameter distribution mitigates the complication of a model. Additionally, pooling acts as a feature reduction model. It applies a collection of adjacent pixels in feature map and produces a value for representing some principle. Also, feature map of 4×4, and max pooling exhibits the max value for all 2×2 blocks and limits the feature dimension.

Feature maps undergo normalization prior to feed the subsequent layers. Moreover, it generates the sum from various adjacent maps at similar positions. Classification is performed in FC layers. Hence, neurons from neighboring FC layers are connected directly. Hence, activation function of these layers are named softmax and depicted as,

$$\text{soft max }(\mathrm{x})_i = \frac{\exp\,(x_i)}{\sum_{j=1}^{n} \exp\,(\mathrm{x_j})} \tag{8}$$

Softmax is constrained from the simulation outcome within (0,1), and make sure the activation of neurons.

Furthermore, some other models applied in AlexNet training, such as over-lapping pooling and training multiple graphics processing units (GPUs), are identified. Therefore, classification accuracy of AlexNet has surpassed the optimal schemes with massive contribution.

C. Image Classification

Finally, the GBT model is applied to allocate the appropriate class labels to the input image. It is a typically applied model in Negative binomial logarithm likelihood $\log\,(\mathrm{h} + e^{-2\mathrm{t}F})$, $\mathrm{t} \in$

$(-\mathrm{h}, +\mathrm{h})$.It is simple in optimization of loss function, however, it is complicated for optimizing general function using Gradient Descend (GD) framework [21]. In order to overcome these problems, Freidman has developed a model which exploits negative gradient of loss function to fit Classification and Regression Tree. The special procedure of this model is depicted in the following:

Consider that there are N sample sets and simulate the weak classification models:

$$f_0(x) = \arg\min_c \sum_{i=1}^{N} L\,(y_i, c) \tag{9}$$

The tth round ith sample loss's Negative Gradient Direction is depicted as:

$$r_{ti=} \left[\frac{\partial L\big(y_{ir}, f(x_i)\big)}{\partial f(x_i)}\right]_{f(x)=f_{\text{f-1}}(x)} \tag{10}$$

Here, $(x_i, r_{it})i = 1,2, \ldots m$ has been applied to fit tth Decision Regression Tree, and concerned leaf node is $R_{tj}, j = \mathrm{h}, 2, \ldots J$. J defines the count of leaf nodes. The sample of each node requires the resultant value c_{tt} to reduce the loss function.

$$c_{tj} = \arg\min_c \sum_{x_i \in R_{\mathrm{t}j}} L\,(y_{i'} f_{t-1}(x_i) + c) \tag{11}$$

Reload the iteration and accomplish a robust classifier.

$$f_t(x) = f_{t-\mathrm{h}}(x) + \sum_{j=1}^{J} c_{tj}\, I\big(x \in R_{tj}\big) \tag{12}$$

Finally, the robust classifier has been attained by,

$$f(x) = f_M(x) = f_0(x) + \sum_{t=1}^{M} \sum_{j=1}^{\mathrm{J}} c_{tj}\, I\big(x \in R_{tj}\big) \tag{13}$$

In case of classification issues, the Negative binomial logarithm likelihood $L(y, F) = \log\,(1 + e^{-2\mathrm{y}F}), \mathrm{y} \in (-1, +1)$is measured. Thus, the negative gradient error is accomplished by,

$$r_{ti} = -\left[\frac{\partial L\left(\mathrm{t}_{i,} f(x_i)\right)}{\partial f(x_i)}\right]_{f(x)=f_{\mathrm{t}-1}(x)} \tag{14}$$

$$= \frac{y_i}{1 + \exp\big(\mathrm{t}_i f(x_i)\big)} \tag{15}$$

Hence, the optimal Residual Error value all nodes are expressed by,

$$c_{tj} = \arg\min_c \sum_{x_i \in R_{\mathrm{t}j}} log\Big(1 + \exp\big(-\mathrm{y}_i(f_{t-1}(x_i) + c)\big)\Big) \tag{16}$$

Also, the majorization applies approximate value and replace them accordingly.

$$c_{tj} = \frac{\Sigma_{x_i \in R_{\mathrm{t}j}} r_{ti}}{\sum_{x_i \in R_{fj}} |r_{ti}|\,(1 - |r_{ti}|)} \tag{17}$$

3. RESULTS PAGE STYLE

The performance of the DCNNAN-GBT model is tested using Chest X-ray dataset [22]. It comprises 27 images under Normal class label and 220 images under COVID-19 class label. The sample test images are illustrated in Fig. 2.

