International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. 12, No.1 (Dec-2022)

https://dx.doi.org/10.12785/ijcds/1201117

Covid - 19 Patient's CT Images Classification: StackAlexNet-19 A Deep Learning Approach

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Received 23 Jun. 2021, Revised 31 Dec. 2022, Accepted 9 Sept. 2022, Published 31 Dec. 2022

Abstract: At present, the whole world is infected by COVID-19. It targets affecting the respiratory system and worsens for people with other health complications like diabetes, cardiovascular diseases, cancer, lung disorder, and so on. The availability of test kits is not adequate and symptoms of COVID-19 similar to pneumonia are deadly, which claims millions of people. The COVID-19 test kits are time-consuming and even reduce the detection rate. Therefore, in the current study, an automatic CT image classification technique for COVID-19 and Non-COVID patient identification is proposed. In this paper, a StackedAlexNet-19 convolution network for automatic classification of lung CT images is proposed. The proposed StackedAlexNet-19 model consists of different pre-trained methods like ResNet 101, Xception, NASNet, MobileNet, and InceptionV3. Based on the pre-trained model, input CT images are processed and integrated for the detection of abnormalities in COVID-19 CT images of patients. The StackAleNet-19 model is evaluated and comparatively examined with the existing techniques. The dataset for processing consists of 1359 CT images composed of COVID, non-COVID, and other infections. The validation range is set as 50 for each case with a total value of 150 and the network is trained with CT images of 1069 for classification. The analysis of results expressed that StackAlexNet-19 exhibits higher accuracy, sensitivity, and specificity value of 93.67%, 0.93, and 0.97 respectively. The proposed StackAlexNet classification technique achieves an accuracy of 93.67%. The developed model provides improved accuracy than the existing techniques. The StackAlexNet-19 facilitates the intervention of COVID-19 without any human intervention.

Keywords: COVID-19, StackAlexNet-19, Deep Learning, Stacking, Image Classification

1. INTRODUCTION

At present, Novel COVID-19 (coronavirus) also belongs to the class of SARS-Cov-2 infection. COVID-19 contains positive-strains of RNA virus belonging to the class of zoonotic. RNA virus leads to severe acute respiratory symptoms causing distress and pneumonia. It is highly infectious and transmitted using droplets from the aerosol and respiratory system. By WHO, COVID-19 is declared as a global pandemic impact on more than 230 countries [1]. The number of new COVID-19 infected cases is drastically increased to over 15 million throughout the world [2]. Typical symptoms of COVID-19 are fever over 100^0 C, tiredness, loss of taste, dry cough, loose bowels, headache, and conjunctivitis. In the worst cases, symptoms are varied such as pneumonia, shortness of breath, multi-organ failure, and patient demise. The severe infection leads to pneumonia and leads to death for the infected patient. On the other hand, COVID-19 is more contagious which spreads easily from person to person hence that needs to be detected quickly to limit the spread. However, with the rapid development of infection even developed countries are collapsing to provide advanced medical facilities. To control a pandemic, aggressive testing is required for preventing the pandemic. At present, RT-PCR (Reverse Transcription Polymerase Chain Reaction) test is adopted for detecting COVID-19 [3]. RT-PCR is involved in the detection of sputum of virus RNA or nasopharyngeal swab. This RT-PCR test is more time-consuming but on the other hand, the COVID-19 case is eventually increased day by day in countries like the USA, India, Brazil, and other countries [4]. Also, the cost of PCR is more expensive as it costs around 6500INR [5]. PCR exhibits a minimal detection rate and to achieve accurate results repeated tests are required. To prevent this pandemic, a fast and accurate method is required for

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COVID-19 diagnosis. To achieve faster results Chest X-rays and CT are adopted for detection of the COVID-19 pandemic. Several researchers expressed that X-ray and CT exhibit abnormalities in the COVID-19 infected patients. Both techniques are effective for earlier COVID-19 detection than conventional RT-PCR tests. In the early stage, identification of COVID-19 is performed with an effective imaging technique that limits the disease spread [6]. The medical physician is focused on designing an effective support tool integrated with artificial intelligence techniques for COVID-19 diagnosis. Artificial intelligence method [44] involved in infected lung CT image segmentation. In recent years, artificial intelligence is rapidly growing in terms of deep learning techniques such as detection of an object, recognition of speech, the interaction of drugs, and classification of images [7,43]. Specifically, the deep learning technique [45] exhibits promising results in the field of image processing [8]. In the image segmentation process, several methods are adopted for achieving power and robustness [9]. Medical image processing with deep learning exhibits promising results for image classification and segmentation [10]. Any CT scan image can be between 4 and 7 MB in size, making it difficult to convert this large image to a byte stream and use it for training. An encoder is first used to compress large images while maintaining their original properties, and then a decoder is used to recover the original image. Since the task at hand is image classification, an encoder is used to compress large images while maintaining their original properties, followed by a decoder to recover the original image. It's likely that the encoder and decoder could lose some of the image's properties during this process. Owing to a lack of visibility, the picture may not be appropriate for testing. In these cases, the image is reconstructed before being labelled correctly.

