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(Research Article)

Unlocking COVID-19 patterns: Exploring deep learning models for precise recognition and classification of CT images

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Abstract

Coronavirus is a pestilence sickness that truly affects old individuals and patients with persistent illnesses and causes life threatening diseases. Preventing the entire world from this epidemic, quick and accurate detection of COVID-19 plays a crucial role. To contain the advancement of Covid, it is important to build up a dependent and fast technique to recognize the individuals who are influenced and segregate them until full recovery is made. In this study, we introduce a groundbreaking deep CNN model, leveraging the latest advancements in the field, to accomplish precise categorization of COVID-19 CT images. We employ the publicly available HUST-19 dataset, encompassing an impressive collection of 13,980 CT scan images. By harnessing the power of this extensive dataset, our model aims to improve the precision and reliability of COVID-19 classification. In our research, we propose three innovative architectures for deep convolutional neural networks (CNNs), known as AlexNet, Inception V3 and VGG19 models, to get the accurate diagnosis of COVID-19 patients based on images obtained from a CT scan.

In order to assess the effectiveness of CNN-based models in a quantitative manner, we employ several key metrics, including Accuracy, Precision, Recall and F-score. The findings of our study indicate that all these three architectures gave remarkable results but InceptionV3 came on the top with testing accuracy of 99.95% with precision, recall and f1-score of 1, 1, and 1 respectively. The results underscore the potential of our suggested method in accurately diagnosing COVID-19 cases utilizing CT scan images.

Keywords: Coronavirus; Convolutional Neural Network; AlexNet; InceptionV3; VGG19

1. Introduction

The origin of the COVID-19 pandemic in December 2019 can be traced back to Hubei, China, as reported by the WHO [1], within the densely populated region of Hubei. This unprecedented pandemic has already claimed millions of lives and infected over 100 million people worldwide.

Currently, tests that are extensively employed for diagnosing Covid-19 rely on genetic analysis known as RT-PCR tests. The accuracy of these tests is remarkably high and can detect a minute quantity of the virus in a sample from a patient. However, with the emergence of new strains of Covid-19, the PCR test has not been very reliable in identifying the existence of the mutated virus. [2-3].

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Radiological imaging, particularly CT scans, has gained recognition as a rapid diagnostic method for Covid-19. CT scans have shown extreme responsiveness in detecting Covid-19 symptoms and potentially precede laboratory testing. Chest CT scans have a crucial role in the diagnosis of Covid-19 affected people with severe respiratory symptoms.

In this research, various deep learning techniques are used for categorizing a Covid-19 dataset into two groups: infected and not infected. Three CNN models, including AlexNet, Inception V3 and VGG19, are employed for this purpose. The dataset is fed into these CNN models, and different statistical variables such as accuracy, precision, recall and F-score are computed.

1.1. Related Work

Multiple studies have explored the use of advanced medical methods of visualization, such as MRI, X-Ray of chest (CXR), and CT, to boost up the understanding of lung infections. For instance, in [4], CNN was proposed to distinguish Covid-19 patients using CT (Computed Tomography) scan images. For recognition of Covid-19 in the lungs using CT scans, Qingsen Yan et al. [5] introduced the COVID-SegNet network structure.

In a different approach, a diagnosis system for early detection of Pneumonia using chest X-ray scan images was presented by Ayan E. et al. [8]. The preliminary outcomes indicated that the Xception network was outperformed by the VGG16 architecture in terms of classification accuracy (87%).

Excluding advanced deep learning models developed at the individual level, Wang, L et al. [6] proposed the Covid-Net architecture, a custom-designed network for the classification of Covid-1 patients based on characteristics, noncovid-19 patients individuals, and pneumonia cases. This lightweight architecture, employing projection-expansion-projection-augmentation (PEPX) design principles, achieved the accuracy of classification of 94%, surpassing laboratory testing results.

Table 1 Classification performance of Deep CNN models using different COVID-19 image datasets

S.no	Author	Dataset source	Dataset Details	Models Used	Accuracy (%)
1.	Abbas et al. [9]	SARS and COVID-19 images [10]; Normal images [11][12]	196 (COVID-19 infected = 105, non-infected= 80, SARS = 11)	ResNet	95.12
2.	Oh et al. [13]	Infected images of covid-19 [10]; images depicting normal and pneumonia conditions.[14]	15,043 (COVID-19 infected = 180, non-infected= 8851, pneumonia = 6012)	Patch based CNN	88.9
3.	J. et al. [15]	Infected images of covid-19 [16]; Normal images [16]	19,685 (COVID-19 infected = 4001, non-infected = 9979, undecided= 5705)	13-layer CNN with PLR algo.	95.31
4.	Yıldırım [17]	COVID-19 images [16]; Normal images [16]	19,685 (COVID-19 infected= 4001, non-infected = 9979, undecided= 5705)	1D CNN	86.67

2. Material and methods

This research employs three various CNN based models, namely AlexNet, Inception V3, and VGG19, to accomplish the task of classifying COVID-19 cases applying CT (Computed Tomography) scans. Fig. 1 illustrates the put forward model architecture for effectively differentiating COVID-19 infected human beings from healthy individuals. These outcomes are then juxtaposed against ground truth labels, and the F1 score is computed to evaluate the precision of the models.