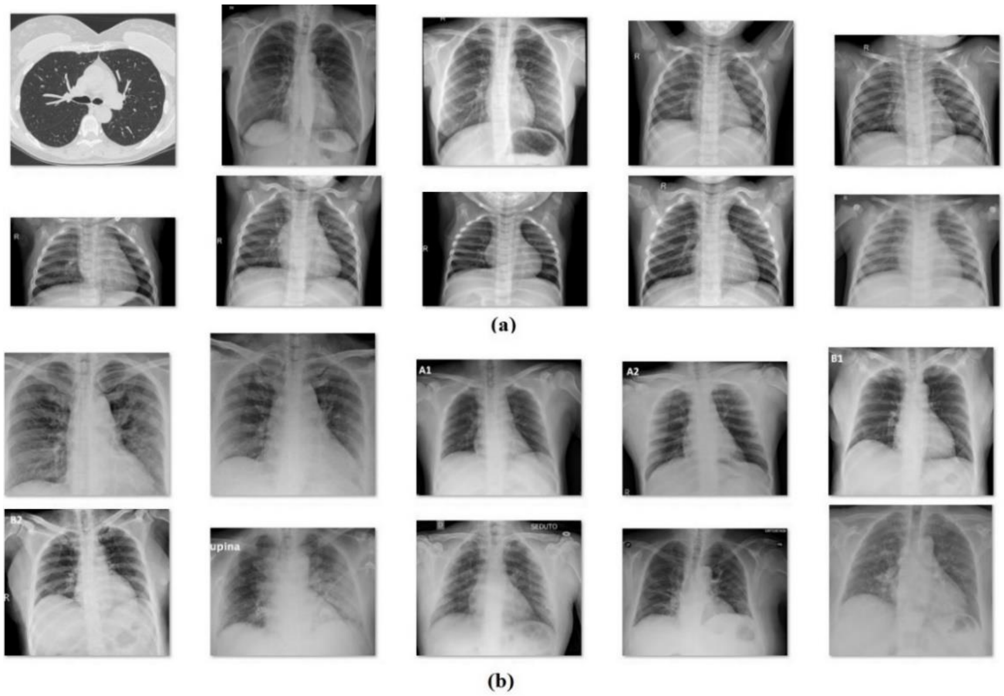

Fig. 2 a) Normal b) COVID-19

Table 1 and Fig. 3 examines the COVID-19 diagnostic outcome of the DCNNAN-GBT model interms of distinct measures. The simulation outcome demonstrated effective detection and classification performance. On fold 1, the DCNNAN-GBT model has achieved a higher Sens. of 94.12%, Spec. of 92.38%, and Acc. of 93.25%. Similarly, on fold 2, the DCNNAN-GBT method has attained a superior Sens. of 94.64%, Spec. of 90.87%, and Acc. of 93.56%. Next to that, on fold 3, the DCNNAN-GBT methodology has reached a maximum Sens. of 94.78%, Spec. of 93.31%, and Acc. of 94.89%. Afterward, on fold 4, the DCNNAN-GBT approach has obtained a higher Sens. of 94.19%, Spec. of 93.87%, and Acc. of 94.73%. Simultaneously, on fold 5, the DCNNAN-GBT model has reached a superior Sens. of 93.86%, Spec. of 94.07%, and Acc. of 94.21%.

Table 1 Results of Proposed DCNNAN-GBT Model in terms of different Measures

Five Fold Validation	**Sensitivity**	**Specificity**	**Accuracy**
Fold-1	94.12	92.38	93.25
Fold -2	94.64	90.87	93.56
Fold -3	94.78	93.31	94.89
Fold -4	94.19	94.87	94.73
Fold -5	93.86	94.07	94.21
Average	**94.32**	**93.10**	**94.13**

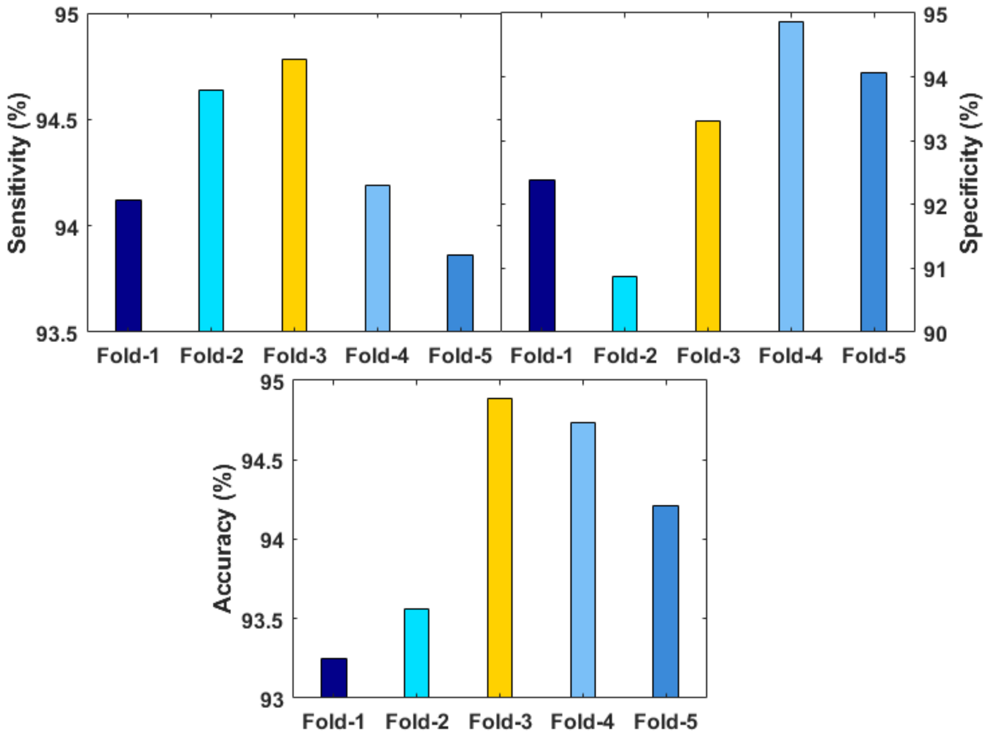

Fig. 3 Result analysis of DCNNAN-GBT model interms of sensitivity, specificity, and accuracy

