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Original Article

Experimental Analysis Using Hybrid Convolutional Neural Networks, Gradient Boosting Classifier, and Differential Algorithm for Detection of COVID-19 from X-Ray Images

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Abstract *- A significant number of individuals have lost their lives due to the new COVID-19 virus. The coronavirus has ruined many people's lives, and the healthcare system is struggling a lot because of it. Since the virus can harm the lungs severely, it's essential to find it early. To detect COVID-19 from X-ray images, this study presents a novel hybrid approach that combines convolutional neural networks, gradient-boosting classifiers, and differential algorithms. This strategy offers a synergistic fusion of deep learning, ensemble learning, and optimization strategies. In the context of COVID-19 detection by X-ray imaging, the adaptive integration of these disparate methodologies constitutes a groundbreaking attempt to address the shortcomings of current methods and significantly improve diagnostic accuracy. This study recommends using a computer program called CNN to help identify COVID-19 in chest X-ray images. For this study, scientists used a collection of 13,000 chest X-ray pictures. With CLAHE's help, researchers improved the original dataset. The research used advanced computer programs to find essential details in the pictures and then used a method to focus on the most valuable parts. To prevent overfitting, the model locks in the weights of the dense layers trained in previous rounds. This enables it to fit the new thick layer and optimize the convolutional layers while retaining the previously learned data. The final layer of the CNN Model was replaced with the Gradient Boosting Machines classifier for classification. The results showed that the suggested approach was 98% specific, 97% sensitive, and 98% accurate. According to study data, the suggested approach performed better than previous COVID-19 detection investigations based on X-ray imaging.*

Keywords *- COVID-19, Contrast Limited Adaptive Histogram Equalization (CLAHE), Neural Networks, Gradient Boosting Machines, Differential Feature Selection algorithm.*

1. Introduction

For the past few years, one of the biggest threats to public health has been the COVID-19 epidemic. In the early months of the pandemic, the COVID-19 reproduction number, which indicates the number of other people an infected individual may infect, varied from 2.24 to 3.58 [1, 2]. The virus is easily transmitted from person to person and can have devastating effects on people of all ages. Over 2.9 million people have died worldwide from COVID-19, a highly infectious virus illness caused by SARS-CoV-2. This makes it the worst global health catastrophe since the 1918 influenza pandemic. COVID-19 causes various symptoms, most of which present 5.2 days after infection. Common signs and symptoms include fever, dry cough, exhaustion, headache, hemoptysis, diarrhea, dyspnea, and lymphopenia. The droplets are too large to float far, so they can only spread through personal touch. The specific lengths of COVID-19's survival are unclear, although a recent study predicts it can survive up to 3h in the air. However, consensus on solutions to these questions is still lacking throughout the broader health research community. Lung tissue is vulnerable to infection by COVID-19. In the early stages, some individuals may show no symptoms at all, whereas fever and cough are the norm for the vast majority. Other potential adverse effects include headaches, sore throats, and muscle aches.

Cough syrup, painkillers, fever reducers, and antibiotics are recommended to patients based on their symptoms rather than the cause of their sickness. The patient must be admitted to the hospital, where they will get treatment in the Intensive Care Unit (ICU), possibly with mechanical ventilation. COVID-19's severe symptoms and ease of transmission have led to its fast global expansion [3]. Providing mechanical ventilation to severely sick patients admitted to the intensive care unit has a disproportionately sizeable daily impact on healthcare facilities. Therefore, intensive care unit bed capacity must be significantly increased. Early diagnosis is essential in the scenario mentioned above because it increases the likelihood that patients will receive the needed therapy while decreasing the strain on the healthcare system. Due to the lack of early diagnosis tools in most parts of the globe and the presence of medical pre-conditions such as cancer, chronic liver, lung, and renal disease, and diabetes, COVID-19 remains a lethal illness [4].

While Real-Time Polymerase Chain Reaction (RT-PCR) detection tools are widely available, low-income nations still lack the resources to screen their whole populations as soon as possible. Two distinct severity levels are associated with this viral infection in humans. When a coronavirus infection sets in, you can count on one thing: it won't be good for research lungs. Therefore, physicians recommend patients use an oxygen meter to track their oxygen levels and catch any discrepancies quickly.