2.1. Dataset used

In this analysis, the construction and development of numerous models were undertaken utilizing a dataset sourced from the publicly available HUST-19 dataset [16]. The dataset employed for this purpose consisted of 13,980 computed tomography (CT) scan images, comprising 4,001 CT (Computed Tomography) scan images depicting individuals impacted by Covid-19 and 9,979 CT (Computed Tomography) scan images of healthy individuals. Specifically, 4,001 CT scans representing positive COVID-19 cases (referred to as pCT) and 9,979 CT scans representing negative cases (referred to as nCT) can be obtained by accessing the provided link: https://ngdc.cncb.ac.cn/ictcf/HUST-19.php

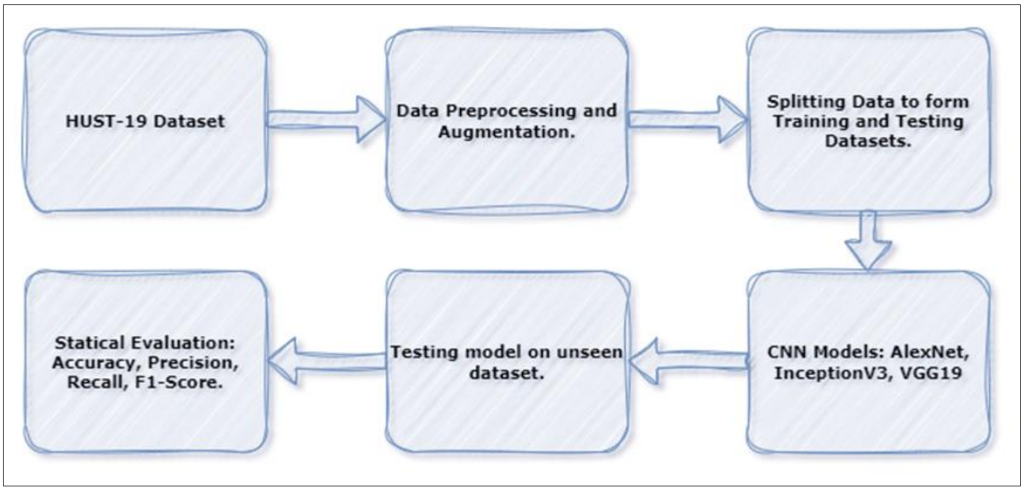

Figure 1 Proposed model for COVID-19 classification using HUST-19 dataset

Furthermore, the dispersion of positive and negative cases within the COVID-19 database is depicted in Table 2. So, we have 4,001 scans classified as pCT, and 9,979 scans labeled as nCT.

The shape of the image while training process was: (224 * 224 * 3).

Table 2 The distribution of medical images used in proposed study

S. No.	Total Number images	Number of Covid negative images	Number of Covid positive images
1.	13980	9979	4001

2.2. Pre-processing of dataset

Figure 2 illustrates a significant aspect of this report, namely the implementation of horizontal and vertical flipping. This flip augmentation technique is facilitated through the utilization of a boolean argument, either "horizontal_flip" or "vertical_flip," within the constructor of the ImageDataGenerator.

