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Novel Artificial Intelligence Learning Models for COVID-19 Detection from X-ray and CT Chest Images

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Abstract - **Covid-19 was first found in Wuhan, China, in December 2019. Covid-19 spreads very fast around the world, and it became a pandemic disease. Specific medicines were discovered yet to cure covid-19. It affects the day to day lives of humans and also the economy of all the countries. It remains a challenge in the early diagnosis of covid-19. Polymerase Chain Reaction (PCR) test is the most commonly used test for detecting covid-19, but it produces significant false positives and false negatives, not reliable. Recently, X-Ray and CT imaging of lungs were used to detect covid-19. In this paper, we propose three artificial intelligence (AI) models for COVID-19 image analysis. These three models include a simple artificial neural network model under machine learning (sANN_ML), a proposed convolutional neural network model under deep learning (pCNN_DL), and a proposed VGGNET based model under transfer learning (pVGG_TL). Besides, we also developed a novel activation function E-Tanh, by extending the Tanh activation function. For all our models, we used ReLU and E-Tanh activation functions. These AI models are used to analyze X-ray and CT images of the chest to detect COVID-19. The COVID-19 datasets experimented with the proposed models were collected from public image repositories maintained by research and medical centers. Among three models, sANN_ML and pVGG_TL models performed well and produced 100% accuracy in detecting COVID-19 from X-ray images. The performance of pCNN_DL, which comes under the family of convolutional neural networks (CNN), did not perform well due to the availability of a small number of datasets for training. The performances of all three models for CT images are low when compared to the detection of COVID-19 in X-ray images. The proposed E-Tanh activation function is performed at par with the ReLU activation function.**

Index Terms - Artificial Intelligence (AI), Artificial Neural Network (ANN), Convolutional neural networks (CNN), COVID-19 detection, CT, Deep Learning (DL), E-Tanh, Machine Learning (ML), Transfer Learning (TL), VGG, X-ray.

INTRODUCTION

Corona Virus (Covid-19) has first occurred in Wuhan city of China. It created a pandemic situation for the entire world [1]. Some of the common symptoms of the coronavirus that were found in 85% of corona-affected patients are fever. Cough is found in 70% of corona-affected patients. About 43% of patients were reported shortness of breath [2]. There is also a possibility of abdominal problems for covid patients. Recently it was found that this disease might be asymptotic, but it still spreads to other people. The severity of covid-19 may vary from mild to critical. Mild symptoms include no symptoms, mild cough, and fever. Acute symptoms of covid-19 may consist of failure of the respiratory system or multiorgan failure [3] [4].

Real-time reverse transcription-polymerase chain reaction (RT-PCR) tests are used for diagnosing COVID-19.

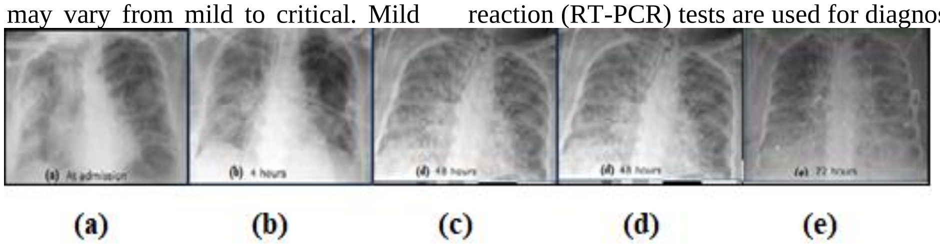

Figure 1. X-ray images of 72 years older woman affected by COVID-19 (a) At admission (b) 4 hours (c) 24 hours (d) 48 hours (e) 72 hours (**https://radiologyassistant.nl/chest/lk-jg-1, last accessed on 4.6.2020.)**

This test generates results with a lower sensitivity of sixty-five to ninety-five percentages [5]. It takes more than a day to produce the test results. The role of medical imaging plays a vital role in the early diagnosis of COVID-19. Radiology plays a crucial role in diagnosing and identifying COVID-19 infection using X-ray and CT images. The radiological findings of COVID-19 show that the conditions are ground glass patterned areas. Handcrafted feature extraction techniques are required for conventional medical image classification approaches [6]. Imaging studies of COVID-19 had reported some changes in the lungs, such as opacities in the right infrahilar airspace [7], opacity in the region of the left lower lung [8]. Some researchers had found ground-glass opacities (GGO) or mixed ground-glass opacities along with vascular dilation in the lesions in most of the COVID-19 patients [9], interlobular septal thickening and signs of air bronchogram [10], peripheral focal which affects both the lungs in 75% of patients [11]. Chest X-ray images taken for 76 years older woman at regular intervals is shown in Figure 1 along with explanations.

