Journal of Intelligent Systems and Internet of Things
Vol. 16, No. 02, PP. 42-59, 2025
DOI: https://doi.org/10.54216/JISIoT.160204

Transforming Public Health with AI and Big Data Deep Learning for COVID-19 Detection in Medical Imaging

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Abstract

For public health systems worldwide, the COVID-19 epidemic has presented hitherto unheard-of difficulties. Rapid and accurate virus detection is essential for successful treatment and containment. This paper explores the transformative potential of Artificial Intelligence (AI) and Big Data in public health, focusing on applying deep learning techniques for COVID-19 detection in medical imaging. We discuss the integration of AI-driven solutions in healthcare, the role of big data in enhancing diagnostic accuracy, and the implications for future public health strategies. The COVID-19 pandemic started in Dec 2019 and has wreaked havoc on our lives ever since. One such youngest addition to the coronavirus family has claimed the lives of almost half the world's population. With the introduction of constantly evolving forms of this infection, locating the infection early on would still be essential. Even though the PCR test is the best and most utilized approach for identification, non-contact procedures such as chest radiography and CT scans have always been recommended. In this context, artificial intelligence is integral to the early and precise diagnosis of COVID-19 via lung image processing. The primary aim of this study is to evaluate and contrast multiple deep learning improved strategies for detecting COVID-19 in CT and X-Ray medical images. We employed four strong CNN methods for the COVID-19 images of the binary classification challenge: ResNet152, VGG16, ResNet50, and DenseNet121. The suggested Attention-based ResNet framework is created to choose the appropriate architecture and training settings for models automatically. In the diagnosis of COVID-19 utilizing CT-scan images, the accuracy and F1-score are over 96 percent. In addition, transfer-learning methods were used to address the lack of information and shorten the training time. Enhanced VGG16 deep transfer learning design was used to accomplish multi-class categorization of X-ray imaging tasks. Enhanced VGG16 was shown to have 99 percent accuracy in detecting X-ray imaging from three classes: Normal, COVID-19, and Pneumonia. The algorithms' accuracy and validity were tested on well-known public datasets of X-ray and CT scans. For COVID-19 diagnosis, the presented approaches outperform previous methods in the literature. In the fight against COVID-19, we believe our research will aid virologists and radiologists in making better and faster diagnoses.

Received: December 08, 2024 Revised: February 03, 2025 Accepted: March 04, 2025

Keywords: Public Health; AI; Big Data; Deep Learning; COVID-19; Medical Imaging

1. Introduction

The COVID-19 pandemic has highlighted the need for innovative approaches to public health challenges. While effective, traditional diagnostic methods often lack the speed and scalability required for a global health crisis. Artificial Intelligence (AI) and Big Data offer promising solutions to enhance the detection and management of infectious diseases. This paper aims to explore the role of deep learning in medical imaging to detect COVID-19 and its potential to transform public health [1].

Deep Learning for COVID-19 Detection in Medical Imaging

Applications in medical imaging have demonstrated outstanding potential for deep learning, a branch of artificial intelligence. X-rays and CT scans are examples of medical imagery from which Convolutional Neural Networks (CNNs) and other deep learning models may automatically identify and diagnose illnesses. To enable quick and precise diagnosis in the context of COVID-19, deep learning models have been created to recognize distinctive patterns of lung infection [2].

The Role of AI and Big Data in Public Health

AI and big data have transformed the healthcare industry. By incorporating these technologies into public health, disease surveillance, early identification, and individualized care can all be enhanced. While Big Data allows for gathering and processing real-time data from various sources, AI algorithms can analyze enormous volumes of data to find trends and forecast epidemics [3].

Chest X-rays and CT scans are two possible methods for quick and early detection of COVID-19 in people with symptoms. Additionally, CT demonstrated high sensitivity in identifying COVID-19 during the initial patient evaluation. In extreme cases, a false negative obtained by RT-PCR detection might be successfully rectified. To determine whether a person is COVID-19 positive, however, a specialist must interpret these X-rays and CT scans, which makes the process difficult and time-consuming. X-rays of the chest are the initial diagnostic method to detect COVID-19 activity. On the other hand, a lone Chest X-ray image does not correctly display promising results in predicting and ensuring the required [4-6].

To resolve these issues, the findings from some of these medical data are merged and forecasted with suitable classifications, and the suggested model's accuracy is enhanced over the regular test image based on those classifications. Appropriate features must be retrieved from all these images to categorize COVID-19 images. Extracting features using COVID-19 images is difficult due to daily variations in attributes and variance from one case to the next. We also need to differentiate from many other respiratory infections. Advantages of when it is implemented, but on the other hand, with constraints that varied depending on the work, could not provide sufficient substantial features [7]. Many conventional machine-learning techniques have already been applied to classify digitized chest data automatically. To use an SVM Classification Classifier model, three frequent patterns were generated from the pulmonary surface to distinguish between malignant and benign lung nodules. Using a grey-level co-occurrence matrix technique, a backpropagation network was used to categorize imagery as normal or malignant. Deep learning, specifically convolutional neural networks (CNNs), can remove valuable features in picture categorization tasks. This feature extraction process necessitates using transfer-learning approaches, wherein the pre-trained CNN models collect the general properties of massive data like ImageNet and then apply them to the job at hand. If enough labeled images are available, deep learning algorithms are better than traditional neural network models [8].

The CNN model is one of the most popular deep-learning algorithms for diagnostic imaging, and it produces excellent results. The capacity of CNN to obtain feature representation from property pictures is essential to its basic efficacy, even in the face of machine learning algorithms. Pre-trained models like DenseNet, ResNet, and VGG-16 are, therefore, instrumental in this process and seem very promising for COVID-19 diagnosis utilizing chest CT and X-ray images. Transferring learned information from a previously trained network that finished a task to a new task is a commonly used technique for CNN architecture training. Most academics, especially in the medical profession, prefer this method [9-13]. It is quicker and more effective because it does not require a big annotation training dataset. Transfer education can be Shallow Tuning adapts individual the previous classification layer to innovative tasks and leaves the constraints of the rest of the layers untrained;

- In this case, the deep tune function is used to retrain the variables before the which were network from end to end;
- Adequate tuning wants to progressively prepare so much layer after layer besides adjusting the having to learn variables unless a vital performance boost is achieved. In identifying X-ray images, transfer knowledge through a fine-tuning process performed admirably.

The significant contributions of the presented method are given as follows:

- To train a model faster, the proposed system employs transfer learning. The models for training compute the weights that are fine-tuning to the task hand, and it would be identifying COVID-19. The three approaches are integrated via stack to forecast output class.
- The single neuron serving as the meta-model in this system accurately predicts the input class based on the results of the three preceding models. To train a model faster, the proposed system employs a learning approach.
- The pre-trained models' weights are correctly tuned for training at the hand and put class, and the three approaches are integrated via stacking. The meta-model in this model is a single neuron, which correctly forecasts output type based on the results of the three models mentioned above.

The residual part of the paper is discussed as follows: Section 2 focuses on the related existing works for COVID-19 detection cases. Section 3 discusses the proposed work and the details of the algorithms presented in this study. Section 4 illustrates the graphical plots and tabular representation for the experimentation of the proposed and existing methods. Section 5 describes the summarization of the proposed work and concludes with the enhancements of it.