This paper proposed a StackAlexNet-19 model for COVID-19 detection with reduced cost and detection time. The paper's main focus was to find a more accurate result towards the detection of Covid. Even though there are pieces of literature on the topic, the StackAlexNet classification technique achieves an accuracy of 93.67 percent which is more than Resnet, Transfer Learning and Xception models by 0.66,0.67 and 4.07 percent respectively and makes our model better from other algorithms. One of the major problems was that the test kits did not provide correct results, and a large number of false-positive cases were discovered in the test kits' results in developing countries. So, introducing technology in detection could at least help to bring down human errors. When we include technology for covid detection, it does not ensure a 100% accuracy, but a 93.7% accuracy can ensure very small chances of error. The proposed StackAlexNet-19 incorporates a pre-trained model such as Inception v3, Xception, MobileNetv2, NASNet, and ResNet-101. The stacked model is involved in feature extraction and integrated to achieve more accuracy. To analyze the proposed StackAlexNet-19, lung CT images are applied and processed with 5 pre-trained models. In contrast to other machine learning models in the literature, the proposed StackAlexNet-19 has higher precision, accuracy, and sensitivity, according to the comparative study. Paper organization is as follows: Section 2 presents the existing literature and section 3 provides data processing adopted in StackAlexNet-19. In section 4, the operation and algorithm for StackAlexNet-19 are presented. In section 5, performance metrics and comparative analysis is presented followed by the conclusion in section 6.

2. Related Works

This section presents the deep learning method for COVID-19 detection. To detect COVID-19, lung level segmentation was performed for processing X-ray images as well as CT scan utilizing deep learning technique [11]. In [12], the author developed a CNN for COVID-19 detection which utilized X-ray images. The adopted technique incorporated a transfer learning technique with the implementation of deep learning architecture. The deep learning architecture considered for analysis was Inception-ResNetV2, InceptionV3, and ResNet50. The developed CNN model was trained with selected 100 images with 5 cross-validation techniques. The analysis of results expressed that InceptionV3 and ResNetV2 provide accuracy of 97% and 87% respectively. However, this approach utilized 100 images with limited size and led to overfitting. Hence, for the proposed algorithm, a large database needs to be considered for validation of the dataset. Also, [13] proposed a deep learning method for CT image classification. The developed deep learning model was evaluated using VGG-16 with consideration of X-ray images. The simulation analysis stated that an accuracy value of 90% was achieved for COVID validation and non-COVID classes. This research also utilized a minimal database of 50 cases in which 25 COVID and 25 non-COVID cases are considered. A similar study was conducted in [14] in which training was provided by CNN for the Image NET database. The database consists of x-ray images and performs classification under four classes such as normal, COVID – 19, non-COVID-19, and bacterial. The analysis expressed an overall accuracy of 83.5%. COVID-19 CT images were processed in [15] using the transfer learning algorithm process. The analysis consists of 275 CT scan images and processed with 14 chest x-ray and 169-layer DenseNet. The transfer learning model performance exhibited a ROC curve value of 82.4% and an accuracy value of 84.7%. The collected databases consist of 347 COVID-19 infected patients' CT images as well as 397 non-COVID patients.