Emerging deep learning-based approaches are very effective and efficient for medical image classification [12] [13]. Feature extraction is done automatically in deep learning-based techniques, and it is capable of learning more complicated patterns in image data. One of the significant disadvantages of deep learning models is the requirement of large amounts of labeled data for training the network. It also requires enormous computational resources. Transfer learning (TL) is a popular approach to deep learning in which a model that was developed and trained for a task is reused. This pre-trained model acts as a starting point to introduce a new model for a similar task. It gradually reduces the amount of training time, the requirement of substantial computational resources, and training data.

The recent works on COVID-19 chest X-ray images include developing some deep learning models [14 – 21]. The list of existing methods available for COVID-19 detection and the inference we made from them is given in Table 1. In this work, we have developed three novel AI models based on machine learning, deep learning, and transfer learning for COVID-19 image analysis from X-ray and CT images. The models are i. simple artificial neural network model under machine learning (sANN_ML), ii. proposed convolutional neural network model under deep learning (pCNN_DL) [22] and iii. proposed VGGNET based model under transfer learning (pVGG_TL). Besides, we also have formulated the proposed activation function(AF), E-Tanh, by extending the conventional Tanh AF. We have utilized the proposed activation function E-Tanh for the first two models: sANN_ML, pCNN_DL. The third model, pVGG_TL, is chosen based on the experiments carried out by Rehman et al. [23]. The experiment was conducted among Alexnet, Googlenet, and VGGNET for image classification and concluded that VGGNET was highly capable of extracting features. The proposed learning-based AI models can learn the finer details in the X-ray and CT images that are not visible to the human eye, enabling early prediction of COVID-19.

Table 1. Existing Methods for COVID-19 Detection using Deep Learning Techniques

S.NO	**METHOD USED FOR COVID-19 DETECTION**	**INFERENCE**	**REFERENCE**
1	CovidXNet	Seven CNN layers along with VGG19, Google MobileNet, DenseNet. VGG19 and denoising architectures produce better results in Covid19 detection.	[14]
2	CovidNet	It is designed as a multiclass classification model. It produced good results in Covid19 detection	[15]

		when compared to VGG19 and ResNet50 models in terms of sensitivity.	
3	Computer-Aided Diagnostic System	They have designed a computer-aided diagnostic system for Covid19 detection in CT images.	[16]
4	Deep Learning Algorithm based on Transfer Learning	They have used a pre-trained Inception model for training the deep neural network.	[17]
5	Covid19 detection software	U-Net architecture is used to segment the lungs, and these segmented results are fed into three-dimensional deep neural networks to diagnose Covid-19.	[18]
6	Covid19 detection	The infected regions are segmented from the CT images. These segmented infected regions are fed into a deep three-dimensional architecture for the classification of infection types.	[19]
7	Covid19 diagnosis using machine learning	They have extracted the features from covid CT images and then used a support vector machine for classifying covid-19 affected patients. They have inferred that Grey Level Size Zone Matrix had provided better results for feature extraction.	[20]
8	Covid 19 CT images segmentation	Residual attention U-Net is used for segmenting Covid-19 chest CT images.	[21]

The remaining part of the article is organized as follows. In Section 2, materials and metrics used for the performance evaluation of the models are discussed. In section 3, the architectures of the proposed models are presented. In Section 4, the experimental results are analyzed and discussed. Section 5 concludes the work along with the future enhancements.

MATERIALS AND METRICS

We have used an X-ray image dataset and a CT image dataset collected from internet repositories maintained by research and medical centers in the proposed work. The detailed description of the datasets used for our experiments is given in Table 2, and the evaluation metrics are given below. The sample slices for positive and negative cases of COVID-19 in X-Ray modality are shown in Figure 2. The sample slices for positive and negative cases of COVID-19 in CT modality are shown in Figure 3.