2. Literature Review

Authors in [21] proposed a unique stacked ensemble for diagnosing coronavirus from such a person's chest CT scans or chest x-ray imaging. The suggested model is a layered ensemble used before heterogeneous machine learning models. Some transfer learning techniques are VGG-19, ResNet, DenseNet, and Fully Connected Networks, the four pre-trained DL models analyzed (WideResNet 50 2). By adjusting the amount of extra fully connected tiers in each before the model, prospective candidates for the classification algorithm were obtained. After an extensive search, three of the most incredible various models were chosen to create a weighting approximate heterogeneity stacked ensembles.

Early diagnosis of coronavirus-positive cases prevents the diseases from spreading more in the population and allows for earlier public treatment [22]. Imaging of CT and Chest X-ray images have recently shown conspicuous characteristics that demonstrate the strictness of COVID-19 images in the lungs. The scientific progress of AI technology in the deployment of based on deep learning in the healthcare profession continues to be decisive in handling large amounts of data to quick and accurate outcomes in diagnostic imaging to make a diagnosis of pathogens more efficiently and precisely with assistance in remote locations. Utilizing convolution 2D techniques, a method is proposed for analyzing chest X-ray pictures to identify COVID-19 for binary classifications with a precision of 99 percent and validation data of 98 percent, with a loss of roughly 0.15 percent.

Keep an eye on them to make quick decisions and take meaningful tasks for surveillance, treatment, and medication. Rapid recognition of the coronavirus [23] was a challenging and time-consuming task that CAD (Computer-Aided Diagnosis) techniques effectively addressed. The CXR (chest X-ray) technique has become a low-cost and practical option for the CT scan and Real-Time Polymerase Chain Reaction (RT-PCR) test, previously the most frequently employed for COVID-19 identification. Until now, only a few computer-aided design approaches for detecting COVID-19 have been developed, but various problems have hampered their effectiveness. This paper presents a deep convolutional neural network based on ResNet32 and the Convolutional Block Attention Module. Kaggle's dataset with CXR was used to fit the classifier.

COVID-19, a new coronavirus illness, is a global public health disaster. A fatal disease has infected over 230 million individuals around the world. COVID-19 should, therefore, be detected early and consistently. The most common method of detecting this virus is by an RT-PCR test. The above testing is not 100 percent accurate because it has been known to produce false positives and negatives. Some modalities, such as X-rays or CT scans, provide further comprehensive lung images and are more reliable. In a chest CT collection, this research analyses multiple deep learning techniques that help to identify COVID-19 using the transfer learning technique. VGG-16 surpasses all these other models on the dataset, with an accuracy of 85.33 percent [24].

Clinicians employ RT-PCR tests to diagnose COVID-19, which have a high rate of False Positive (FP) and False Negative (FN) findings that take a lengthy time. One way to increase the True Positive (TP) ratio is to run many experiments simultaneously. On the other hand, CT scans and X-ray pictures can be used to identify Covid-19-related pneumonia earlier. Upwards of 95% efficiency can be reached using recent deep learning methods. To diagnose pneumonia, we employed 8 CNN (CovNet)-based deep learning models, including ResNet 152 v2, InceptionResNet v2, Xception, Inception v3, ResNet 50, NASNetLarge, DenseNet 201, and VGG 16. The obtained comparative shows that the proposed algorithms can distinguish Covid-19 positive cases [25].

A deep learning framework can be developed to aid in the analysis of CT scans and provide diagnostics that would expedite the treatment of the condition. This study used retrieved features from chest X-ray and CT images to modify a deep learning system to identify COVID-19. Following the application and comparison of numerous transfer-learning models, a VGG-19 model was modified to deliver the best results for disease diagnosis. One thousand photos were used as a sample to assess each model's diagnostic accuracy. With 99.4% precision and 97.4% sensitivity, the VGG-19 model offers the highest precision, sensitivity, specificity, and 99.4% specificity. Machine learning and image analysis performed well in timely identifying the coronavirus [26].

Researchers present an approach to examining the possibility of deep transfer learning in developing a classification to identify coronavirus-positive patients utilizing CT and CXR imaging in this research. The data preprocessing method expands the training datasets to lessen overfitting and improve the model's generalization capacity. To use a data preprocessing method, we evaluated a set of pre-trained deep learning models: ResNet50, InceptionV3, VGGNet-19, and Exception. According to research, deep learning is better at finding coronavirus cases. The VGGNet-19 model beats the other three models presented using the CT image dataset when each modality is considered separately, according to the findings of the tests [27].

Deep neural networks have recently shown promise in various computer vision tasks, especially medical imaging. In this study, we evaluated and tested the DenseNet network for classifying COVID-19 chest X-ray pictures. This also used a public database with 6432 chest X-ray images classified into three classifications. Transfer learning and fine-tuning are used to train the DenseNet modeling variations, DenseNet121, DenseNet169, and DenseNet201. After analyzing the data, it was found that DenseNet201 had the best accuracy rate for COVID-19 classifications in chest X-ray images, at 0.9367, and the most minor validation loss, at 0.1653 [28].

A patient should wait an extended period to acquire the findings of a blood test to detect Covid-19. Our approach uses a Deep Learning technique to detect COVID-19 quickly. Deep Learning and Neural Algorithms Logistic regression is a statistical tool for predicting the outcome of Radiology data, such as CT scans and X-ray images, which are fed into these algorithms. With the aid of the approach, positive instances of Covid-19 will be recognized more quickly [29]. This research focuses on building a deep-learning approach for detecting and diagnosing COVID-19 utilizing chest CT scans. A public database was employed for this, which included 349 CT scans of 216 patients with COVID-19 clinical abnormalities and CT scans of 397 healthy people. Accuracy, precision, recall, Matthews' coefficients correlation (MCC), and F-measure criteria were used to evaluate diagnostic accuracy. A 10-fold cross-validation procedure was used to assess the approach's reliability. According to the data, CNN has an accuracy rate of 92.63 percent, precision of 92.95 percent, recall of 93.18 percent, MCC percent of 85.20, and F1-measure of 93.06 percent. Based on the results achieved with the approach taken within the focus of this research, the mentioned approach could be used as a supplement to or as a replacement for traditional therapeutic tests in coronavirus outbreaks [30].

For the identification and classification of COVID-19, a transfer learning method with precise adjustment was used in this study. VGG16, DenseNet-121, ResNet-50, and MobileNet were employed as before models. Deep learning models were developed using a dataset of 7232 (COVID-19 vs healthy) chest X-ray images (accessible on Kaggle). A local dataset of 450 chest X-ray images from Pakistani patients was gathered or used for tests and predictions. Many essential characteristics such as recall, specificity, F1-score, accuracy, loss graphs, and confused matrix were generated to verify the algorithms' accuracy. VGG16, ResNet-50, DenseNet-121, and MobileNet attained an accuracy of 83.27 percent, 92.48 percent, 96.49 percent, and 96.48 percent, respectively [14-17].

The objectives of this paper were to see how deep learning, machine learning, and image processing can help with fast and accurate COVID-19 identification from two of the most used neuroimaging techniques: chest X-rays and CT scans. In this study, researchers used chest X-rays and CT scans to assess the effectiveness of ML and DL approaches for COVID-19 detection. CNN models (CNNs) based on the Alexnet Model were proposed for CAD of coronavirus from CT and X-ray images. Here, the effectiveness of this technique was tested on the data set obtained. COVID-19 CT and X-ray scans were categorized, and CT scans were used to track the progression of the individuals' disease [18].