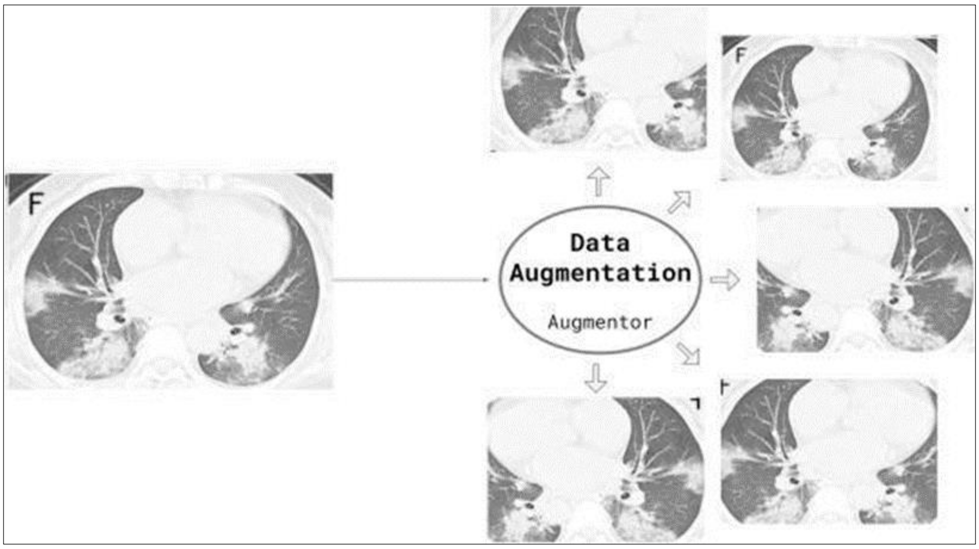

Figure 2 Augmentation Images

2.2.1. Data augmentation approaches

The scale of the dataset is a critical aspect in the realm of deep learning, as data-driven approaches heavily rely on the abundance of data. Data augmentation, as conceptualized by Data Tanner and Wong, serves as a means to indirectly address complex problems by expanding the dataset. Hence, data augmentation techniques become indispensable as they synthetically produce annotated training data from the existing dataset.

In our specific study, we applied both horizontal and vertical flipping to our dataset. Vertical flipping involves reversing the rows of input image pixels, while horizontal flipping involves reversing the columns of pixels. This flip augmentation technique was implemented using boolean arguments, namely "horizontal_flip" or "vertical_flip," within the constructor of the ImageDataGenerator. Figure 3 shows the augmentation configuration that we used in our experiments.

```
# Data augmentation and normalization
train_datagen = ImageDataGenerator(
    rescale=1.0 / 255,
    rotation_range=15,
    width_shift_range=0.1,
    height_shift_range=0.1,
    shear_range=0.1,
    zoom_range=0.1,
    horizontal_flip=True,
    fill_mode="nearest",
)
```

Figure 3 Data augmentation configuration

2.3. CNNs

CNNs are a type of artificial intelligence model utilized for the extraction of information through direct manipulation of input data. They operate as a machine learning model. CNNs have gained significant popularity in recent times, owing to their impressive performance in image processing tasks, particularly in the realms of categorization, recognition, and segmentation.

2.3.1. AlexNet

AlexNet, a notable CNN architecture, transformed the field of computer vision. Developed by Alex Krizhevsky under the guidance of Ilya Sutskever and Geoffrey Hinton, AlexNet surpassed the LeNet architecture in terms of depth and complexity. It comprises 8 layers, including 3 fully connected (FC) layers and 5 convolutional (conv) layers.

AlexNet incorporates dropout layers to mitigate the problem of overfitting. Dropout randomly selects a portion of neurons during training, effectively preventing them from participating in the learning process. This regularization technique helps generalize the network's performance to unseen data.

Table 3 presents a summary of the AlexNet model, detailing its architecture, that we used. The architecture comprises 5 convolutional layers and 3 dense layers, interspersed with pooling and activation layers.

2.3.2. InceptionV3

InceptionV3 is a cutting-edge deep learning model for computer vision tasks that belongs to the Inception family of convolutional neural networks (CNNs). Developed by researchers at Google's DeepMind, it represents a significant advancement in image recognition and understanding. Released in 2015, InceptionV3 builds upon its predecessors, InceptionV1 and InceptionV2, with the goal of improving both accuracy and efficiency in visual recognition tasks.

The primary objective of InceptionV3 is to tackle the challenges posed by deep networks that become increasingly computationally expensive and prone to overfitting as they grow in depth and complexity. To address these issues, the model introduces several innovative architectural elements and techniques that enable it to achieve state-of-the-art results while maintaining a more streamlined design.

One of the standout features of InceptionV3 is its use of the "Inception module," which employs a combination of different convolutional filter sizes (1x1, 3x3, and 5x5) within a single layer. This allows the model to capture features at multiple scales and effectively learn diverse patterns from the input data. Furthermore, the model incorporates the concept of "factorization" by breaking down large convolutional filters into smaller ones, further reducing computational complexity.

Table 3 Description of AlexNet Model Summary

Layer (type)	Output Shape	Param
conv2d_10 (Conv2D)	(None ,54,54,96)	34944
max_pooling2d_6 (MaxPooling 2D)	(None ,26,26,96)	0
conv2d_11 (Conv2D)	(None ,22,22,256)	614656
max_pooling2d_7 (MaxPooling 2D)	(None ,10,10,256)	0
conv2d_12 (Conv2D)	(None ,8,8,384)	885120
conv2d_13 (Conv2D)	(None ,6,6,384)	1327488
conv2d_14 (Conv2D)	(None ,4,4,256)	884992
max_pooling2d_8 (MaxPooling 2D)	(None ,1,1,256)	0
flatten_2 (Flatten)	(None ,256)	0
dense_6 (Dense)	(None ,4096)	1052672
dropout 4(Dropout)	(None ,4096)	0
dense_7 (Dense)	(None ,4096)	16781312
dropout 5(Dropout)	(None ,4096)	0
dense_8 (Dense)	(None ,1)	4097
Total params: 21,585,281		
Trainable params: 21,585,281		
Non -trainable params: 0		