Table 2 and Fig. 4 demonstrates the comparative analysis of the classification results obtained by the DCNNAN-GBT model interms of Sens., Spec., and Acc. The figure portrayed that the ANN model has shown insignificant outcomes by offering the least Sens. of 87.45%, Spec. of 82.91%, and Acc. of 85.09%. At the same time, the DT model has demonstrated slightly improve outcomes by attaining a Sens. of 87%, Spec. of 85.89%, and Acc. of 86.71%. In line with, the CNN model has depicted an even enhanced outcome with the Sens. of 87.73%, Spec. of 86.97%, and Acc. of 87.36%. Along with that, the ANFIS model has resulted in a moderate Sens. of 88.48%, Spec. of 87.74%, and Acc. of 88.11%. Likewise, the KNN model has Acc.omplished reasonable results with the Sens. of 89%, Spec. of 86.31%, and Acc. of 88.91%. Similarly, the XGBoost model has exhibited nearly Acc.eptable outcomes with the Sens. of 92%, Spec. of 87.45%, and Acc. of 91.57%. Concurrently, the LR model has demonstrated competitive outcome with a Sens. of 93%, Spec. of 87.83%, and Acc. of 92.12%. At last, the presented DCNNAN-GBT model has achieved a superior Sens. of 94.32%, Spec. of 93.1%, and Acc. of 94.13%.

Table 2 Comparative analysis of Proposed DCNNAN-GBT Methods

Models	**Sensitivity**	**Specificity**	**Accuracy**
DCNNAN-GBT	94.32	93.10	94.13
Convolution Neural Networks	87.73	86.97	87.36
Artificial Neural Network	87.45	82.91	85.09
ANFIS	88.48	87.74	88.11
Logistic Regression	93.00	87.83	92.12
XGBoost	92.00	87.45	91.57
K-Nearest Neighbour	89.00	86.31	88.91
Decision Tree	87.00	85.89	86.71

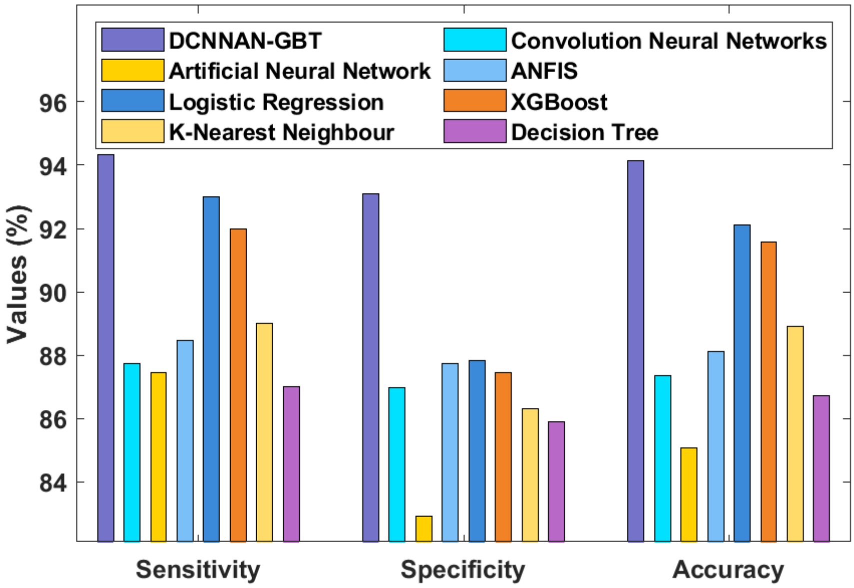

Fig. 4 Comparative analysis of DCNNAN-GBT model with existing methods

4. CONCLUSIONS

This paper has developed a new DCNNAN-GBT model for COVID-19 analysis and classification. The input images are primarily pre-processed using GF technique. Moreover, AlexNet method is utilized as a feature extractor for deriving a useful set of feature vectors. Besides, GBT model is applied as a classification technique to assign correct class labels to the input images. A widespread experimental analysis was performed to highlight the effective COVID-19 diagnostic outcome. The experimental results pointed out that the DCNNAN-GBT model has resulted in a maximum average sensitivity of 94.32%, specificity of 93.10%, and accuracy of 94.13%. Therefore, it can be used as a proper tool to determine and classify COVID-19. In future, the hyperparameters in AlexNet model can be tuned for improved outcomes.

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