COVID-19 has been successfully identified utilizing computed tomography (CT) scans & X-rays to assess the lung picture. However, it takes a team of radiologists and a lot of time to review each report, which would be time-consuming. As a result, this work proposes an automatic COVID-19 recognition and categorization algorithm based on deep neural networks (DL). Pre-processing, extraction of features and classifications are all performed using the provided method. The input image is processed using the median filtering (MF) method at such an earlier stage. The VGGNet-19 model, built on a convolutional neural network (CNN), is then used as a feature representation. Finally, to identify and classify the presence of COVID-19, an artificial neural network (ANN) is used as a classification algorithm [19].

Researchers worldwide are investigating new machine learning approaches, like deep learning, to help medical experts diagnose COVID-19 disease using medical information like X-ray films and CT scans. Machine learning techniques for demonstrating the first COVID-19 identification from chest X-rays would have effectively controlled this epidemic because the facility for chest X-rays is available even in smaller cities and is significantly less expensive. As a result, researchers suggest a Convolutional Neural Network (CNN or ConvNet) for identifying the presence and absence of COVID-19 illness in this paper. We compare the CNN model to machine learning techniques based on ancient and transfer learning. Compared to machine learning algorithms, the suggested CNN is more efficient (KNN, SVM, DT, etc.) [20].

Deep learning algorithms can identify COVID-19, an essential task for today's therapy options determined based on data. On the other hand, diagnostic imaging approaches and the development of artificial intelligence, machine learning, and deep learning give outstanding performance, notably in detection, classification, and segmentation. These developments have enabled clinicians to monitor the body, enabling more precise diagnostic and non-surgical patient assessment. Other imaging technologies can be used to detect COVID-19, but as computed tomography (CT) is the most popular, we employed it. To recognize COVID-19 (CNN), we also use a deep learning model based on a convolutional neural network [21].

3. Proposed Work

*A. **System Model***

In this section, the proposed methodology is given in more detail. The methodology uses transfer-learning models for the classification of coronavirus images. Fig.1. represents the system model for the proposed work. In this filtering, the spatial domain process is applied to the image pixels, and the manipulation is implemented pixel-by-pixel. A filter mask shifts from one pixel to another by doing several operations. It will remove the noise by smoothing the image.

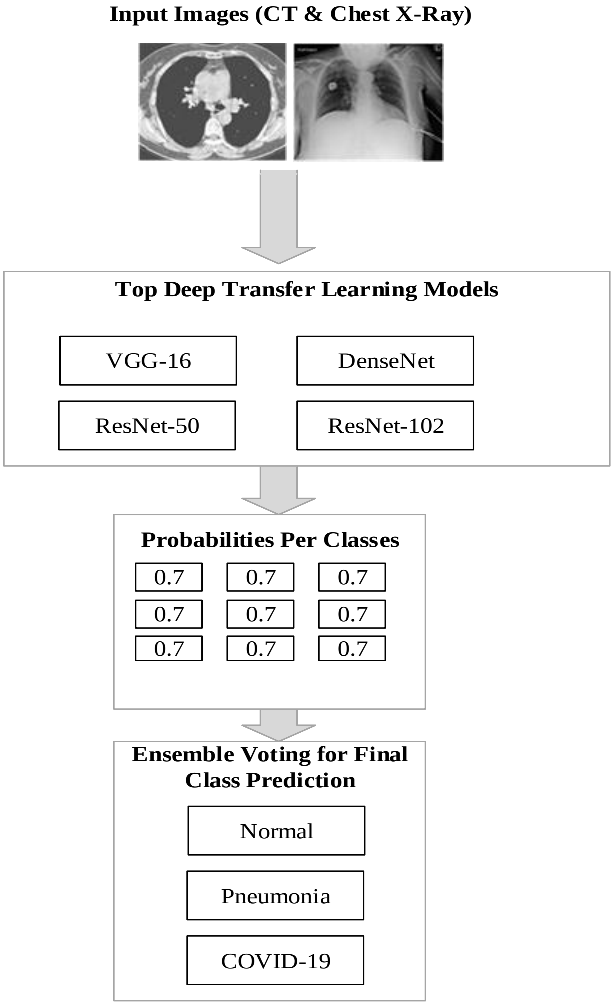


Figure 1. System Architecture

As mentioned earlier, spatial domain, filtering is classified into two classes of filters: linear filter and non-linear filter. The mean and wiener filters are the most widely used linear filtering techniques, and the median filter is a class of non-linear filtering. In the mean filter, the mean (average) value is taken from the computation of neighbors and the center pixel values, which are computed in the $N \times N$ Size. After the calculation of the center pixel value, it is computed as follows:

$$Y(M, N) = Mean\ \{X[i, j], [i, j] \epsilon\ w\} \qquad (1)$$

Where w Are the pixel positions in the neighborhood

Then, we describe the Wiener filter, which filters the consistent pixel values that define the constant power additive noise. This filtering technique is used for adaptive filtering of the image pixel-wise. By computing the pixels in the neighborhood, two variations are computed, including Mean and Standard Deviation. The mean is calculated as follows:

$$\mu = \frac{1}{N \times M} \sum_{(n_1, n_2 \in \eta)} a(n_1, n_2) \qquad (2)$$

The standard deviation is given as

$$\alpha^2 = \frac{1}{N \times M} \sum_{(n_1, n_2 \in \eta)} a^2(n_1, n_2) - \mu^2 \qquad (3)$$

Where η represents the N$\times$ M Of the current pixel. With this estimation, the pixel-wise Wiener filter was applied over the denoised image, which is computed as follows:

$$b(n_1, n_2) = \mu + \frac{\alpha^2 - v^2}{\alpha^2} (a(n_1, n_2) - \mu) \qquad (4)$$

Where v^2 Represents the noise variance.

The median filter works by the pixels in the window sorted in the Ascending Order. The median value of the $N \times M$ The image is changed based on the central pixel values. Then, it is defined by the following:

$$Y(M, N) = Median\ \{X[i, j], [i, j] \epsilon\ w\} \qquad (5)$$

Where w It is the pixels of the neighborhood.

Image enhancement is a procedure that uses quality enhancement techniques to improve the image contents (lines, edges, corners, brightness of the image, etc.). Histogram Equalization is used for image contrast enhancement to minimize the redundant pixels on each image. This process increases the contrast level of the image and the computation speed in CBMIR. Histogram equalization is a technique that improves the image's visual quality by adjusting the noisy and blurred pixel values. A histogram is a graph that a Discrete Function represents. In other terms, it is a graphical depiction of the intensity distribution of an image. It is more applicable for images with Dark Backgrounds and Foregrounds. The process of histogram equalization for contrast enhancement is as follows:

(1). Read the input image
(2). Compute the Histogram, Probability of each pixel, and Probability Density Function (PDF) of the input image
(3). Implement the histogram equalization, represented in eqn. (5)

The histogram contains two axes: the X-axis and the Y-axis. Both axes represent the event of the pixels in the given image. The “Bars “define the frequency of pixels occurring in the image. For a given input image, the histogram is computed as follows:

$$H(r_k) = n_k \qquad (6)$$

Where r_k is the kth gray level value ranging from 0 to L-1, and n_k Is the number of pixels in the image which have the gray level in r_k.Then, we compute the event probability presented in the tendency for the event to occur. The following equation can calculate the probability of each pixel.