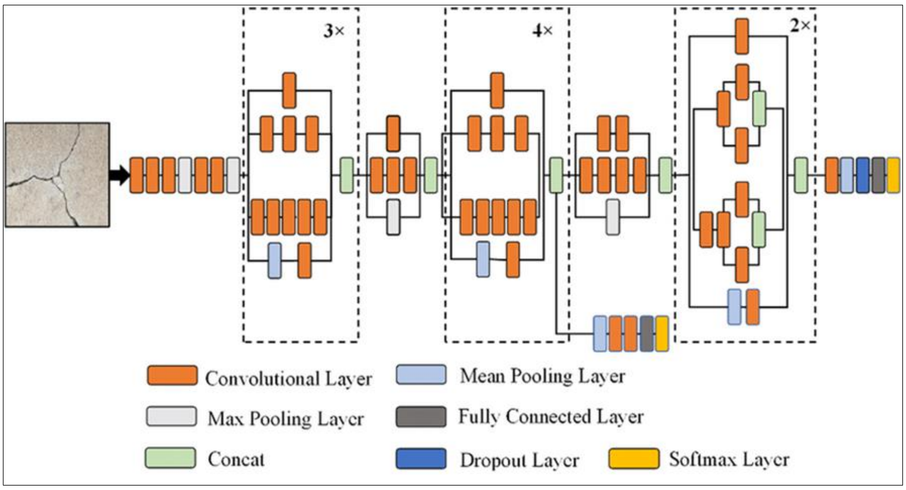

Figure 4 Image showing InceptionV3 [18] architecture

InceptionV3 also employs "batch normalization" and "auxiliary classifiers" during training to accelerate convergence and mitigate overfitting. The auxiliary classifiers, in particular, introduce intermediate classification objectives at various depths of the network, promoting the learning of both low and high-level features, thus contributing to better gradients throughout the architecture.

The inceptionV3 model has proven to be highly versatile, excelling in various computer vision tasks such as image classification, object detection, and segmentation. Its success can be attributed not only to its architectural innovations but also to its robustness in feature extraction and representation learning, allowing it to generalize well to diverse datasets and unseen data.

2.3.3. VGG19

The VGG19 model is a powerful convolutional neural network (CNN) architecture that has significantly influenced the field of deep learning, especially in computer vision tasks. Developed by researchers at the Visual Geometry Group (VGG) at the University of Oxford, the VGG19 model is an extended version of the VGG16 model, featuring 19 layers of trainable parameters, including 16 convolutional layers and 3 fully connected layers.

Released in 2014, the VGG19 model achieved remarkable performance on various image recognition challenges, such as the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) competition, which further solidified its reputation as one of the most influential and widely used deep learning architectures.

The success of VGG19 can be attributed to its simplicity and uniformity in architecture. The model uses small 3x3 convolutional filters throughout the network, which provides a deeper representation while keeping the number of parameters manageable. This design philosophy, with its multiple layers and smaller filter sizes, allows VGG19 to learn hierarchical features from raw image data efficiently, making it adept at capturing intricate patterns and complex structures within images.

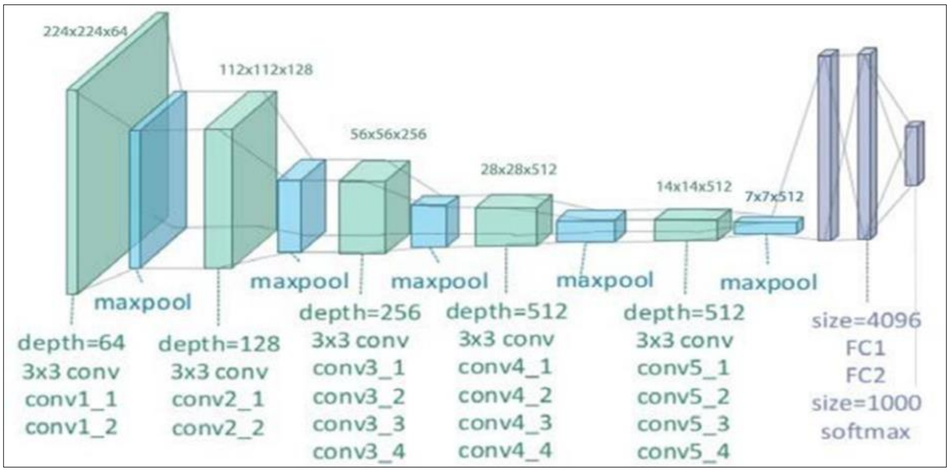

Figure 5 VGG Model Diagram [19]