Some researchers utilized a capsule model instead of CNN for processing a large amount of data with consideration of various parameters. In [16] the author developed a COVID-19 capsule network for identification from X-ray images. Analysis of results stated that the capsule network provides 95.7% accuracy, 90% sensitivity, and 95.8% specificity. Achieved results were compared with the SVM and ResNets 50 model developed in [17]. However, the SVM model provides 95.38% accuracy, a sensitivity of 97.29%, and 93.47% specificity. Through analysis, it was concluded that the capsule-based model exhibited promising results compared with the SVM model. In [18], developed an AI mechanism for analysis of COVID-19 infected patient CT images. The data for analysis were collected from five different hospitals with 723 positive cases. The consolidated cases for analysis were 1136 images and provided 0.974% sensitivity and 0.922% specificity. The developed method integrated the classification and segmentation process with the addition of lesions. For segmentation, this model used 3D V-NET, U-NET++, FCN-8S. For image classification InceptionV3, ResNet50 are adopted. For the trained 732 case dice, the coefficient achieved was 0.754 by 3D U-net ++. The integrated 3D U-net ++ and ResNet50 provided an OCR curve value of 0.991, a sensitivity of 0.974, and a specificity value of 0.922. In practice, re-training was improved with a continuous model for improving lesion regions. But the research does not clearly state the results which belong to either segmentation or classification process since both are an independent process. In [19], DNN was developed for automatic COVID-19 detection in x-ray images. The developed method was stated as Dark CovidNet with the implementation of the classification model. The developed classification model incorporated a real-time object detection system. The developed model incorporated a convolution layer count of 17 and provided an accuracy of 98.08% and the multi-class value was achieved as 87.02%. In [20], a classification of the COVID-19 database was introduced through the transfer learning approach. To withstand the normalization of dataset and noise elimination, cost-sensitive attributes and smooth loss function were considered. The model was trained based on the publicly available CT chest dataset for the classification of COVID-19 patients. The developed method provided 93% accuracy, 94% specificity, and 91% sensitivity. In [21], for the classification of chest CT images in COVID-19, the CNN model was included. In this CNN model, a multi-objective differential evolution technique was included. Similarly, in [22] a CNN network with Xception pre-trained model was developed for classification. The analysis was based on the consideration of X-ray images obtained into 4 classes as Pneumonia, COVID 19, Normal, and Pneumonia bacteria. Analysis of results expressed that classification accuracy achieved was 89.6%. In [23], feature extraction was performed for the classification of COVID and Non-COVID for X-ray images. In [24], a Resnet was developed for the extraction of features with a classification model for differentiating COVID and non-COVID images. The developed classification model utilized a smooth loss function. This model provided an accuracy value of 93.01%. The developed model was based on pre-trained 121 layers DenseNet architecture adopted in [25] for pneumonia detection. The data selected for analysis were collected from 30,805 patients with the characterization of 120 images. The developed model was extended for the detection of 14 diseases from different X-ray images. In [26], an image extraction with pre-trained inceptionV3 was focused on classification. The image features were extracted through embedding an ANN. This system classified data through segregated distinctive respiratory diseases for achieving a higher accuracy value of 99.01%. In [27], a deep domain adaptation (DDA) method was developed for pneumonia and COVID-19 classification with consideration of distinct features. The developed DDA method exhibited 0.985 AUC and achieved 92.98% of F1_Score. In [28], adopted pre-trained ResNet50 for extraction of features integrated with SVM classifier. This ResNet50 method provided an accuracy of 95.38% with the application of binary classification. In [29], a DarkNet method was developed for filtering various layers of the method for the classification of X-ray images. The classification was based on the categorization of Pneumonia, Normal, and Covid-19. The DarkNet model with filtering provided the accuracy value of 98.08% with a binary classification value of 87.02%. A stacked pre-trained VGG19 model was developed with the inclusion of 30 layers with feature extraction for COVID detection [30]. For COVID-19, the logistics regression method was used to classify X-Ray images. In [31], comparatively examined pre-trained models and Resnet50 for detection of COVID-19. Through analysis, it was concluded that Resnet50 provided a higher accuracy value of 98%. In [32], a deep learning the method was developed for early COVID-19 detection. By considering the values of 3D CNN and HU, pre-processing in X-ray images was done for feature extraction. In [33], a novel technique was proposed for the classification of X-ray images as normal, COVID-19, and pneumonia. For abnormalities detection, this method combined the pre-trained chexnet method. In [34], it was integrated with SSD RetinaNET. The method was evaluated with databases containing chest X-ray images collected from 26,684 patients. Every image was labeled with consideration of various classes related to radiological reports. The classification of pneumonia patients was categorized as Normal, Opacity in the lung, Not normal, or Lung Opacity. Also, in [35], the author utilized CNN architecture for chest X-ray classification.

The CNN model included InceptionV3, InceptionResnetV2, and Exception for classification.
Further, the CNN model of X-ray chest images was evaluated based on consideration of different statistical techniques such as Markov chain Monte Carlo (MCMC) and genetic algorithms for tuning hyperparameters. In [36], feature extraction with a pre-trained model was focused. The pre-trained model included in CNN was AlexNet and VGG16. The features extracted from those models were reduced through the maximal and minimal value of relevance algorithm and redundancy. The resultant set of features were presented as input to the classification algorithm. The classification was based on consideration of pneumonia and non- pneumonia images such as Linear Regression, KNN (K Nearest Neighbours), DT (Decision Tree), and LDA (Linear Discriminant Analysis). Some dimension reduction techniques used by the researchers can also be applied for this work such as Yuanhang Su et al. [37] suggested a trainable scaling factors that serve as an attention mechanism to adaptively change memory decay. The design proposed is called the extended LSTM (ELSTM). Finally, the authors proposed a based bidirectional recurrent neural network to build a device that is resistant to previous incorrect predictions. Extensive tests on various language tasks are carried out to demonstrate the superiority of the proposed ELSTM and DBRNN solutions (tree-structured multi-stage principal component analysis) are defined in [38]. The TMPCA process, unlike traditional word-to-vector embedding methods, performs dimension reduction at the sequence level without using labeled training data [39]. The tree-structured multi-linear principal component analysis (TMPCA) is a novel data dimension reduction technique proposed in [40]. In Table 1, an overall summary of the literature is presented.

	Normal	Covid-19	Other Infections	Total
Training	325	349	395	1069
Validation	50	50	50	150
Testing	50	50	50	150
Total	425	449	495	1369

Table2. Data split for Stack AlexNet-19

3. Design Methodology

This section provides a brief description of the proposed classification model. At first, the dataset description is presented followed by the feature selection for classification. In the next subsection, the data preparation process is evaluated followed by the implementation of the proposed model.

3.1 Dataset Description

During pandemic the Healthcare system and infrastructure was working with their full potential and thus a huge dataset could not be collected. However, in such times also we were able to get a small test dataset.