$$p(r_k) = \frac{n_k}{M \times N} \qquad (7)$$

Where n_k Is the number of pixels and $M \times N$ is the image 2-dimensions, M represents the Rows, and, N Represents the Columns. Then, the PDF is proposed. In general, the PDF of the input image is equal to the value 1. The PDF function is given as follows:

$$p_k = \sum_{i=0}^{k} n_k \times \frac{1}{M \times N} \qquad (8)$$

Finally, we apply histogram equalization, which enhances the quality of the input image and corrects the image intensity. For Discrete cases, the histogram equalization is given as follows:

$$S_k = (L-1) \times p_k(r) \qquad (9)$$

Where $p_k(r)$ represents the PDF

*B. **Fast Attention-based ResNet***

The continual manifestations of fresh research in deep and distributive learning are driven by an unpredictable rise in the ability to make tremendous progress and collect information, as well as advancements in hardware technologies, such as high-performing computers. Although transfer learning is superior to traditional neural networks, its antecedents are exceptional. Transfer learning uses transforms and graph technology to create a multi-layer classifier model. Learning techniques that have lately been created have achieved excellent results in various uses, such as sound and voice analysis, visual information preparation, and computational linguistics.

Deep learning guides computers to function as humans, which is functioning naturally. For instance, deep learning is considered the significant technology behind driverless car technology, and it functions to recognize the stop signal [2]. The deep learning process is essential in regulating consumer devices such as mobile phones, televisions, tablets, etc. In deep learning, the model based on the computer is used to learn classification functions with sound, image, text, etc. In addition, the performance of profound learning results in accuracy, and occasionally, it performs higher than the human level.

Deep learning is the deep machine learning architecture that includes several layers and the perceptron through the brain. The recognition accuracy is the finest achievement in the process of deep learning [3]. Consumer electronics encounter user expectations, and it is considered a safety and critical application similar to driverless cars. The two significant uses of deep learning are listed in the following,

- The computing power is essential in deep learning, and efficient deep learning is denoted as high performance through GPUs with parallel architecture. The collective clusters and cloud computing are used to permit team enhancements and reduction of training time in the deep learning network
- The massive amount of labeled data is essential for deep learning. For instance, a lot of images and lengthy videos are crucial for driverless car developments

In general, neural network architectures are used in deep learning methods; thus, they are denoted as deep learning neural networks. In addition, the term deep denotes the number of hidden layers in a neural network. Notably, two or three hidden layers are present in the traditional hidden layers, and the deep networks include more than 150 layers [4]. The deep learning models are trained through labeled large datasets and architectures based on the neural network, and this process takes place without the interference of manual feature extraction. The deep learning methods are considered as the learning feature with hierarchies with future functionalities and the deployments of details directly from data with the dependency of all the following functions in the use cases based on the tasks that are required and are beneficial through the composition of lower level features the in the hierarchies. The details are in additional formats with all the functions and deployment, and further uses in the deployment change with all the additional formats [5]. The automation in learning features includes various levels of abstraction that permit the patches to be acquired with the affiliation process in the learning functions. Affiliations are added, and the system permits learning complex tasks by mapping input and output directly from the data. The additional process with all the functionalities takes place in the absence of human-crafted features.

Attention-based ResNet is used to perform feature extraction and classification. The architecture of the proposed model is depicted in Fig. 2. The learning rate of the proposed model is set to 0.0001, and the number of epochs performed for classification is 10. The extracted set of features has many irrelevant and redundant features that need to be removed because they reduce the accuracy of the process. We are performing a feature selection process that eliminates redundant and irrelevant features. The attention module is responsible for extracting features by learning the weights of the features corresponding to the attacks. The output of the attention layer can be computed as,

$$Atn_i(Z) = Q_i(Z).F_i(Z) + F_i(Z) \qquad (10)$$

Where, $Q_i(Z)$ denotes the attention weight and $F_i(Z)$ Denote the features. In the attention layer, the relationship between the features is computed to achieve more relevant information from the features, which can be calculated as,

$$R(F_1; F_2) = \int_{F_1}^{n} \int_{F_2}^{n} p(F_1, F_2) \log \frac{p(F_1, F_2)}{p(F_1)p(F_2)} dF_1 dF_2 \qquad (11)$$

Where $p(F_1, F_2)$ Denote the function of probability between the features. F_1 and F_2 and $p(F_1)$, $p(F_2)$ Denote the individual function of marginal density respectively. The inception layer learns specific features deeply by reducing the initial patch size, affecting the original information required for the classification process.

Based on the selected features, classification is done. This process calculates whether the given unknown packet is standard or malicious. The softmax layer performs this classification in which the cross entropy is computed to determine the output loss, which can be calculated as,

$$Loss\ (x) = -\sum_{k} \log(st(x)_k)\, q_i \qquad (12)$$

Where the softmax $st(x)$ A vector can be formulated as,

$$st(x)_k = \frac{e^{x_k}}{\sum_m e^{x_m}} \qquad (14)$$

The classification is performed by increasing the score corresponding to the input images.

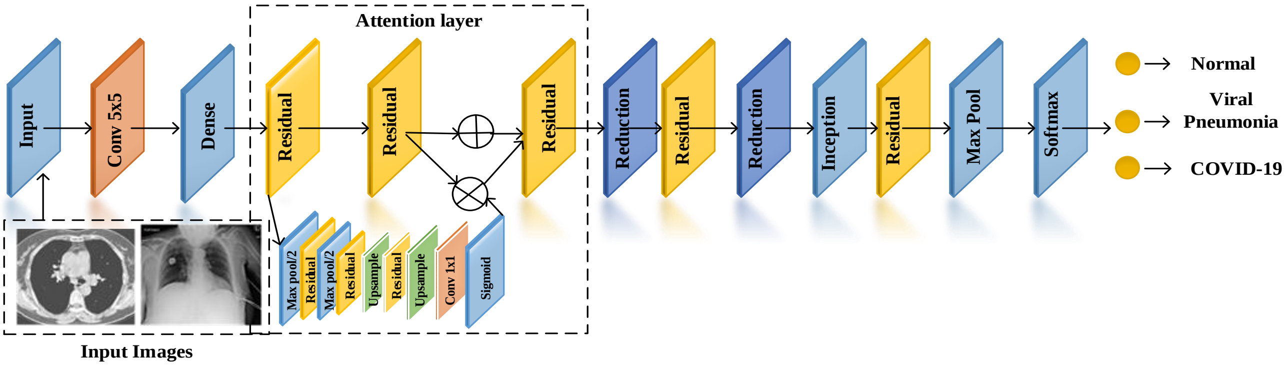


Figure 2. Attention-based ResNet

C. *Enhanced VGG-16 Architecture for X-Ray Images*

Under deep learning techniques, feature extraction and classification in this process are done using the VGG-16 architecture. The split region's features are first extracted. Three layers comprise the proposed VGG-16: a convolutions layer, a fully linked layer, and a softmax layer. Compared to VGG 19, VGG 16 extracts features at low levels utilizing a small kernel size and fewer layers. The image's features are extracted using the maximum and average pooling layers. From the segmented region, these layers extract the following features: color features, including Mean, Standard Deviation, Skewness, Local Intensity, and

Kurtosis; texture features, including Entropy, Correlation, Homogeneity, ASM, and Entropy; and finally, shape features, including. Then, the result of max pool and average pooling are concatenated and sent to the convolution layer with the size of 7×7 by sigmoid function open function(δ). The result of the convolutional layer is defined as follows,

$$C(F) = \delta(f^{7\times7}[F_A; F_M]) \qquad (13)$$

Where, $F_A \in r^{1\times h\times w}$ and $F_M \in r^{1\times h\times w}$ The results were obtained by average pooling and max pooling, respectively; h represents the height, and w represents the layer's width.