Automating the detection of illnesses is only the latest use of Artificial Intelligence's (AI) proven efficiency and good performance in automated picture classification difficulties using multiple machine learning approaches. Moreover, machines that learn and make choices based on massive amounts of information's.

Artificial Intelligence (AI) can execute tasks that previously required human intelligence by accomplishing calculations and forecasting based on raw data. With its focus on the automatic extraction and classification of image data, deep learning is a set of ML algorithms that have shown great promise in several fields, including medicine [5, 6]. Tools that aid radiologists and clinicians in making more accurate determinations are the focus of research efforts across the globe. Several AI techniques have been applied to search for the best radiology and medical image processing networks.

Research can now more accurately diagnose COVID-19 and other AI-related lung inflammations. The World Health Organization (WHO) suggests RT-PCR as the primary approach for diagnosing coronavirus disease. Although X-rays and CT scans are commonly utilized, they should be favored only when the RT-PCR test cannot be performed quickly [7]. The findings of a nasal swap test performed at multiple times of the day tend to differ.

For example, if the test is administered first thing in the morning rather than at night, the likelihood of a positive result increases. Additionally, a substantial proportion of false-negative findings considerably slowed the discovery of individuals who were COVID-19-positive. The RT-PCR has a modest 70% accomplishing rate and only 60%-70% sensitivity. In addition, chest X-ray imaging is positive when RT-PCR is falsely negative [8]. The broad availability of X-ray imaging has made it a vital tool in various medical and epidemiological contexts. Chest X-ray shows promise for emergency circumstances and therapy due to its quick operation, low cost, and ease of use by radiologists. However, previous research [9] observed substantial variations in chest X-rays taken from patients with coronavirus, as shown in Figure 1.

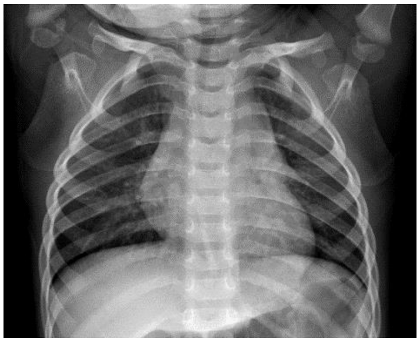


Fig. 1 COVID-19 X-ray image

In the realm of medical research, deep-learning-based networks such as Convolutional Neural Networks (CNNs) [10] and Recurrent Neural Networks (RNNs) [11] have been used extensively and have often yielded commendable results in areas such as speech recognition, computer vision, and Natural Language Processing (NLP).

CNN has demonstrated promising results in medical image processing for tasks such as classification, localization, and segmentation of pictures. CNNs work well for this sort of problem. In humans, the virus most often manifests as pneumonia when it attacks the lungs. The outcome is a severe depletion of the body's oxygen supply. The only way to stop this virus's spread is to create a vaccine, as there is currently no treatment. This leaves testing and tracing as the only viable options. The Polymerase Chain Reaction (PCR) technique is widely utilized in scientific medical investigations.

However, as the number of instances increases, it has become practically difficult to complete enough PCR testing due to the time and cost involved. Thus, further testing is needed to swiftly recognize sick people so they may be quarantined or isolated. Infections have been detected using several deep-learning methods so far. However, the outcomes of these deep learning methods are inadequate when applied to a medical diagnosing system. Neural networks have found widespread use due to their adaptable architecture and ability to deal with highly non-linear systems.

The COVID-19 pandemic's worldwide breakout has highlighted the importance of precise and effective diagnostic instruments. Because it is readily available and has a short turnaround time, X-ray imaging has become a helpful diagnostic modality for COVID-19 identification. However, the difficulties in recognizing COVID-19 patterns from X-ray pictures have forced scientists to investigate sophisticated computer techniques.

To improve COVID-19 identification from X-ray images, this study addresses the shortcomings of current methods. It suggests a novel strategy incorporating hybrid Convolutional Neural Networks (CNNs), gradient-boosting classifiers, and differential algorithms. Conventional techniques for COVID-19 identification from X-ray pictures have been hindered by issues such as low specificity, sensitivity, and susceptibility to changes in imaging circumstances.

Furthermore, the intricate and nuanced patterns of COVID-19 in X-ray pictures present a significant challenge to traditional image processing methods. Due to these restrictions, sophisticated and reliable computational models are now required to increase the precision and dependability of COVID-19 diagnosis utilizing X-ray pictures.