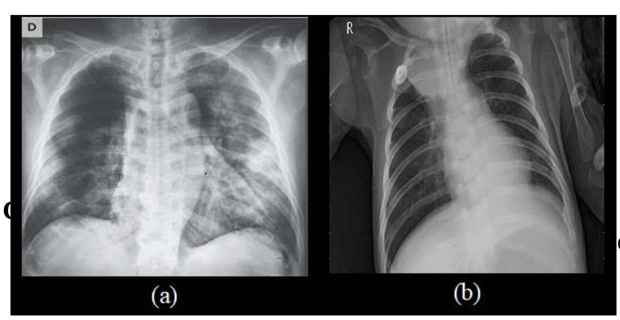

Figure 2. Sample X-ray images (a) Covid Positive (b) Covid Negative

Evaluation Metrics

The evaluation metrics that are used in the proposed methods are listed below.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (3)$$

TP – True Positives, TN – True Negatives, FP – False Positives, FN – False Negatives.

Table 2. Description of COVID-19 Datasets used in the Proposed Method

S.NO	IMAGING MODALITY	NUMBER OF COVID-19 POSITIVE CASES	NUMBER OF COVID-19 NEGATIVE CASES	REFERENCE
1	X-Ray	12	13	Cohen [24]
2	X-Ray	125	500	Wang et al. [25]
3	CT	349	397	Zhao et.al [26]

PROPOSED AI MODELS

In this work, three novel AI models were developed and tested in machine learning, deep learning, and transfer learning techniques:

i. Simple artificial neural network model under machine learning (sANN_ML)

ii. Proposed convolutional neural network model under deep learning (pCNN_DL)

iii. Proposed VGGNET based model under transfer learning (pVGG_TL).

sANN_ML Model

In the first approach of this work, the machine learning (ML) model is used. The architecture of sANN_ML is shown in Figure 4. It consists of three dense or fully connected layers. One layer as input, another as a hidden layer, and the third layer for output. The output shape of the input layer is set to 768. The number of parameters in the input layer is 2360064. The output shape

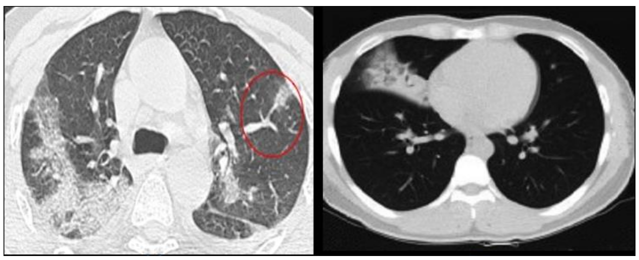

Figure 3. Sample CT Images (a) Covid Positive (b) Covid Negative

of the hidden layer is 384, and there are 295296 parameters. The shape of the output layer is two, and the number of parameters is 770. Therefore, the total number of trainable parameters is 2656130. Four sub-models have been developed using this architecture with the existing ReLU function and the proposed activation function E-Tanh for classifying the COVID-19 images. They are:

i. sANN_ML with ReLU activation function for classifying COVID-19X-ray images

ii. sANN_ML with proposed activation function E-Tanh for classifying COVID-19X-ray images

iii. sANN_ML with ReLU activation function

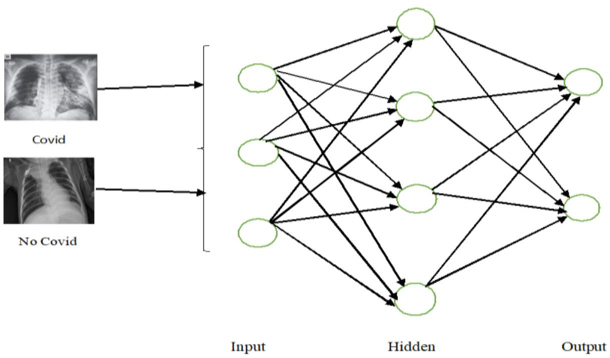

Figure 4. Architecture of sANN_ML Model

for classifying COVID-19 CT images

iv. sANN_ML with proposed activation function for classifying COVID-19 CT images

pCNN_DL model

The second approach of this work is using the DL model. This architecture includes five convolutional layers, batch normalization, and stopping criterion (pCNN_DL) and is shown in Figure 5. In the first two layers, thirty-two filters along with 3 x 3 strides were used. In the subsequent three layers, sixty-four filters were used. We have used max-pooling in all five layers with 2 x 2 strides. We have developed four sub-models using existing ReLU and proposed activation functions for X-ray and CT image analysis.