In this study, the CT lung image dataset is collected from the Kaggle dataset with COVID and non-COVID patient CT images [41]. The publicly available dataset incorporates different types of pathologies for pre-processing of jpg format. The CT image dataset varies images at different dimensions ranging from 152 to 1853. The analysis expressed that the average height of the image is 491 and the average width value of 124 - 383. On the whole, the average width value is measured as 1485. The dataset is classified with lesion segmentation to differentiate COVID and non-COVID patients. The analysis is based on the consideration of image lesions with consideration of various labels such as pleural effusion, ground glass, and consolidation. All image label lesions are presented for scanning CT lung images. The intensity of pixels is normalized between the range of 0 and 1. Table 2 presents the details about the classification of the dataset for training, testing, and validation.

3.2 Maintaining the Integrity of the Specifications

The neural network is based on the structure of the cerebral cortex. Those perceptions are based on the characteristics of natural neurons. The characteristics of a single neuron are based on a logistic regression model with two functions in each neuron which combines input features and activation function. The neuron output is characterized as a usable number with consideration of fundamental information at hidden layers with several neurons. The CNN network output is classified based on certain values for the prediction of the certain probability of features. CNN hidden layers adjust the weights with the backpropagation algorithm for optimization of weights and loss function.

Table 1. Summary of the Literature

Ref	Dataset	Number of Data	Database	Method	Accuracy	Sensitivity	Specificity
11	X-ray & CT scan	-	-	CNN	-	-	-
12	X-ray	100	-	InceptionV3	97	-	-
				Inception-ResNetV2	87		
13	X-ray	50	-	VGG 16	90	-	-
14	X-ray	50	NET	CNN	83.5	-	-
15	CT	275	-	DenseNet	84.7	-	-
16	X-ray	-	-	Capsule Network	95.7	90	95.8
17	X-ray	-		SVM	95.38	97.29	93.47
18	CT	1136	Five Hospitals	Artificial Intelligence (AI)		97.4	92.2
20	CT	-	-	Transfer Learning	93	91	94
22	CT	-	-	Xception	89.6	-	-
24	CT	-	-	Resnet	93.01	-	-
26	X-ray	120	-	inceptionV3	99.01	-	-

3.3. AlexNet Convolutional Neural Network for image segmentation

AlexNet is involved in the identification of tasks in input CT images. The performance is based on the detection of an object, image segmentation, image recognition, and tasks related to computer vision. Usually, CNN with more than 2 layers is characterized as AlexNet which is adopted for task completion. To the input images, AlexNet extracts the basic features by considering various layers such as convolution layers or Kernels, CNN layer for pooling, and fully connected layer (FC). At last, probabilistic characteristics classification as 0 and 1 is performed with the application of Softmax. The AlexNet model consists of distinct filters, and every filter extracts various features and activation mapping techniques. To achieve the desired output volume through multiple maps for activation, it is integrated with stacking. AlexNet layer gains input with specific volume and different shapes in output volume. A convolution layer incorporates different parameters that are the stride, filter count, and activation. For achieving maximal efficiency through average pooling or max pooling, the convolution layer is integrated with the pooling layer. The convolution operation is employed in a neural network for eliminating overfitting in a neural network with the consideration of significant features.

3.4. Transfer Learning

In the transfer learning process, a particular pre-trained model dataset is provided with weights for achieving efficient dataset classification. Generally, transfer learning is conducted in two ways those are described as follows:

- Feature Extraction: In the feature extraction technique, the model is trained with a standard ImageNet dataset. Then classification is included in the model for elimination of redundancy. The other part of the network performs feature extraction for running the classification algorithm.
- Fine Tuning: In this stage, rather than supplant and classifier, training pre-trained model is adjusted with the progression of training each layer of the network model. Generally, transfer learning is applied for the limited availability of

data, and it prevents weight overfitting and randomization effects for achieving better training.

4. STACKALEXNET-19 MODEL IMPLEMENTATION

The main objective of the proposed StackAlexNet-19 model is the automatic differentiation of CT images of the collected dataset. The analysis is based on COVID-19 and non-COVID classification with minimization of pneumonia detection time with an increase in efficacy. In this section, the proposed StackAlexNet-19 model used for COVID-19 detection of an infected person through CT lung images is discussed. For the collected CT image dataset, random models are examined with consideration of weights with the estimation of biased trade-offs. To eliminate trade-off problem transfer learning as well as multiple pre-trained Alexnet is applied in this paper. The process of fine-tuning is examined based on the application of several models such as Inception v3, Xception, ResNet101, NASNet, and MobilenetV2. The developed pre-trained model is examined with pre-trained models for improving classification. The developed model is involved in the identification of unique features for extraction.

The stacking model is a class of ensemble technique and operates in AlexNet. This employs a neural network for the classification of the dataset for the prediction and estimation of dataset features. The feature prediction model is defined as an estimate-learner approach for forecasting. This provides a stacked model that is considered as a single significant classification model. The stacked mode exhibits the advantage of sub-model projection directly included within the estimated learner. The weights of the model are fine-tuned based on the estimation of image Relu function estimation. Further, in sub-models' weights are fine-tuned for estimate-learner model aggregation. The performance of this layer is estimated with equation (1) and (2) as follows:

Relu Function:

$$y(\xi) = max(0, \xi) \quad (1)$$

Softmax:

$$f(a_i) = \frac{e^{a_i}}{\sum_e a_i} \quad (2)$$

The developed StackAlexNet-19 model imports pre-trained weights with the stacking of a larger dataset to achieve robust features. In figure 1, the overall process of StackAlexNet-19 is presented. StackAlexNet-19 is involved in the processing of a larger dataset.