The suggested approach combines the best features of three different computing approaches: a differential algorithm, a gradient-boosting classifier, and hybrid convolutional neural networks. To address the drawbacks of current techniques, this hybrid approach combines the strengths of deep learning, ensemble learning, and optimization algorithms.

With the use of the Hybrid CNNs, complex patterns suggestive of COVID-19 in X-ray images are captured, aiding in feature extraction and hierarchical learning. The Gradient Boosting Classifier combines the predictive strength of several weak learners to improve classification accuracy. As this is going on, the Differential Algorithm optimizes overall performance, adjusting the model to fit a variety of datasets and reducing problems caused by heterogeneous data.

With regard to improving the state-of-the-art in COVID-19 detection from X-ray pictures, this hybridized architecture has considerable promise. The suggested strategy seeks to improve the model's robustness over various imaging settings, decrease false positives and negatives, and increase diagnostic accuracy by utilizing the complementing strengths of several algorithms.

These developments are essential for enabling prompt and precise identification of COVID-19 cases, which supports efficient disease control and public health initiatives. This work offers a potential advance in computer-aided COVID-19 diagnosis by X-ray imaging and adds to the ongoing efforts to optimize diagnostic approaches.

The research is organized as follows: Part 2 discusses some secondary sources. Section 3 outlines the research-suggested approach and model for detecting COVID-19 with deep convolution. The experimental results are presented in Section 4, while the methodology and comparisons to previous research are discussed in Section 5. At long last, the report ends.

2. Related Works

There is a pressing need for a rapid, accurate, and remote detection method because of the widespread impact COVID-19 has already had on research daily lives and the increasing number of people infected with newly developing variations. A person's cough may be the most telling symptom of COVID-19 infection. Even in the presence of a preexisting respiratory disorder, they can be utilized as a crucial component in determining whether or not the person is infected with COVID-19.

A scalable technique based on real-time "COVID cough" detection using a machine learning model trained on a publicly available "COVID cough" recorded dataset [12]. The model evaluates the data and returns a diagnosis to the patient. The World Health Organization (WHO) issues a worldwide health alert, classifying the illness as a pandemic requiring urgent action. It is crucial to rapidly identify the positive cases to stop the spread of this disease and start treating afflicted people as soon as possible. Due to a lack of uniform electronic device storage solutions, the demand for collaboratively-suggested devices has grown.

Using radiological imaging methods, new evidence has surfaced suggesting that these images reveal remarkable details regarding COVID-19 contamination-an attempt to unambiguously detect lung impedances caused by COVID-19 without accepting the erroneous one. Morphological Dilation [13] is a framework for calculating edges using a Laplacian metric. Morphological Dilation is a technique for expanding missing edges in a picture, which improves the system's accuracy, and Laplacian aids in obtaining the magnitude structure of the lungs as well as the deficiencies. For its edge calculations, Laplacian employs a single kernel rather than the usual pair of kernels used by other edge detection methods.

The initiative's primary goal is to install this system at entryways to campuses, airports, healthcare facilities, and workplaces where the transmission of COVID-19 is most likely due to human contact. According to studies, wearing a face mask will reduce the risk of affecting by an order of magnitude. This is a two-class (with mask and without mask) object identification and classification problem. A hybrid and conventional model integrating deep learning will be demonstrated for face mask recognition.

Python, OpenCV, TensorFlow, and Keras were used to create the face mask detector [14]. Before entering the building, everyone should check their faces for signs of infection and wear a mask if necessary. Anyone discovered without a face mask will set off an alarm. As a result, businesses across the country are reopening, and an increasing number of cases of COVID-19 are being recorded. If everyone takes the necessary safeguards, research can end it.One of the most essential applications of deep learning algorithms is the CAD system, or computer-aided diagnosis. For this purpose, a CNN network employing Rmsprop and SGD with momentum as optimizers has been suggested [15]. Research has ported the system to CPU and GPU to save development time.

The next step is to develop a practical medical application that immediately identifies the corona class in chest X-rays. Accuracy, specificity, and sensitivity for the attained classifications were better than traditional models. Consequently, COVID-19 class identification may now be used in a time-sensitive medical setting in real-time.