The proposed VGG 16 model's fourth pooling layer is the convolutional layer containing the retrieved features. Then, the extracted results are sent to the fully connected layer, comprising three layers: flatten, dropout, and dense. The softmax layer, the final dense layer, was employed by VGG 16 to classify the features. It classifies the features by computing the weight value based on the relevance of the features using the Attention Estimator. Then, it divides the input image into normal and abnormal categories (Affected by CAD). The classification result is defined as follows,

$$C(p = q/s) = \frac{e^b}{\sum_j e^{b_j}} \qquad (15)$$

Table 1: Features

Color features Mean	**Texture features** Entropy	**Shape features** Artery diameter
Standard deviation	Correlation	Artery area
Skewness	Homogeneity	Artery angle
Local intensity	ASM	Artery length
Kurtosis		Eccentricity
		Roundness
		Dispersion
		Convexity
		Solidity

Where q and s represent the probabilities collected from the SoftMax layer, we finally classify the results into normal and abnormal classes.

Pseudocode: VGG 16

Input: Segmented region (SR)
Output: Normal (N) or abnormal (AN)
{
Begin
Initialize $\{fc, fs, ft\}$
$fc \leftarrow \{fc1, fc2, ..fcn\}$ // color features
$fs \leftarrow \{fs1, fs2, ..fsn\}$ //shape features
$ft \leftarrow \{ft1, ft2, ..ftn\}$ //texture features
Initialize VGG 16
VGG 16← raw training data send to VGG 16 for featured extraction
for $i \leftarrow o\ to\ n$ do
Extract fc from SR
Extract fs from SR
Extract ft from SR
$F \leftarrow \{fc, fs, ft\}$
Use a layer of average pooling to extract the features. F_A
Extract the features by max pool layer F_M
Concatenate the features using eqn ()
Classifying the images using eqn() by a softmax layer
Class← $\{N, AN\}$

```
End for
}
Return class
End
}
```

4. Experimental Results and Discussion

The databases, experimentation techniques, and assessment measures are all discussed in this section. This section details the experiments with the proposed results and the performance of the existing approach concerning the number of iterations and the datasets.

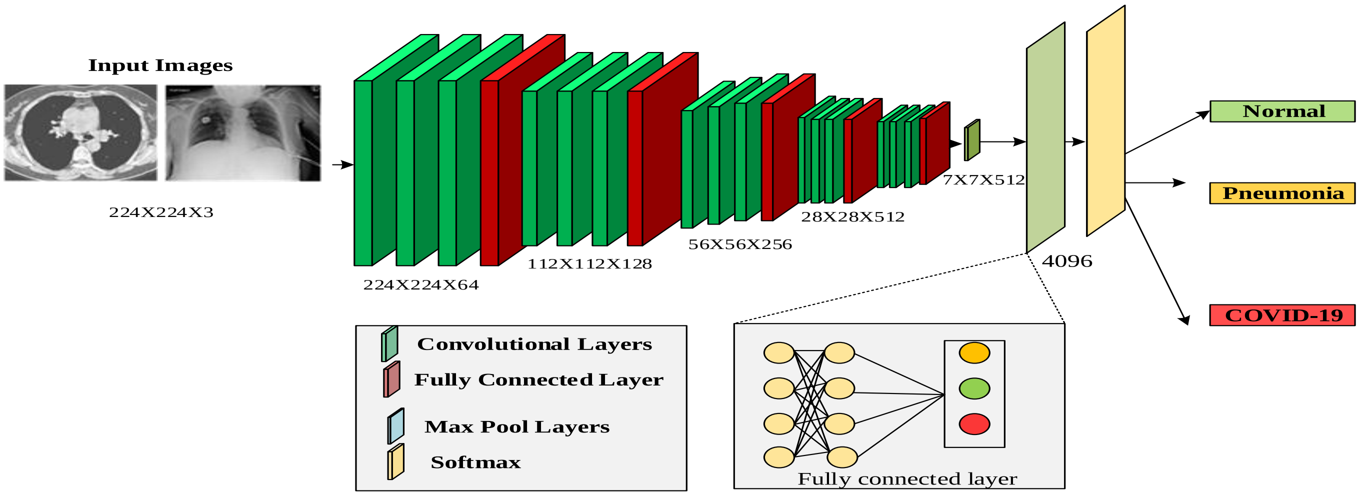


Figure 3. Process of VGG 16

D. Dataset

The dataset utilized to evaluate the proposed model is detailed in this section. Five different databases from different nations were acquired. Two databases provide chest x-ray imaging, while others include chest CT scans.

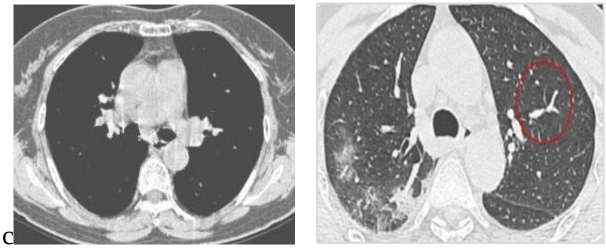
Every database was divided into three parts: a test set, a validation set, and a training set. To evaluate the model's flexibility well, the test set must have at least 200 and 400 images. The test set's size determines the verification set is size; the more significant the test set, the more prominent the testing set will be, and conversely. The other images were used to develop a training set.

To perform the presented approach, the test and the validation test sets are organized, consisting of the same partitions of the positive and negative image samples. The hyper-parameters are tuned based on the training and test sets of the coronavirus images. The descriptions of the datasets are given as follows:

a. CT Images Dataset: It comprises around 349 CT images for 216 persons (coronavirus) and 397 for non-corona virus patients. Both positive and negative cases of images are collected from the hospitals that regard the coronavirus only. Some of the samples of coronavirus images in both positive and negative classes are given in Fig. Further, the details of the dataset are as follows:

- Types of Images: CT Images
- Size of Dataset: 746 CT Scans
- Positive Case images in Total: 349
- Negative Case images in Total: 397
- Validation Size Set: 118 Scans
- Training Size Set: 425 Scans
- Test Size Set: 203 Scans

c



(a) (b)

Figure 4. (a). COVID-19 Negative, (b). COVID-19 Positive

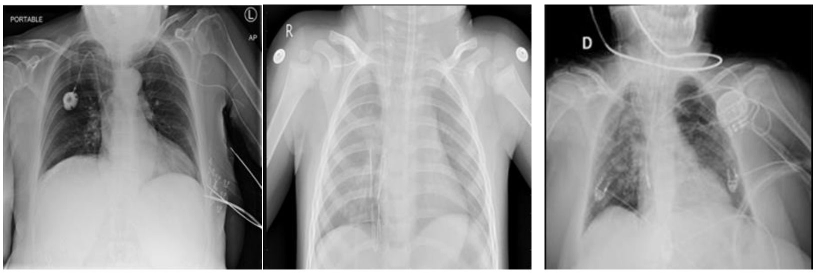
b. COVID-19 Images Collection Data: This database comprises images from the public community, such as physicians and hospitals. The description of this dataset is given below.