They are:

i. pCNN_DL with ReLU activation function for classifying COVID-19X-ray images

ii. pCNN_DL with proposed activation function for classifying COVID-19X-ray images

iii. pCNN_DL with ReLU activation function for classifying COVID-19 CT images

iv. pCNN_DL with proposed activation function for classifying COVID-19 CT images

pVGG_TL Model

The third approach of this work is based on transfer learning (TL) using the VGG network. The pre-trained VGG network comes under CNN, which has been trained using the ImageNet dataset. The primary purpose of using pVGG_TL is to transfer the learned weights, bias, and features in diagnosing COVID-19. This is followed by applying these parameters with training our new input dataset, i.e., CT scan images and X-ray image dataset, separately. We had only a smaller amount of dataset, and so we used pre-trained weights. The model is modified by replacing the last layers with the intended layers to adopt the pre-trained network for the proposed work. Further, our collected datasets have been used for other training networks, as shown in Figure 6.

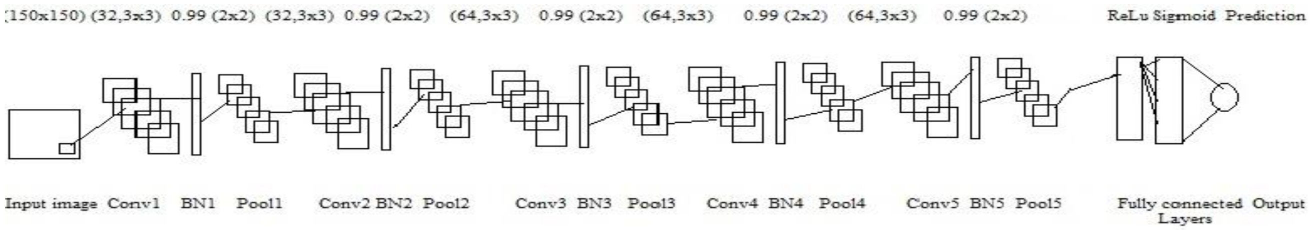

Figure 5. Architecture of pCNN_DL Model

Proposed Activation Function (E-Tanh)

We have proposed a new activation function by extending the existing conventional tanh() AF. It is given by:

$$f(x) = \alpha * e^{x} * \tanh(x) \quad (4)$$

Like ReLU [27] and swish [28] activation functions, our activation function is bounded below and unbounded above. Our activation function is non-monotonic in nature. The plot of the novel activation function and its derivative is shown in Figure 7. The derivative of the above activation is given by:

$$f'(x) = \alpha * e^{x}(\tanh(x) - \tanh^{2}(x) + 1) \quad (5)$$

bounded below is also merit since it consists of solid regularization effects. Our activation function differs from ReLU because it generates negative outputs for negative inputs since it is non-monotonic. The non-monotonic property of our activation function improves the flow of the gradient. The non-monotonic property also provides robustness to the learning rates and various initializations. The property of smoothness handles optimizing and generalizing the training.