Multiple clinical trials and experts have confirmed that chest CT scans are the gold standard for detecting COVID-19 in the clinic. Conventional RT-PCR testing may produce higher percentages of false positives and negatives than ideal. Artificial Intelligence (AI) has been the impetus for creating several COVID-19 management systems. Given the current data dearth, a transfer learning strategy is used to identify COVID-19 in chest CT scans [16].

Overfitting was seen in the first few iterations of several deep learning models, even though VGG-19 performs better with medical picture data. The optimal settings for the VGG-19 transfer learning model for distinguishing COVID-19 patients from controls. Three model parameters-activation function, loss function, and training batch size-were tested in research experiments.

Since the COVID-19 epidemic has severely disrupted the international medical system, reliable therapy is desperately needed right now. The use of CAD has been crucial in managing COVID-19 because it boosts diagnostic efficiency, allowing clinicians to provide a swift and specific diagnosis. The research mission is to find a way to identify and categorize anomalies properly. In [17], YOLOv5 is used as a model on the dataset made available by the Kaggle platform.

There are two main categories into which specific objective detection systems fall: one-stage and two-stage. Faster RCNN and the YOLO family of models are used as representations.

Then, Section 3 provides a comprehensive description of the YOLOv5 model. Section 4 displays the outcomes of the experiment and comparisons made. As a statistic for research trials, research settles on mean Average Precision (mAP), where a more significant value indicates a more accurate model.

Although the research mentioned above projects offer novel strategies for COVID-19 diagnosis and management, a common flaw in a number of them is their dependence on particular datasets, which may restrict how broadly applicable the suggested models can be.

For example, the face mask recognition system is trained on a dataset that focuses on two-class identification (With Mask and Without Mask) [14], whereas the "COVID cough" detection method uses a dataset devoted to COVID-19 cough recordings [12]. Similarly, training on particular medical imaging datasets is required for the CNN network-based categorization of chest X-rays, and the identification of COVID-19 in chest CT scans [15, 16].

This data-centric restriction might make the models less flexible to different populations and imaging settings, impacting how well they function in real-world situations where datasets may be heterogeneous.

Securing resilience over an expanded array of datasets is essential to effectively implementing these systems in various public health and clinical contexts. In light of COVID-19's dynamic nature and changing forms, resolving this constraint is critical to maintaining the dependability and efficacy of these AI-based solutions.

3. Methodology

At first, images of lungs are loaded into a convolutional neural network. Afterwards, the network is trained, and features are recovered from less-than-ideal images. The best characteristics are then extracted using a heuristic approach. A more precise separation between COVID-19 pneumonia and healthy categories is achieved.

3.1. Dataset Preparation

This study [18] employed a chest X-ray database as a laboratory guinea pig. This collection has 3500 COVID-19 instances and 10,000 normal images, making it one of the most popular public X-ray datasets. Figure 2 shows the sample images from the dataset.

However, only X-ray pictures of Normal and healthy subjects were included in this analysis. Accordingly, 256 and 256 matrix-resolved investigations of COVID-19 and healthy persons are included in the collection. Figure 3 shows the proposed system workflow.