- **Types of Imaging:** Chest X-Rays
- **Size of Dataset:** 579 Images
- **Training Size Set:** 309
- **Validation Size Set:** 70
- **Testing Size Set:** 200
- **COVID-19 Positive Cases:** 342
- **COVID-19 Negative Cases:** 237

c. CT Set COVID-19: This dataset consists of the original CT scan imaging for 377 patients. 15589 CT scan images were used for CT scan images, of which 95 were coronavirus and 282 were regular patients, respectively. The detailed description of this dataset is as follows:

- **Types of Images:** CT Scan Images
- **Size of Dataset:** 12058 Scans
- **Positive Images:** 2282
- **Negative Images:** 9776
- **Training Set:** 11, 400
- **Validation Set:** 258
- **Testing Set:** 400

d. COVID-19 Radiography Dataset: This dataset contains two hundred images for +COVID-19; 1341 images are healthy, and 1345 are fever-infected. Some of the test samples in this dataset are as follows:



(a) (b) (c)

Figure 5. (a). Healthy Image, (b). Pneumonia and (c). +Ve COVID-19 Images

- **Images Type:** X-Ray
- **Sum of Images:** 2541
- **Negative Images:** 2686
- **Positive Images:** 1200
- **Training Size Set:** 3086
- **Testing Size Set:** 400
- **Validation Size Set:** 400

e. SARS-CoV-2 CT Scan Images: This database comprises 1252 positive CT scan images, whereas the remaining 1230 images are classified as non-infected viruses. The description of this dataset is as follows:

- Images Type: CT Scan Images
- Size of Dataset: 2482 Images
- Negative Images: 1230
- Positive Images: 1252
- Training Size Set: 1800
- Testing Size Set: 400
- Validation Set Size: 400

To mitigate the model of over-fitting issues of the training case, the training size has increased from 1275 images collected using data augmentation: Rotation Random, Flipping Horizontal, and Jittering Colour.

Data Preprocessing / Augmentation Techniques

Using data augmentation methods, some of the enormous volumes of datasets must be tested using transfer learning or deep learning techniques. Hence, this paper considers some of the techniques as a data augmentation to use such type of datasets mentioned above:

- **Resize / Crop by Random:** This step represents the cropping of the input image to the unsystematic size of the image and the aspect ratio
- **Rotation by Random:** This step represents the rotation of a given sample by random using an angle
- **Horizontal Flip by Random:** This step represents the flip action for the given input image randomly in a horizontal manner
- **Colour Jittering:** This step represents the random modification of the input image's contrast, saturation, and brightness.

Training Settings: The overall work is implemented through a Python framework, in which the variables are fixed for all experiments. The list of variables and their range is as follows:

- Deep Learning Model: Python (PyTorch library)
- No. of Epochs: 1 to 100
- Learning Rate: 0.003
- Optimization Technique: ADAM
- Loss: Cross Entropy
- Size of Batch: 16
- Resized CroppingScale in Random: 0.5 to 1.0
- Rotation Angle Range: - 5 degree - + degree
- Flipping Possibility Rate: 0.5
- Resized Size of Cropping in Random: 224

E. Comparison Analysis

Classification accuracy is the degree of precision with which COVID-19 and viral pneumonia are classified. The classification accuracy of the presented method can be formulated as,

$$Accuracy = \frac{T_r P + T_r N}{T_r P + T_r N + F_l P + F_l N} \times 100\% \qquad (16)$$

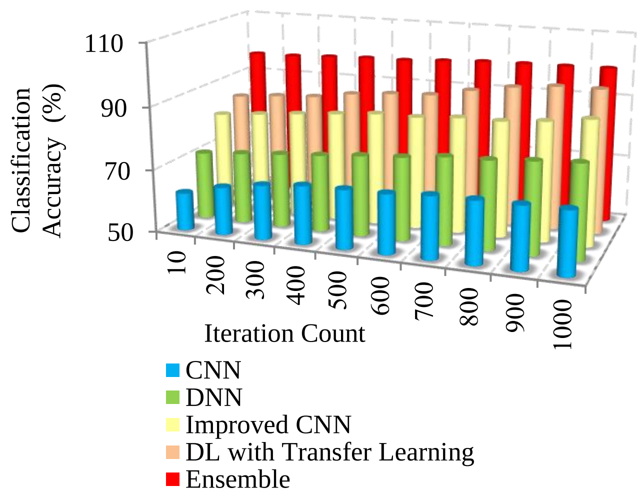


Figure 6. Iteration count vs. classification accuracy

The greater the classification accuracy, the greater the efficiency of the approach. Figures 6 and 7 show how the number of iterations and sample size affect the classification accuracy of the proposed strategy compared to the already used methods. The comprehensive feature extraction and categorization ensure that the suggested ensemble model has a high level of classification accuracy.

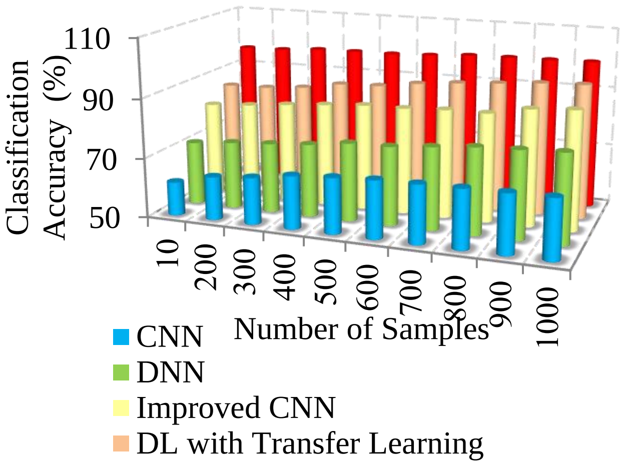


Figure 7. Number of Samples vs. classification accuracy

The feature set is generated from many features using a pre-trained model to eliminate the redundant features. The selection of transfer learning in the model is based on a recent study and literature analysis that contributes to increased classification accuracy. The existing approaches considered both necessary and redundant classification features, which degraded the accuracy.

Table 4.5 provides the existing approaches based on the number of users and iterations, along with a numerical analysis of the classification accuracy of our proposed method. The accuracy of the existing methodologies is only approximately 62% to 72%, compared to the precision of our process, which is about 95% to 96%, respectively. This means that COVID-19 and non-COVID-19 images can be accurately classified using the method that has been described.

Table 3: Classification Accuracy

Methods	**Classification Accuracy (%)**	
	Iteration Count	No of Samples
CNN	61% $\pm$0.05%	62% $\pm$0.04%
DNN	71% $\pm$0.02%	72.6% $\pm$0.03%
Improved CNN	84% $\pm$0.03%	85.5% $\pm$0.04%
DL with Transfer Learning	92% $\pm$0.02%	92.5% $\pm$0.1%
Ensemble	95% $\pm$0.2%	96.2% $\pm$0.5%

The precision is the measure of relevancy in the classified images. The precision of an approach can be formulated as

$$Precision = \frac{T_rP}{T_rP+F_lP} \times 100\% \qquad (17)$$

The comparison of the precision of the presented method and the existing approaches concerning iteration count and the number of samples is illustrated in 8 and 9. The figure shows that the precision of the proposed Ensemble approach is high due to the implementation of spatial domain filtering, thereby eliminating the noise.