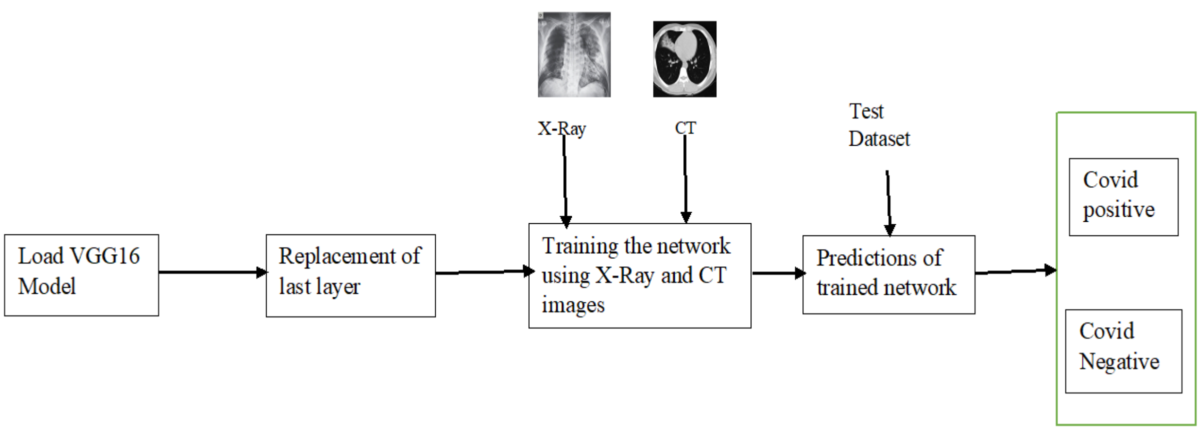

Figure 6. Architecture of pVGG_TL Model

Hyperbolic tangent (tanh) works better than sigmoid function. It is a mathematically shifted version of the sigmoid function. The gradient of tanh is stronger than sigmoid. The derivatives are sharper for the tanh function. Our activation function E-Tanh performs well when compared to ReLU and swish activation functions. The properties of our activation function are advantageous since it satisfies the properties such as non-monotonic, smoothness, bounded below, and unbounded above.

To prevent saturation while the training becomes slow when near to zero gradients, unboundedness property is suitable. The activation functions such as tanh and sigmoid are bounded above and below. To stay in the linear system of these functions, the network must be carefully initialized. The property

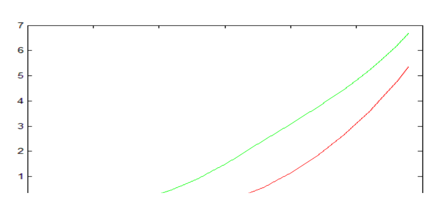

Figure 7. The Proposed Activation Function E-Tanh (Red) and its Derivative (Green)

Results and Discussions

We carried out experiments by applying the proposed sANN_ML, pCNN_DL, and pVGG_TL models on the material pool of X-ray and CT images for COVID-19 detection. Further, experiments were done using the models with the existing ReLU activation function and proposed activation function E-Tanh. Finally, performance analyses have been done with some of the existing AI models and discussed.

S. No	Model	Total Slices	True Positives (TP)	True Negatives (TN)	False Positives (FP)	False Negatives (FN)
1	sANN-ML	10	5	5	-	-
2	pCNN-DL	10	1	5	-	4
3	pVGG-TL	10	5	5	-	-

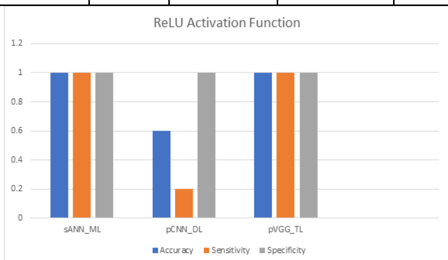

Figure 8. Performance metrics computed for X-ray images using ReLU activation function

X-ray images

In the first set of experiments, we used X-ray images. We used 625 X-ray images for training the networks. For testing, we used 10X-ray images, five images withCOVID-19 positive, and five images withCOVID-19 negative. Initially, all the models, sANN_ML, pCNN_DL, and pVGG_TL, were trained using the ReLU activation function and then tested with 10 test X-ray images. The predictions made by the models and the performance metrics computed for them are given in Table 3.

Table 2 and Figure 8 show that the sANN_ML and pVGG_TL models performed well by making a 100% prediction. However, the convolutional neural network model pCNN_DL model did not make good predictions. From Table 2, it can be seen that out of 5 images with Covid-19 positive, pCNN_DL can detect only one case. However, it can predict the Covid-19 negative cases and thus increases the specificity values.

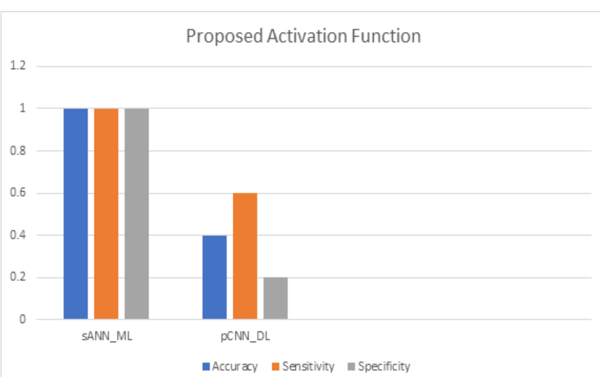

Figure 9. Performance measures for sANN_ML and pCNN_DL models for X-ray images using our novel activation function E-tanh

Next, we trained sANN_ML and pCNN_DL using our proposed activation function E-tanh with the same 625 X-ray images. We set α=1.5 in E-tanh. The models were then used to predict from the 10 test X-ray images. The prediction made by the models is given in Table 4.