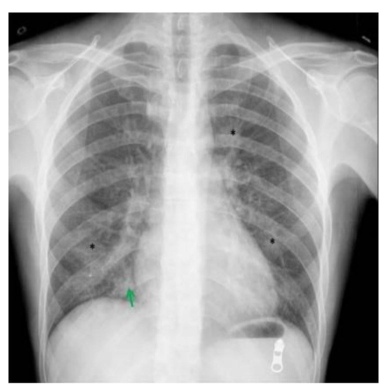


Fig. 2 Dataset sample image

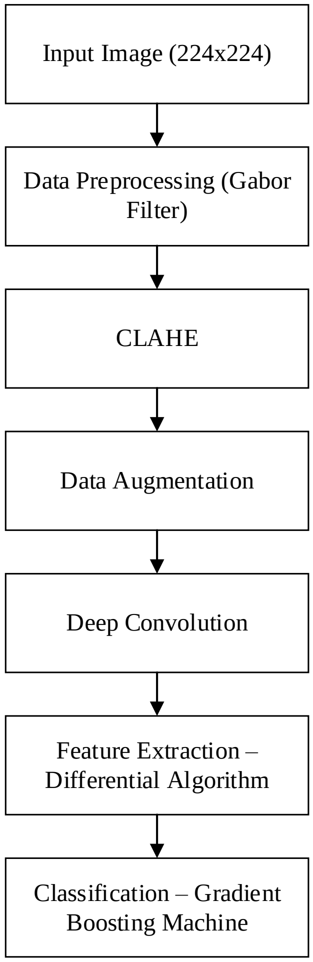


Fig. 3 Proposed workflow

3.2. Image Pre-Processing

X-ray pictures cannot be imported directly into a CAD program. Before they can be used, they must undergo extensive pre-processing. Many types of picture pre-processing are employed to remove unwanted noise and improve image quality.

The overall efficiency and precision of the system benefit from this improvement. Edge detection, texture categorization, feature extraction, and disparity estimation are some of the many uses for the linear Gabor filter in image processing. The picture is blurred using the Gaussian filter to decrease noise and then analyzed using the Gabor filter, which passes frequencies within a specified range while reducing those beyond the band. A Gaussian that a plane wave has modulated is known as a Gabor filter [19].

Over the course of the previous few decades, contrast enhancement algorithms have developed to achieve their goals better. Improving the image's look for visual interpretation and making future actions more accessible or more efficient are the two significant reasons to boost contrast. Most contrast enhancement methods involve adjusting the histogram in some way, either globally or locally. Excessive improvement, in comparison, is removed via CLAHE, a type of Adaptive Histogram Equalization (AHE). With CLAHE, an image is not fully displayed; instead, it is divided into tiny segments.

The random borders are removed, and nearby panels are mixed using bilinear interpolation. This technique could be employed to improve the contrast of images. Equalizing just the brightness channel of an HSV image yields far better results than equalizing all channels of a BGR image [20]; hence, CLAHE may also be used on color photos. The CLAHE strategy gets around the flaws in global methods by emphasizing local differences instead. Images were then normalized using the N-CLAHE technique to draw attention to finer details for analyzing machine learning classifiers.

3.3. Data Augmentation

Supervised Deep Learning models rely heavily on the quantity and variety of training data for their prediction accuracy. A good analogy for the relationship between the performance of a deep learning model and the amount of training data it needs is the relationship between rocket engines and the massive amounts of fuel they need to fulfill their missions. For deep learning to work, research needs vast data, but collecting hundreds of photos is sometimes impractical.

This is where data augmentation comes in handy. Data augmentation and picture enhancement methods give the classifier a more representative sample. All the data taken from the original dataset was augmented with images by horizontally flipping them, rotating them, and shifting their width and height. Due to the non-horizontal nature of chest X-rays, vertical flip was not used. The dataset was expanded to include 20,000 photos after image enhancement, with 10,000 COVID-19 and ten thousand healthy chest X-rays. Histogram equalization and the spectral, grayscale, and cyan components of picture enhancement were also used.

3.4. Feature Extraction

To make raw data more manageable, research may use a feature extraction technique to reduce its dimensions. It entails reducing the complexity of tools needed to characterize a huge data set correctly. One of the biggest obstacles in analyzing complicated data is the sheer volume of variables. It is not uncommon for classification algorithms to overfit the training sample and perform badly on subsequent samples, making it impractical to use them for analyses involving many variables.

The process of creating combinations of the variables to avoid these issues while still accurately characterizing the data is known as feature extraction. To analyze and provide results, tremendous volumes of data often have many variables. The goal of feature extraction methods is to reduce complexity without compromising accuracy. These methods choose and combine characteristics to reduce data volume. One well-liked statistical approach to extracting textural features from photos is the Gray Level Co-Occurrence Matrix (GLCM) [21].

3.5. Convolutional Mechanism

In machine learning, convolutional neural networks extract attributes for categorization. Figure 4 shows the proposed architecture. In this case, photos and the original data are fed into a convolutional network, and the network automatically extracts the attributes using the convolution function.