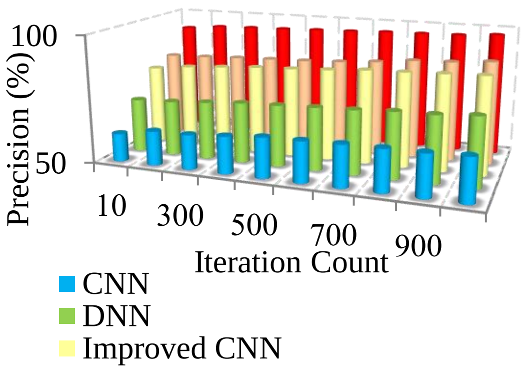


Figure 8. Iteration count vs. precision

Further, the classification of the face and the non-face regions was performed using feature extraction, in which the optimum approach was used to select features. The lack of consideration of pixel-based features and the removal of the noise level in the images of the existing approaches resulted in reduced precision. The superiority of the proposed pre-trained approach is illustrated in Table 4, which presents the numerical comparison of the presented method and existing approaches in terms of iteration count. The presented method's precision is 95% to 96%, whereas the existing approaches possess a precision of about 61% to 71%, respectively. From this, we can conclude that the presented method performs better in achieving increased precision than other approaches for coronavirus and non-coronavirus images.

Table 4: Precision

Methods	**Precision (%)**	
	Iteration Count	No Of Samples
CNN	61% $\pm$0.05%	63% $\pm$0.04%
DNN	70% $\pm$0.02%	73.6% $\pm$0.03%
Improved CNN	82% $\pm$0.03%	86.5% $\pm$0.04%
DL with Transfer Learning	91% $\pm$0.02%	93.5% $\pm$0.1%
Ensemble Model	94% $\pm$0.2%	97.2% $\pm$0.5%

Recall is also known as sensitivity, which describes the degree of agreement between the categorized images. It is an important indicator to consider when assessing an approach's effectiveness. The recall of a method can be calculated using,

$$Recall = \frac{TP}{TP+FN} \quad (18)$$

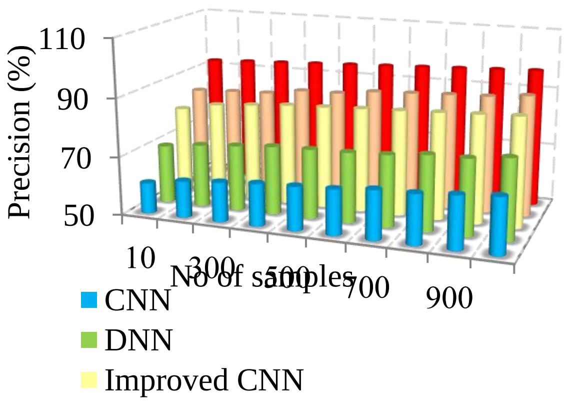


Figure 9. Iteration count vs. precision

Fig. Compares recall of the presented method and existing approaches concerning several iterations for both cases of medical images. The recall of the presented method is high due to the implementation of effective pre-processing techniques to eliminate the noise and correct the illumination.

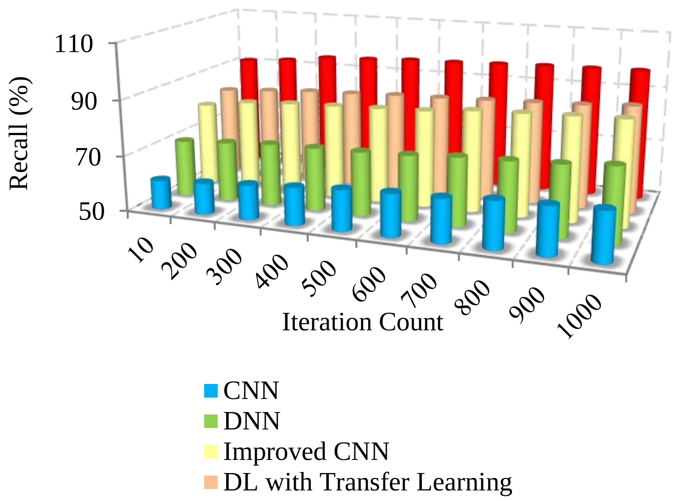


Figure 10. Iteration Count vs. Recall

Further, considering diverse features such as high-level and low-level features improved the recall results of the presented method. The lack of noise elimination and consideration of integrated features restricted the recall of the existing approaches.

The numerical analysis of recall of the presented method and the existing approaches concerning iteration counts is depicted in Table 5. The presented method possesses 94% to 96% recall, whereas the existing approaches possess only about 62% to 72% recall. From this, we can conclude that the presented method is more efficient than the existing approaches in performing coronavirus detection under healthy and viral infection cases.

The F-measure combines precision and recall, calculated by computing the harmonic mean. The F-measure of an approach can be computed as,

$$F - measure = \frac{2 \times TP}{(2 \times TP + FP + FN)} \qquad (19)$$

The comparison of the F-measure of the presented method and the existing approaches concerning iteration count is illustrated in Fig 12. The increased F-measure of the presented method is due to the increase in the value of precision and recall achieved by the presented method.

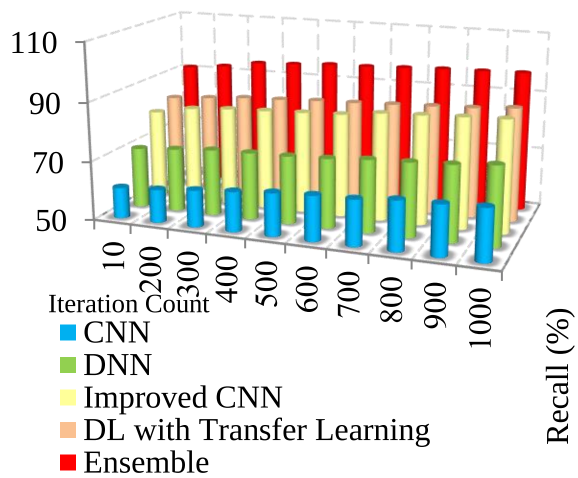


Figure 11. Iteration count vs. recall

Table 5: Recall

Methods	**Recall (%)**	
	Iteration Count	No of Samples
CNN	58.6% ±0.05%	62.5% ±0.04%
DNN	68.8% ±0.02%	73.5% ±0.03%
Improved CNN	84% ±0.03%	84.5% ±0.04%
DL with Transfer Learning	92.5% ±0.02%	93.5% ±0.1%
Ensemble Learning	95.5% ±0.2%	96.9% ±0.5%

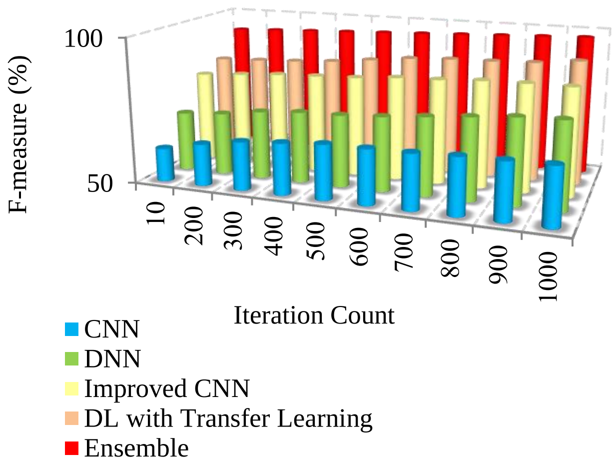


Figure 12. Iteration count vs. F-score

Detection and classification are done by pre-processing the input frames and extracting extensive features from the pre-processed images. The grouping of pixels is carried out to determine the differentiation between the non-similar features, and the classification of coronavirus and non-coronavirus is carried out. Integrating all these significant techniques resulted in increased F-measure of the presented method. The existing approaches performed a few of these techniques, thereby reducing F-measure.