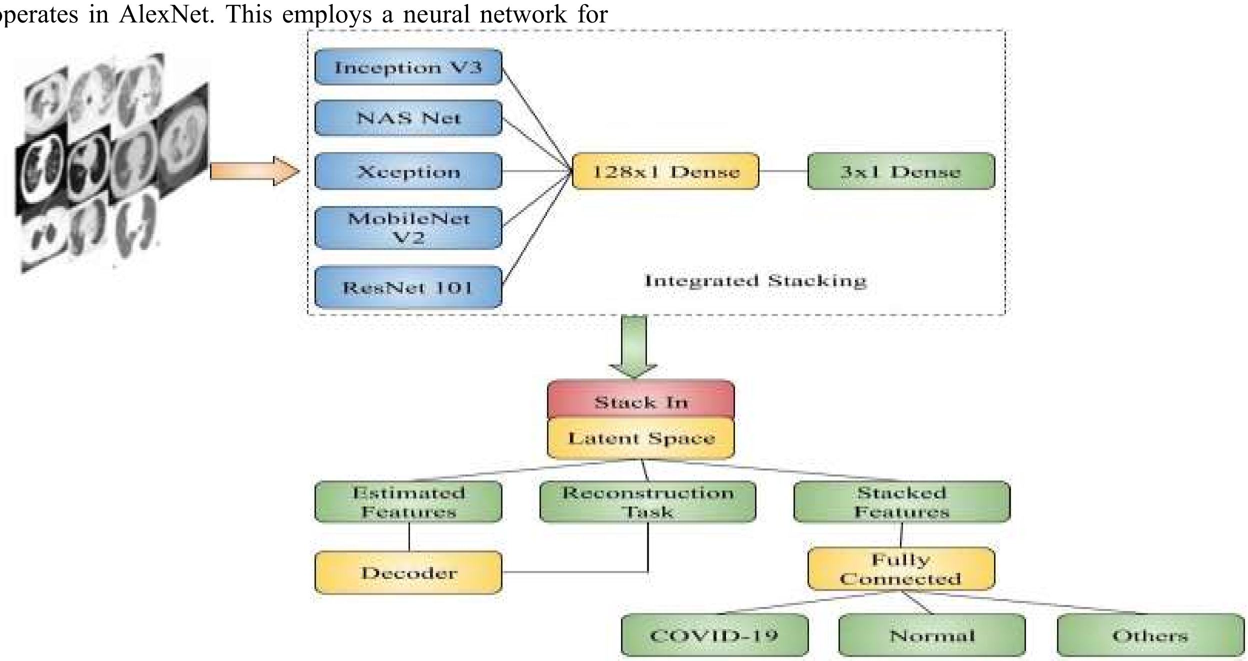

Figure 1: Overview of StackAlexNet - 1

The developed stacking model combines five models to train the network 44 times. The StackAlexNet-19 incorporates binary classification with consideration of 3-class (Normal, Covid, and non-Covid) with five heads at the input layer. Covid-19 causes pneumonia in the lungs but having pneumonia does not certainly mean that it is caused by covid-19. So normal class is for the classification of normal pneumonia which might be caused by other viruses. Whereas covid class is for classifying covid +ve and non-Covid is for classifying covid -ve images. Therefore, three classes are being taken. The input CT images are fed and processed by five-layer and processed accordingly. After completion of the process, a pre-trained model is fine-tuned for forecasting combined with the stacking concept. The integrated stacked output layer is adopted for the dense layer with a stacked model for prediction with the AlexNet convolutional layer. The results are achieved employing passing dense layers with binary classification and SoftMax activation for probabilities prediction. The StackAlexNet-19 randomly generates images and is processed by 5 layers through pre-trained models.

4.1 StackAlexNet-19 model for classification of COVID-19

The inclusion of five pretrained models with distinct capabilities makes StackAlexNet-19 exceptional. Where the first model i.e., Inception V3 is involved in the reduction of computational complexity with building blocks included in inception modules. The Inception module is involved in a significant computation process with a deep neural network for the reduction of dimensionality. The factors considered for Inception V3 are reducing computational cost and overfitting. It incorporates different filters of various sizes involved in parallel computation. The Inception layer includes a 1x1 additional convolution layer for effective computation and robustness. Within the Inception V3 pre-trained model, COVID-19 datasets are implemented with a dense layer of 128 x 1 for classification. The Inception V3 model is pre-trained with efficient feature extraction of the image dimension of 224x224x3 to minimize computational expenses. Through a different iteration process, Adam optimizer is utilized for forwarding and backward classification of images. The second model NASNet is a search algorithm to control neural networks for the classification of deep learning architecture. The NASNet is involved in the training of collected image datasets. The network is pre-trained with 128x1 dense layer architecture for the classification of models. The NASNet pre-trained model is fine-tuned with an input image size of 224x224x3 for reduction and extraction of image features. The StackAlexNet-19 incorporates the Xception model with a dense layer architecture of 128x1. Further, Xception as the third model includes binary and ternary classification layers of 128x1 and 2x1 respectively. The input image fed within the Xception layer is 224x224x3 with various separable layers included for classification. Also, MobileNet and ResNet model is included within StackAlexNet-19 as fourth and 5th model respectively. Both MobileNet and ResNet contain an input layer of 3x1, binary and ternary layer is 128x1 and 2x1 layer for StackAlexNet-19. ResNet process input layer of deep neural network with 101 layers. Image features are processed with a dense layer of StackAlexNet-19 incorporating backward propagation-based Adam optimization. The entire process named as integrated Stacking. In the second phase feature selection, image reconstruction and classification are carried out. The integrated stack serves as a standard encoder for the three tasks, taking a CT scan as input and using its output to generate estimated features, image reconstruction via a decoder, and classification via a fully connected network. In algorithm1, steps for the StackAlexNet-19 classification model are presented.