Instead of manually removing the attribute, the convolution operation is performed using Equation (1), and the matrices learned in the process serve as filters that are slid over the primary input picture. After features have been mapped from input pictures to output labels during training, they are extracted using many convolution layers.

$$(IN * M)_{p,q} = \sum_{x=0}^{m1-1} \sum_{y=0}^{m2-1} \sum_{m=1}^{ic} M_{x,y,m} \, . IN_{i+x,q+y,m} + bv \quad (1)$$

Where *IN* indicates the raw image with height and width in H * *W* dimensions, and *ic* is the no of image channels, *M* is the filter matrix, and *bv* is a bias value for each filter *M*, $p = 0, \dots, H$ and $q = 0, \dots, W$.

The pooling layer decreases the input after the undesired values have been eliminated by the ReLU layer, which follows convolution. The fully connected layer, which acts like the MLP, is then fed the effective input vector. Finally, Adaptive Moment Optimizer (ADAM) classification layers are used in deep convolutional layers; the following equation illustrates the loss function.

$$T(t,d) = \frac{1}{S} \sum_{s=1}^{S} [a_s \log \hat{a}_s + (1 - a_s) \log(1 - \hat{a}_s)] + \Gamma \sum_{u=1}^{S} \|t^u\|_2 \quad (2)$$

Where S denotes the sample size, a_s denotes the actual class for the s^{th} sample, $\hat{a}_s$ denotes the predicted output class for the s^{th} raw data, and Γ denotes the regularization attribute.

Adam Optimizer is a gradient-based optimization technique that efficiently updates neural network weights by calculating the exponentially growing average of the gradient and the square of the gradient.

There are several layers in the deep neural network, each with weights and biases for training. The optimum feature selection approach improves optimization throughput and precision when used with the ADAM optimizer.

3.6. Differential Evolution

The heuristic evolutionary approach known as Differential Evolution (DE) [22] is used to find the persistent problem's minimum value. Binary Differential Evolution (BDE) is refined to tackle choosing characteristics problems.

Mutation, merge, and choosing are its three building blocks. The initial population is created using D dimensions, where D is the optimal number of characteristics. For the mutation operation, three random vectors x_{f1}, x_{f2}, and x_{f3} are chosen for vector x_w such that $f1 \neq f2 \neq f3 \neq w$, where w is a population vector arrangement.

$$diff\ vect_w^e = \begin{cases} 0, & x_{f1}^e = x_{f2}^e \\ x_{f1}, & other \end{cases} \quad (3)$$