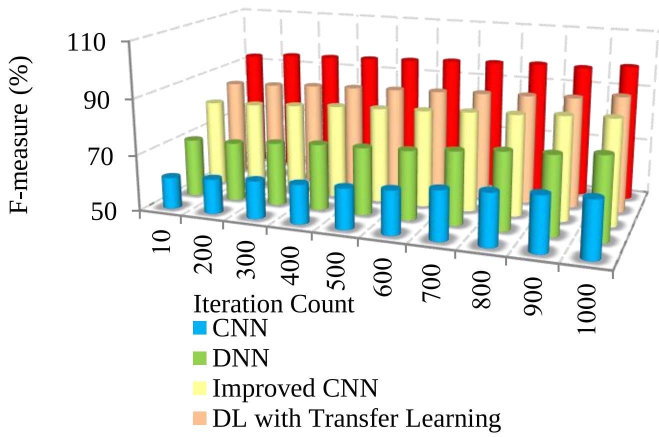


Figure 13. Iteration count vs. F-score

The efficiency of the presented method is proved by the numerical analysis in Table 6. Table 6 compares the F-measure of the presented method with that of the existing approaches in a numerical manner. The F-measure of the presented method is 95% to 97%, whereas the existing approaches possess only about 63% to 72% of the F-measure. From this, we can conclude that the proposed pre-trained model effectively performs facemask detection and classification.

Table 6: F-measure

Methods	F-measure (%)	
	Iteration Count	No of Samples
CNN	61.2% $\pm$0.05%	63.3% $\pm$0.04%
DNN	72.2% $\pm$0.02%	73% $\pm$0.03%
Improved CNN	87.5% $\pm$0.03%	89.2% $\pm$0.04%
DL with Transfer Learning	93.2% $\pm$0.02%	94.5% $\pm$0.1%
Ensemble Learning	96.2% $\pm$0.2%	97.7% $\pm$0.5%

In all conceivable cut-off values, the relationship between an approach's specificity and sensitivity is known as the receiver-operating curve, or ROC. The ROC curve is a chart that illustrates an approach's effectiveness. The portion of the ROC curve closer to the left upper corner represents a better method. Fig 13 depicts the ROC curve of the presented method and the existing approach for both coronavirus and Noncorona virus scenarios from which those processes are evaluated.

From Figure 13, we can conclude that our presented method achieves an excellent ROC curve compared to the existing approach. This increase in the ROC curve is due to the trade-off accomplished by the presented method in the detection and classification of medical images. The existing approaches possess reduced ROC curve values due to the inefficiency caused by noise in the pictures and the lack of integration of high-level and low-level features for classification.

The computational time is the time to compute specific tasks to obtain the desired result. Fig.14 compares the computational time of the proposed and existing approaches to iteration counts. The computational time involved with the existing approaches is high due to the increased time spent training the model.

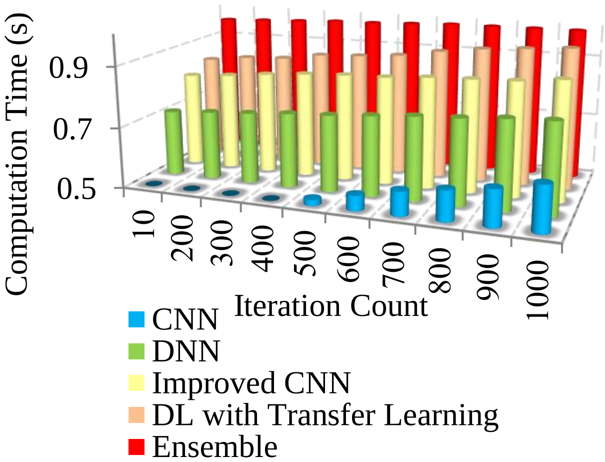


Figure 14. Iteration count vs. computation time

The proposed pre-trained model possesses fewer layers than the existing models and thereby possesses low complexity. This characteristic of our proposed model requires very low computational time to detect and recognize the coronavirus. The presented method provides minimal computation time without compromising the accuracy in detecting and recognizing the coronavirus. The time complexity of our presented method is found to be $O(1)$ With the layerwise complexity of O(n).

The table presents the numerical comparison of the computation time of our presented method and the methods currently used for iteration count. From the table, it is clear that the computation time of our approach is very low, about 0.4 sec, whereas the existing approaches possess an increased computation time of up to 0.9 seconds for both masked and unmasked faces.

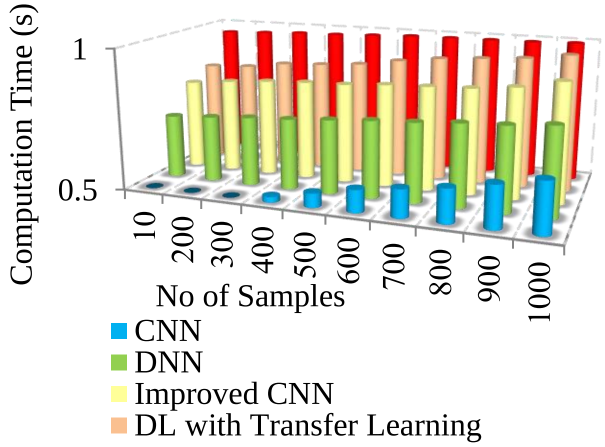


Figure 15. Iteration counts vs. computation time

5. Conclusion

COVID-19 is most commonly encountered due to lung symptoms, which can be identified through genes and studies. Imaging testing can aid in the early detection of coronavirus and, as little more than a result, in managing the cancer's progression. In identifying coronavirus disease, chest X-rays and computed tomography (CT) are helpful imaging modalities. Due to the wide availability of huge annotated images based on transfer learning methods (VGG-16, ResNet, and DenseNet), great strides have been made in what was previously transfer learning models (ResNet, VGG-16, and DenseNet) for medical image classifications. This ensemble learning technique is an accurate representation because it recovers the hierarchy of localized visual elements given input. However, irregularities in the annotation of COVID-19 instances produced on X-ray imaging remain the more problematic component of working on them. In this study, we classified COVID-19 images in a massive chest X-ray and CT database using an ensemble learning system based on developments in the extraction features technique. The suggested methodology provided fast and thorough COVID-19 case classification results and the ability to deal with data inconsistencies and a limited amount of class images. Owing to the ongoing data collection, we intend to broaden the empirical study in the future, validating the technique with large datasets. We want to add a modeling and analysis component to boost the model's utility. Finally, modeling trimming and quantization will increase efficiency and help mobile dissemination.

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