4.2. Algorithm 1: StackAlexNet-19 Classification Model

In this section, we can get to see the algorithm on which we are undergoing classification.

Input: CT image dataset

Output: Classification of CT images based on classes

Steps:

- Read images in the dataset as batches
- Get a trained model and evaluated the predicted values of data
- Stack the prediction parameters for the estimated model for achieving prediction results
- Perform initialization with Xavier (θ_r) with the epoch of 0
- While epoch <= 5 do
- Apply estimated features to AlexNet
- The feature vector is converted in to feature shape
- Estimate the prediction of the feature using the Relu activation function
- Softmax for prediction of features is
  $f(a_i) = \frac{e^{a_i}}{\sum_e a_i}$
- Update hidden layer weights in StackAlexNet- 19 using

$$\theta = \theta - \frac{\left(a \times V_\theta^{corrected}\right)}{\sqrt{S_\theta^{corrected} + \varphi}}$$

The StackAleNet-19 model is mathematically computed based on the consideration of the following equations. The stacked model is fine-tuned with the incorporation of various inputs for the stacked architecture of the model. Generally, sub-model blocks are considered untrained models. The final convolution layer of the training model exhibits effective performance for classification. In the training process, the dimension of input is considered as (224, 224, 3) for processing. Those sub-models contribute to each layer of StackAlexNet-19. The image features

$(\xi_1, \xi_2, \xi_3, \dots, \xi_n)^T$ are applied to the pooling layer. The output of each model is stacked to optimize and classify the images. The obtained features are processed with 128 Relu function with consideration of activation function presented in equation (3) as follows:

Relu Function: $y(\xi) = max(0, \xi)$ (3)

The proposed StackAlexNet - 19 models for softmax function is calculated using the equation (4) -

Softmax Function = $f(a_i) = \frac{e^{a_i}}{\sum_e a_i}$ (4)

The image entropy values of the image measured for StackAlexNet-19 are computed with equation (5).

Entropy: $Loss(y_i) = -\sum y^i \times log y^i$ (5)

The StackAlexNet-19 model is optimized with an estimation of image features for calculation of COVID-19 features which is done with equation (6) as follows -

Optimization:

$$(\leftrightarrow) = (\leftrightarrow) - \frac{\left(a \times V_{d(\leftrightarrow)}^{corrected}\right)}{\sqrt{S_{d(\leftrightarrow)}^{corrected} + \psi}} \quad (6)$$

Or

$$\phi = \phi - \frac{\left(a \times V_{d(\leftrightarrow)}^{corrected}\right)}{\sqrt{S_{d(\leftrightarrow)}^{corrected} + \psi}}$$

Where,($\leftrightarrow$) and ϕ are image weights and bias values; learning rate of deep learning is stated as α; image gradient is represented as V; geometric feature of the image is defined as S, and stability factor of the image is denoted as Ψ. The prediction of loss in the image is calculated based on the cross-function entropy estimation with optimization. The proposed StackAlexNet - 19 model for classification of COVID - 19 model prediction probability is stated in equation (7) as follows:

$y = [P(y_{class1})P(y_{class2})P(y_{class3})]$ (7)

In the above equation, the probability of class is denoted as $P(\alpha)$.

5. PERFORMANCE EVALUATION AND DISCUSSION

This section presents the performance analysis of the StackAlexNet-19 model. The performance metrics considered for analysis are stated. For CT image classification, the metric is based on the confusion matrix. Confusion matrix considered evaluation is based on the evaluation of other parameters such as precision [42], accuracy, F1-Score, recall, and specificity. The parameters are evaluated with the estimation of FP (False Positive), FN (False Negative), TN (True Negative), and TP (True Positive).

Accuracy: It is defined in equation (8)

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (8)$$

Recall or Sensitivity: It is defined in equation (9).

$$Sensitivity = \frac{TP}{TP+FN} \quad (9)$$

Confusion Matrix: It is represented in equation (10).

$$Confusion\ Matrix = \begin{matrix} TP & FP \\ FN & TN \end{matrix} \quad (10)$$

Specificity: It is defined in equation (11)

$$Specificity = \frac{TN}{TN+FP} \quad (11)$$

Where True Positive (TP) is stated as forecast value which is anticipated as a positive AI model.

False Positive (FP) is defined as a forecast value that is estimated as negative initially and later anticipated as positive in an AI model.