Table 4 Model Summary of VGG19

Column1	Column2	Column3
Layer (type) Output	Shape	Param #
input_1 (Input Layer)	[(None,224,224,3)]	0
block1_conv1 (Conv2D)	(None,224,224,64)	1792
block1_conv2 (Conv2D)	(None,224,224,64)	36928
block1_pool (MaxPooling2D)	(None,112,112,64)	0
block2_conv1 (Conv2D)	(None,112,112,128)	73856
block2_conv2 (Conv2D)	(None,112,112,128)	147584

block2_pool (MaxPooling2D)	(None ,56,56,128)	0
block3_conv1 (Conv2D)	(None ,56,56,256)	295168
block3_conv2 (Conv2D)	(None ,56,56,256)	590080
block3_conv3 (Conv2D)	(None ,56,56,256)	590080
block3_conv4 (Conv2D)	(None ,56,56,256)	590080
block3_pool (MaxPooling2D)	(None ,28,28,256)	
block4_conv1 (Conv2D)	(None ,28,28,512)	1180160
block4_conv2 (Conv2D)	(None ,28,28,512)	2359808
block4_conv3 (Conv2D)	(None ,28,28,512)	2359808
block4_conv4 (Conv2D)	(None ,28,28,512)	2359808
block4_pool (MaxPooling2D)	(None ,14,14,512)	0
block5_conv1 (Conv2D)	(None ,14,14,512)	2359808
block5_conv2 (Conv2D)	(None ,14,14,512)	2359808
block5_conv3 (Conv2D)	(None ,14,14,512)	2359888
block5_conv4 (Conv2D)	(None ,14,14,512)	2359808
block5_pool (MaxPooling2D)	(None ,7,7,512)	0
flatten (Flatten)	(None ,25088)	0
dense (Dense)	(None ,512)	12845568
dropout (Dropout)	(None ,512)	0
dense 1(Dense)	(None ,1)	513
Total params: 32,870,465		
Trainable params: 12,846,081		
Non -trainable params: 20,024,384		

2.4. Activation Function

Commencing an introductory project within a neural framework organization characterizes how the weighting of information impact is changed into a result from a hub or hubs within a layer of the network.

The decision of enactment work has a huge effect on the ability and execution of the neural organization, and diverse initiation capacities might be utilized in various pieces of the model.

2.4.1. Rectified Linear Unit (ReLU)

After convolutional layers, there are amended straight units layer (ReLU layer) and max pooling layer. After the convolution layers, the ReLU layer comes next and is utilized as a rectifier unit. In all models, ReLU is utilized as an enactment work, since it is as of now a standard initiation work in picture characterization undertakings. Typically, it is positioned after the ReLU layer and before the subsequent convolution layer [8]. Following the consecutive application of convolution, ReLU activation, and pooling layers, a fully connected layer is commonly utilized. The ReLU function can be represented using Eq. (1).

$$f(x) = \begin{cases} 0 \; if \; x \leq 0 \\ x \; if \; x > 0 \end{cases} \dots\dots..(1)$$

2.4.2. Sigmoid

The sigmoid activation function is a widely used non-linear activation function in artificial neural networks. It maps the input values to a range between 0 and 1, making it particularly suitable for binary classification problems and as an output activation function for models predicting probabilities.

The mathematical formula for the sigmoid function is:

$$f(x) = \frac{1}{1 + e^{-x}} \quad \ldots.(2)$$

3. Results and discussion

Every one of the models were executed on Jupyter notebook utilizing different scikit-learn and TensorFlow libraries. All the experiments were performed using Python of version 3.9.9 as a kernel for all the handling. First, we divide the dataset into 3 sets for training, testing and validation.

Four different parameters (equations 3-6) were used to produce a comparative analysis of performance of different CNN architectures. The following parameters: recall, accuracy, precision, and F-score are calculated for performance-check.

$$Recall = TN/(TN + FP) \ldots.(3)$$

$$Precision = \frac{TP}{TP+FP} \ldots \ldots \ldots \ldots \ldots (4)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \ldots \ldots \ldots \ldots (5)$$

$$F1\ score = \frac{2*TP}{2*TP+FP+FN} \ldots \ldots \ldots \ldots \ldots (6)$$

Here, In the context of evaluating a classification model, we use TP to represent the number of accurately recognize positive cases (true positives), TN to represent the count of truly recognize negative cases (true negatives), FP to indicate the count of mistakenly identified positive cases (false positives), and FN to signify the count of mistakenly identified negative cases (false negatives) [7].