Table 3. Predictions of COVID-19 X-ray images using ReLU Activation Function

Table 4. Predictions of COVID-19 X-ray images using the proposed activation function E-Tanh

S. No	Model	Total Slices	True Positives (TP)	True Negatives (TN)	False Positives (FP)	False Negatives (FN)
1	sANN-ML	10	5	5	-	-
2	pCNN-DL	10	3	1	4	2

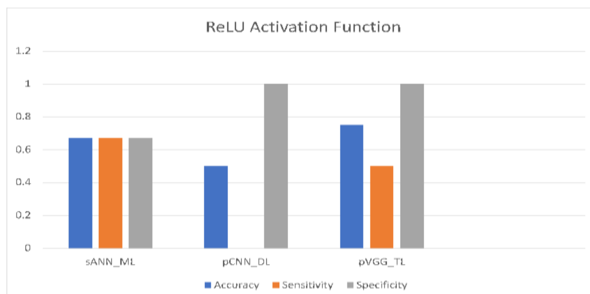

Figure 10. Performance metrics computed for the proposed models with the ReLU activation function for CT images.

We also computed the performance measuring metrics and are plotted in the bar chart given in Figure 9.

Table 4 and Figure 9 show that again ANN model sANN_ML can make a 100% prediction. The CNN model failed to predict to any satisfactory level. Out of 5 Covid positives, it can predict only three correctly. Out of 5 Covid negative cases, it can predict only one case.

For comparison of the performance, the predictions made by the proposed and six existing AI models for X-ray images are given in Table 5.

From Table 5, we observe that the three proposed models, sANN_ML with ReLU activation function, sANN_ML with E-Tanh, and pVGG_TL with ReLU activation function, outperformed the other existing AI models for X-Ray images in detecting the Covid -19 positive or negative cases to 100% accuracy. However, the other two proposed CNN-based models failed to predict any satisfactory level. CNN requires a vast number of datasets for training the model to increase the prediction accuracy. But we used only 625 images for CNN models. This yields poor performance by the proposed CNN-based models.

Table 5. Performance comparison between the proposed and existing models for X-ray images

S.No	Method/Model	Dataset	Accuracy
1	VGG19 [29]	224 covid19 and 504 normal	93.48
2	CovidNet [15]	53 covid19 and 5526 normal	92.4
3	ResNet50 + SVM [30]	25 covid19 and 25 normal	95.38
4	Covidx-Net [14]	25 covid19 and 25 normal	90
5	Deep CNN ResNet-50 [31]	50 covid19 and 50 normal	98
6	DarkCovidNet [32]	125 covid19 and 500 normal	86
7	**sANN_ML + ReLU**	125 covid19 and 500 normal	**100**
8	**sANN_ML + E-Tanh**	125 covid19 and 500 normal	**100**
9	**pVGG_TL + ReLU**	125 covid19 and 500 normal	**100**
10	**pCNN-DL+ ReLU**	125 covid19 and 500 normal	**60**
11	**pCNN-DL+ E-Tanh**	125 covid19 and 500 normal	**40**

CT images

In the second set of experiments, we used CT images of patients with suspected Covid-19. Totally 800 CT images are used for training the networks. For testing, 24 CT images, with 12 images having Covid-19 positive and 12 images with Covid-19 negative, are used.

First, the proposed sANN_ML, pCNN_DL, and pVGG_TL models with ReLU activation function were trained using the 800 CT images. Next, predictions were made in putting the 24 test CT images. The predictions made by these models are given in Table 6.

Table 6. Predictions of COVID-19 CT images using ReLU Activation Function

S. No	Model	Total Slices	True Positives (TP)	True Negatives (TN)	False Positives (FP)	False Negatives (FN)
1	sANN-ML	24	8	8	4	4
2	pCNN-DL	24	-	12	-	12
3	pVGG-TL	24	6	12	-	6

We also computed the performance measuring parameters and are plotted in the bar chart and are shown in Figure 10.