True Negative (TN) demonstrated forecast value as negative and anticipated as unfavorable for the AI model.

False Negative (FN) is stated as a forecast value that is estimated as positive initially and later anticipated as negative in the AI model.

6. RESULTS AND DISCUSSION

In this section, we will discuss the results obtained from our algorithm with the help of graphs and tables altogether.

The proposed StackAlexNet-19 model is examined with consideration of the above-stated parameters. The analysis is conducted based on the consideration of StackAlexNet-19 trained with epochs of 500. The network stopping criteria is set as 10. Initially, pre-processing is employed by StackAlexNet-19 for training and testing of the dataset.

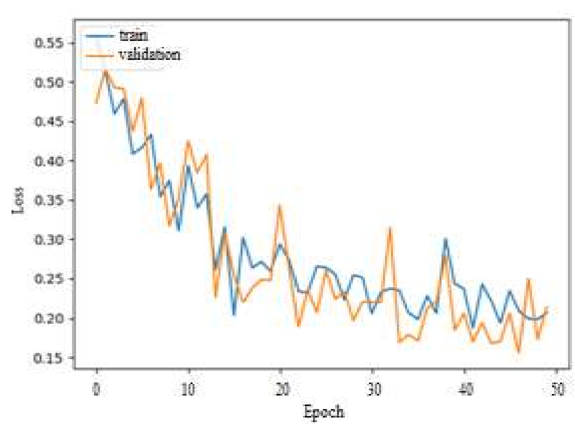

Figure 2. StackAlexNet-19 estimated error plot

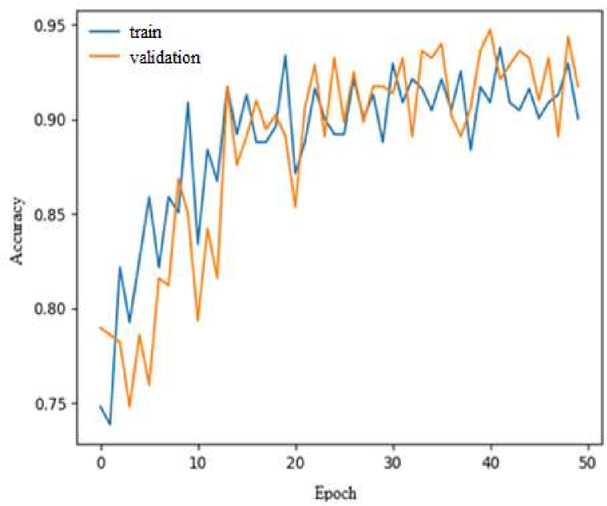

Figure 3. StackAlexNet-19 estimated accuracy plot

In figure 2 and 3, training model loss estimated for StackAlexNet -19 and accuracy estimated using StackAlexNet -19 is presented. The evaluation is based on the consideration of Receiver Operating Characteristics (ROC) for analysis. Based on the estimated ROC, StackALexNet-19 AUC is estimated and comparatively analyzed with existing techniques. In figure 4, the ROC curve is presented for testing and validation.

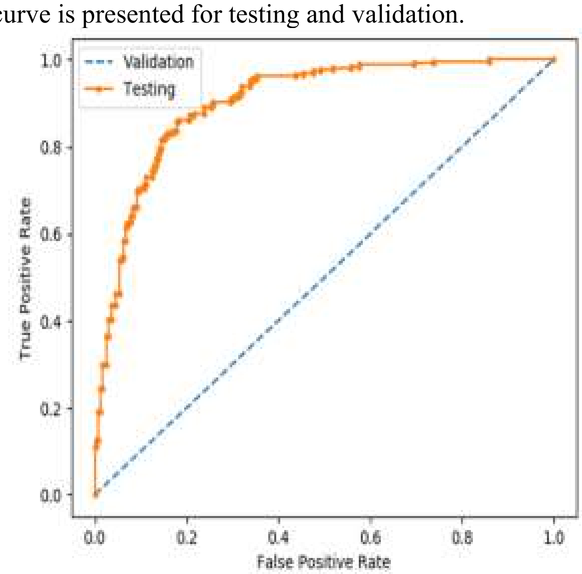

Figure 4. Comparison of ROC

The dataset relies on collected CT images which consist of COVID-19, normal and other infections. The general confusion matrix generated for trained and tested StackAlexNet-19 is presented in Figure 5. The proposed model comparison with multiple deep neural networks used in [42] are presented in Table 3.