3.1. Results Comparison of all three models

3.1.1. Results obtained from AlexNet model

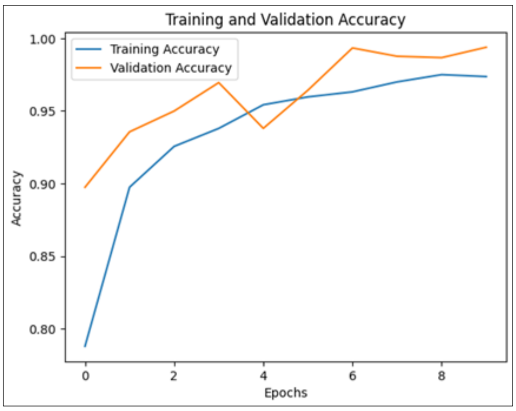

Figure 6 Training and Validation Accuracy

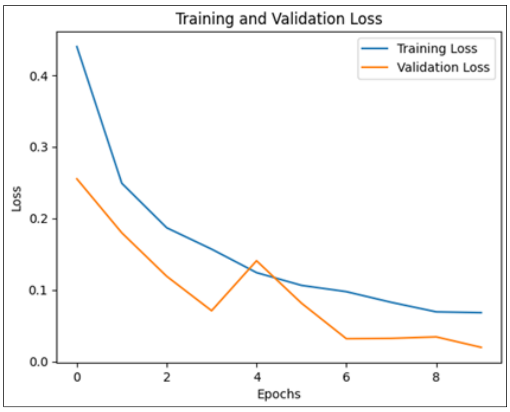

Figure 7 Training and Validation Loss

The model summary of the AlexNet architecture that we used is mentioned in Table 3. Since it is a binary classification problem sigmoid activation function was used in the last dense layer. For the calculation of loss binary_crossentropy was used with Adam optimizer with learning rate of 0.0001. The model was trained for 10 epochs with batch size of 32. The model was trained for total of 21,585,281 trainable parameters with the use of multiprocessing on GPU. The obtained training and validation accuracy for 10 epochs is shown in the figure 6 and training and validation loss for 10 epochs is shown in the figure 7.When the model was tested against unseen dataset the results were remarkable. Test accuracy of 99.61 % was obtained with test loss of 1.58%. After this a classification report was generated for the unseen dataset which comprises of 2,097 new images.

Table 5 Classification report of AlexNet model

	precision	recall	f1 -score	support
nCT_class	1.00	1.00	1.00	1497
pCT_class	0.99	0.99	0.99	600
accuracy			1.00	2097
macro avg	1.00	0.99	1.00	2097
weighted avg	1.00	1.00	1.00	2097

The Confusion Matrix is shown in figure 8 for this unseen test dataset. This confusion matrix shows that model was able to predict 1,494 correct from 1497 nCT images and 595 correct from 600 nPT images.

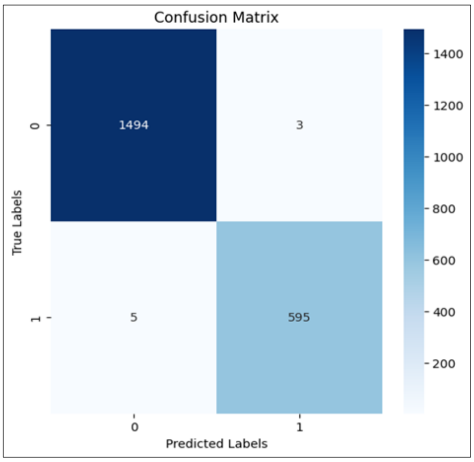

Figure 8 Confusion matrix plotted for the prediction unseen test dataset through AlexNet trained model

3.1.2. Results obtained from InceptionV3 model.

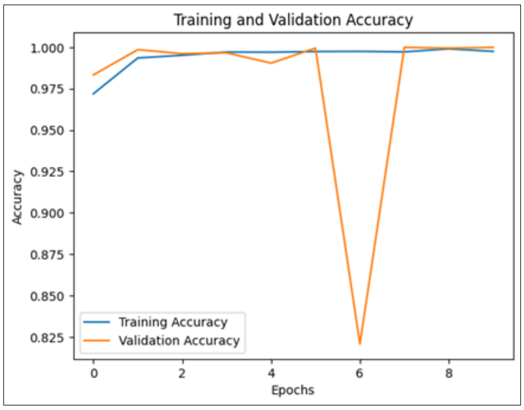

Figure 9 Training and Validation Accuracy

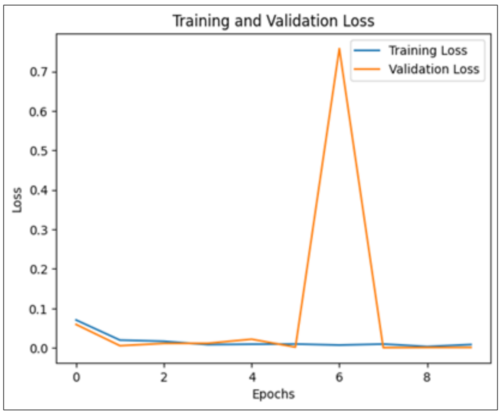

Figure 10 Training and Validation Loss

The model that we used uses InceptionV3 as the base model, upon which we added our custom layers for binary classification. Since it is a binary classification problem sigmoid activation function was used in the last dense layer. For the calculation of loss binary_crossentropy was used with Adam optimizer with learning rate of 0.0001. The model was trained for 10 epochs with batch size of 32. The model was trained for total of 22,817,953 trainable parameters with the use of multiprocessing on GPU. The obtained training and validation accuracy for 10 epochs is shown in the figure 9 and training and validation loss for 10 epochs is shown in the figure 10.When the model was tested against unseen dataset the results were remarkable. Test accuracy of 99.95 % was obtained with test loss of 1.18%. After this a classification report was generated for the unseen dataset which comprises of 2,097 new images.