Table 7. Predictions of COVID-19 CT images using Proposed Activation Function E-Tanh

S. No	Model	Total Slices	True Positives (TP)	True Negatives (TN)	False Positives (FP)	False Negatives (FN)
1	sANN-ML	24	5	10	2	7
2	pCNN-DL	24	4	6	8	6

From Figure 10, we observe that only sANN_ML can perform to 75% accuracy in the prediction. From Table 4, it is noted that out of 12 positive and negative Covid cases, this model can predict only 8 cases in each. The second-best performance is by the pVGG_TL model. It can predict six positive and all the 12 negative cases. The pCNN_DL model failed to identify any positive case at all. However, it can predict the 12 Covid negative cases, and thus its specificity reaches the maximum value. All the models' performance with the ReLU activation function is not up to a satisfactory level for the CT images.

Next, we trained the sANN_ML and pCNN_DL models with the proposed activation function E-Tanh. We trained with the same set of 800 CT images used in the previous experiment and 24 test CT images to test the models. The results predicted by these models are given in Table 7. The computed values of the performance measuring metrics are plotted in a bar chart and shown in Figure 11.

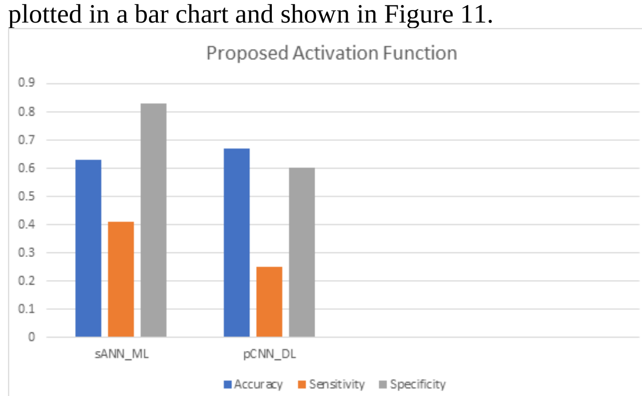

Figure 11. Performance metrics of proposed sANN_ML and pCNN_DL models for CT images using the proposed activation function E-Tanh

From Figure 11, it can be observed that the best performance is by the pCNN_DL model, giving an accuracy of about 68%, followed by the sANN_ML model with an accuracy of about 62%. This shows that the proposed activation function E-Tanh is working better for the CNN model than the simple ANN model. A comparison of the predictions made by the proposed models and four existing AI-based models is given in Table 8.

Table 8. Performance comparison between the proposed and existing models for CT images

S.No	Method/Model	Dataset	Accuracy %
1	DRE-Net [16]	779 covid19 and 708 normal	86
2	M-Inception [17]	195 covid19 and 258 normal	82.9
3	UNet + 3D Deep Network[18]	313 covid19 and 229 normal	90.8
4	ResNet + Location Attention [19]	219 covid19 and 224 normal	86.7
5	**sANN-ML + ReLU**	**349 covid19 and 397 normal**	**67**
6	**pCNN-DL + ReLU**	**349 covid19 and**	**50**

		397 normal	
7	**pVGG-TL + ReLU**	**349 covid19 and 397 normal**	**75**
8	**sANN-ML + E-Tanh**	**349 covid19 and 397 normal**	**63**
9	**pCNN-DL + E- Tanh**	**349 covid19 and 397 normal**	**67**

From Table 8, it can be noticed that the proposed models did not perform well. This indicates that the proposed models are not efficient in making predictions for CT images. This may be due to the inadequate number of images used for training. But among the proposed models, the CNN-based model pCNN_DL has better performance than sANN_ML for the proposed activation function E-Tanh. This gives a supporting hand and boosts our research for future work in data collection and trains the CNN model using our proposed E-Tanh activation function. This will produce a novel deep learning-based CNN model to detect COVID-19 from CT images.

CONCLUSIONS

In this paper, we have made contributions in two areas. One is developing AI models to predict Covid-19 positive or negative cases from X-Ray and CT images of patients with suspected Covid-19. Three AI-based learning models, ANN with machine learning (sANN_ML), a convolutional neural network with deep learning technique(pCNN_DL), and a VGG network with transfer learning technique(pVGG_TL), were developed for detecting COVID-19 from X-ray and CT images. The proposed sANN_ML model produces 100% accuracy. This model also outperformed other AI-based models for X-ray images but failed for CT images. The CNN-based models did not perform well due to the inadequate number of images for training. The second contribution of this work is the development of a novel activation function E-Tanh. This activation function performed well, giving 100% accuracy for X-ray images. Work is in progress to develop an efficient AI model to predict Covid-19 from CT images.

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