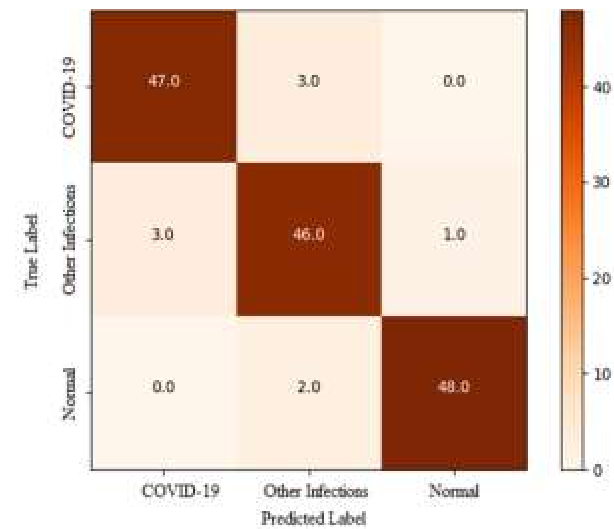

Figure 5: Confusion Matrix for StackAlexNet - 19

Table 3: Comparative Performance Analysis

Methods	Accuracy	Sensitivity	Specificity	AUC
AlexNET[42]	56.67	0.67	0.64	0.66
Inception-ResNet V2[42]	85.33	0.84	0.88	0.90
VGG-19[42]	66.14	0.77	0.61	0.99
VGG-16[42]	62.67	0.67	0.65	0.66
Efficient-Net [42]	90.67	0.91	0.85	0.93
ResNet50[42]	86.67	0.9	0.83	0.88
169-layer DenseNet [42]	83.33	0.91	0.83	0.88
InceptionV3[42]	82.67	0.88	0.78	0.82
CNN 8-layers [42]	74.67	0.8	0.70	0.78
Encoder-Dense [42]	70.04	0.75	0.61	0.72
StackAlexNet - 19	93.67	0.93	0.97	0.97

The above table gives a clear idea of the accuracy and sensitivity of our model as compared to other pretrained CNN models. The StackAlexNet-19 has an accuracy of 93.67 percent which is the highest among other models. In terms of sensitivity, specificity and AUC also the

StackAlexNet-19 again ranks first. As a result, it is clear that the StackAlexNet-19 model, which was used in this study, has a distinct advantage in classifying CT images of patients as corona affected or unaffected. Figure 5 shows a comparison plot for the proposed StackAlexNet-19 model for lung CT image classification.

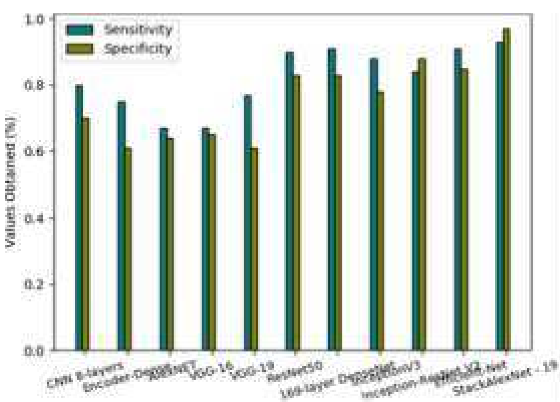

Figure 5: Overall Comparison

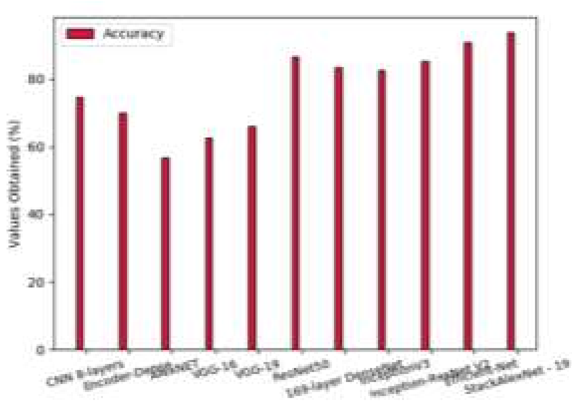

Figure 6: Accuracy Comparison

Figure 6 shows a comparison of the proposed StackAlexNet-19 with current techniques described in the paper [42]. The analysis of results expressed that the proposed classification technique provides higher accuracy than existing techniques.

7. CONCLUSION AND FUTURE WORK

As we know that coronavirus has left the world in a situation of a global pandemic which has affected the livelihoods of a vast section of society. This has also impacted the cash flow in the market which has ultimately led to a fall in the GDP of nations. As this virus is spreading day by day, a major step towards containment of this pandemic is to isolate the people carrying the virus from the rest section of society to stop the transmission of this virus. To isolate the people affected with coronavirus, the diagnostic test is needed to be performed on a huge number of people to categorize them as coronavirus affected and not affected. But, the present healthcare system does not have the adequate amount of test kits and resources to perform Covid tests on such a huge mass.

So, instead of going for physical test kits, we can use AI to know if people are Covid affected or not. The model demonstrates that this is possible by using CT images which can be easily made available at any nearby hospital. Also, this approach is cost-effective and less time-consuming compared to the present practice where one has to wait for a whole day to get results. The effectiveness of this AI-based approach is high as discussed we can see from our result. This whole new approach is a key breakthrough in using technology for the advancement of medical sciences.

If this approach is put into practice, the corona test can be done at home itself. Knowing the results on time can also save many lives and bring down the mortality rate. Along with this, this technology will also save time for doctors as they will no longer be needed to perform the test and reveal the results. This saved time will reduce the workload from the healthcare sector workers and help them focus on the serious cases which need more attention.

The proposed model can prove to be the key factor in bringing the healthcare services back to functioning as a major section of society will be self-sufficient to carry out the test and this, in turn, will cut down the workload of doctors. The model can be used to conduct further research by removing one pre-trained model from the "5-heads" and comparing results. The proposed model can be used for detecting other diseases using CT images.

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