Table 6 Classification Report of InceptionV3

	precision	recall	f1 -score	support
nCT_class	1.00	1.00	1.00	1497
pCT_class	1.00	1.00	1.00	600
accuracy			1.00	2097
macro avg	1.00	1.00	1.00	2097
weighted avg	1.00	1.00	1.00	2097

The confusion matrix is shown in figure 11 for this unseen test dataset. This confusion matrix shows that model was able to predict 1,497 correct from 1497 nCT images and 599 correct from 600 nPT images.

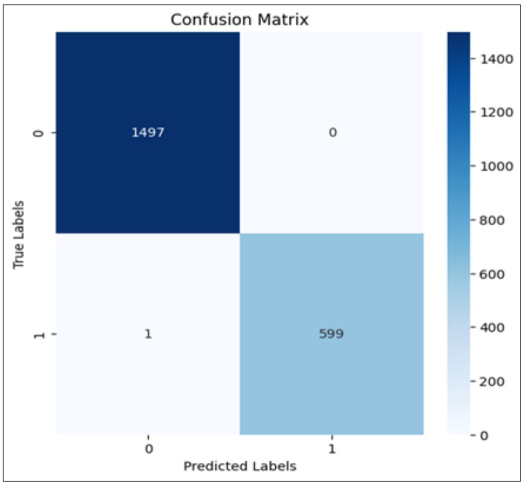

Figure 11 Confusion matrix plotted for the prediction unseen test dataset through InceptionV3 trained model

3.1.3. Results obtained from VGG19 model.

The model that we used uses VGG19 as the base model, upon which we added our custom layers for binary classification. Since it is a binary classification problem sigmoid activation function was used in the last dense layer. For the calculation of loss binary_crossentropy was used with Adam optimizer with learning rate of 0.0001. The model was trained for 10 epochs with batch size of 32. The model has total of 32,870,465 parameter which is very large, so we relied on transfer learning and froze the weights of VGG19 model except our custom layer that is added for binary classification. After freezing the weights trainable parameters reduced to 12,846,081. Then the model was trained for total of 12,846,081 trainable parameters with the use of multiprocessing on GPU. The obtained training and validation accuracy for 10 epochs is shown in the figure 12 and training and validation loss for 10 epochs is shown in the figure 13.

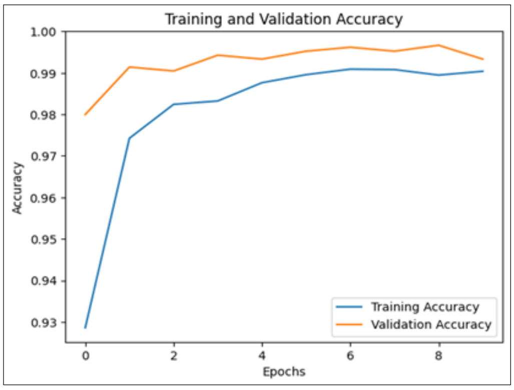

Figure 12 Training and Validation Accuracy

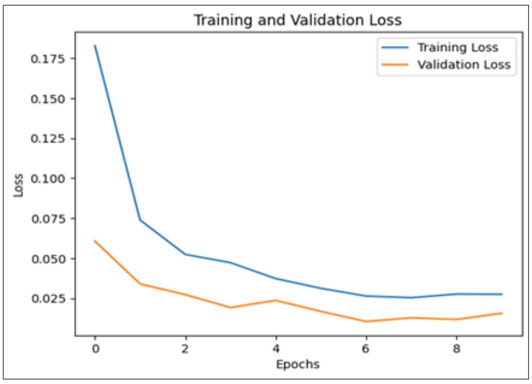

Figure 13 Training and Validation Loss

When the model was tested against unseen dataset the results were remarkable. Test accuracy of 99.76 % was obtained with test loss of 0.72%. After this a classification report was generated for the unseen dataset which comprises of 2,097 new images.

Table 7 Classification report of VGG19

	precision	recall	f1 -score	support
nCT_class	1.00	1.00	1.00	1497
pCT_class	0.99	1.00	1.00	600
accuracy			1.00	2097
macro avg	1.00	1.00	1.00	2097
weighted avg	1.00	1.00	1.00	2097

The Confusion Matrix is shown in figure 14 for this unseen test dataset. This confusion matrix shows that model was able to predict 1,493 correct from 1497 nCT images and 599 correct from 600 nPT images.

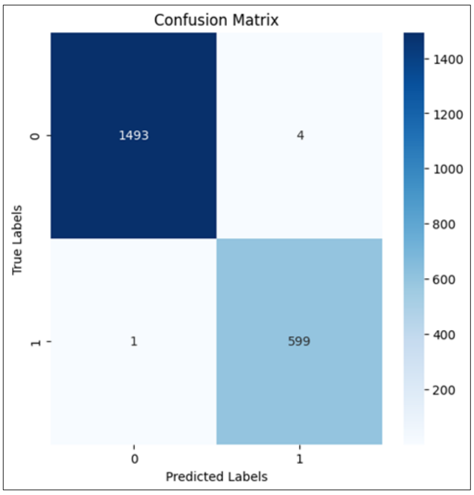

Figure 14 Confusion matrix plotted for the prediction unseen test dataset through VGG19 trained model

3.2. Results Summary

All the models were trained for 10 epochs with sigmoid activation function in last dense layer, loss function as binary cross-entropy and with Adam optimizer. Although all three models show great results, InceptionV3 came on the top with accuracy of 99.95%.

Table 8 Comparison between all three model results

Model Name	Total Parameters	Trainable Parameters	Accuracy	Precision	Recall	F-score
AlexNet	21585281	21585281	99.61%	1	1	1
InceptionV3	22852385	22817953	99.95%	1	1	1
VGG19	32870465	12846081	99.76%	1	1	1

4. Discussion

A lot of research analysis have been suggested so far to detect COVID-19 using medically scanned images obtained from the freely accessible HUST-19 and iCTCF databases, which can be utilized for conducting academic research at https://ngdc.cncb.ac.cn/ictcf/HUST-19.php .

Table 8, brings out the comparative study of the three different deep learning applications in this study. The best results are obtained using Inception V3 having accuracy of 99.95%, with precision, recall and f1-score as 1, 1 and 1 respectively.

In Table 9, The classification accuracy obtained using the system proposed in this paper is compared with the various research work proposed in this field of classification of novel coronavirus. J. et al.[15] have used a 13 layer CNN with PLR algorithm for classification of medical images on the HUST-19 test dataset for categorizing images into two distinct groups: coronavirus and non-coronavirus. The best performance achieved an average precision of 95.31%.

In this study, the CT-scans of covid infected patients and non-infected people were categorized using various CNN models like AlexNet, inceptionV3 and VGG 19. The best results were obtained with InceptionV3 with an accuracy of 99.95%.

Table 9 Outcomes derived from comparable studies

S.NO.	Author	Sources of Dataset	Dataset Details	Model	Performance (%)
1.	J. et al.[15]	Infected images of covid-19 [16]; Normal images [16]	19,685 (COVID-19 = 4001, non-Covid = 9979, undecided= 5705)	13-layer CNN with PLR algo.	95.31: Accuracy 96.29: Sensitivity
2.	Proposed	COVID-19 images: [16]; non-Covid images [16]:	19,685 (COVID-19 = 4001, non-Covid = 9979, undecided= 5705)	AlexNet, inceptionV3, VGG19	Accuracy: 99.95% Sensitivity/Recall: 1

5. Conclusion

The initial identification of Covid-19 occurred in the city of Wuhan in China, and subsequently, the virus swiftly disseminated across various nations globally. Detecting COVID-19 infections at an initial phase plays a crucial factor in curbing the transmission of the disease to individuals in close proximity. Computed Tomography (CT) scans demonstrate various symptoms caused by the coronavirus infection, and various deep learning techniques can be applied for the recognition of COVID-19 using these CT scans.

In this analysis, the HUST-19 dataset acquired the dataset of coronavirus images. Further, three different CNN models i.e. AlexNet, Inception V3, VGG 19 are implemented from scratch. This paper also demonstrates a comparative performance analysis is conducted on various CNN architectures based not just on accuracy but also on various other performance parameters like sensitivity, Specificity and accuracy. The best classification accuracy of 99.95 was achieved using Inception-V3 CNN model.

Future Work

Deep learning-based methods can significantly contribute to minimizing the spread of coronavirus among humans by the early recognition of COVID-19 infections. Moreover, AI-based techniques can observe and keep tabs on individuals neighboring to COVID-19 infected patients by creating online social platforms and pathways of information.

With the evolution of new variants of coronavirus, there is an urge to design AI-based systems which are able to detect coronavirus irrespective of its variant. More extensive investigation utilizing machine learning and deep learning techniques is necessary to advance the development of COVID-19 treatment.

Compliance with ethical standards

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No conflict of interest to be disclosed.

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