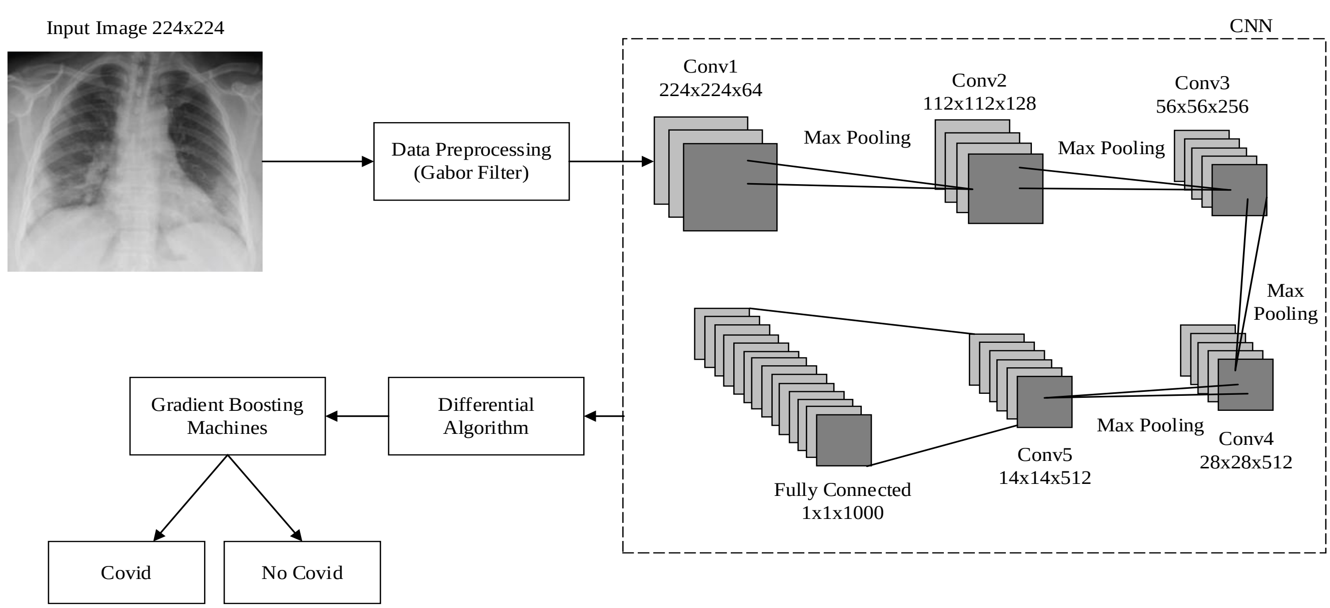


Fig. 4 Proposed architecture

Afterward, the mutation and merge operations are implemented, as shown in the below equations,

$$mute\ vect_w^e = \begin{cases} 1,\ if\ diff\ vect_w^e = 1 \\ x_{f3}^e,\ other \end{cases} \tag{4}$$

$$V_w^e = \begin{cases} mute\ vect_w^e,\ if \gamma \leq CA||e = e_{rand}, \\ x_w^e,\ other \end{cases} \tag{5}$$

Where V indicates the vector, CA ε (0, 1) indicates the merging value, and γε(0, 1) indicates an alternate number. In the selection trials, the fitness value of the try vector Vw will be changed if it is greater than that of the current vector xw.

The decision trees are used to construct the classifiers in the potent ensemble machine learning technique called Gradient Boosting Machine (GBM). The methods use iteration to increase efficiency by correcting previous models' flaws and adding new ones. The number of hidden layers, feature maps, activation and loss functions, and other aspects of the CNN structure are all inspired by models that have been effective in Covid-19 classification.

Scale, compactness, and form are some factors that segment a high-resolution image. To provide the best boundaries of possibly identical pixels, these settings should be fine-tuned by trial and error. All previously learned dense layers are frozen, and only the finally added dense layer is taught at each iteration in the Gradient Boosting - CNN (GBC) architecture. In this part, the research laid the foundation of the proposed methodologies, including its mathematical architecture and the framework for the convolutional layers employed. The last model is built as an additive model of the outcomes by combining various networks N_v iteratively.

$$R_v(K_p) = R_{v-1}(K_p) + x_v N_v(K_p) \tag{6}$$

Where x_v is a vector of weights for each class of the $v-th$ additive model $N_v(K_p)$.

Research can define the additive model of the *v-th* boosting iteration to train the parameters for the proposed model.

$$N_v = N_v(N_{v-1}(M(K_v;\Omega_v)); V_v) \tag{7}$$

Where, loss function j, using the following objective function.

$$(x_v, N_v) = \underset{(x_v, N_v)}{\operatorname{argmin}} \sum_{p=1}^{D} j(a_p, R_{v-1}(K_p) + x_v N_v) \tag{8}$$

Where the trainable parameters of N_{v-1} were trained in the $(v-1)$-*th* epochs and are now frozen. If a convolutional layer is introduced to a GB-DNN, the GBC will fine-tune it after each training cycle. A straightforward approach (x-min)/(max-min) is used to preserve the original data distribution. Two-dimensional plots are then constructed from the normalized data. During the training process, the plots serve as input patches for the CNN.

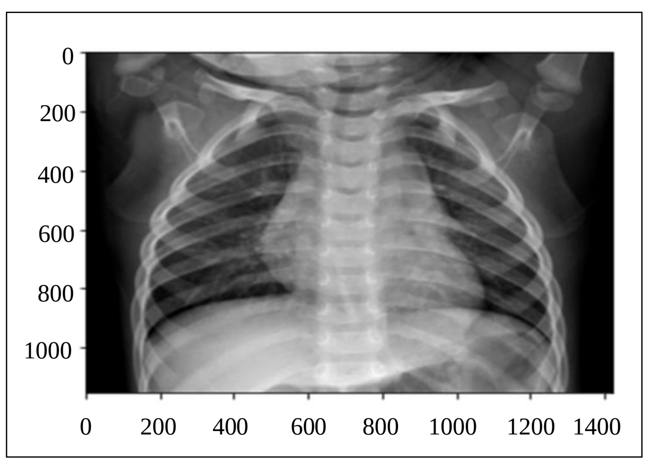
Training/validation databases and test sets are constructed using a random distribution from the entire amount of picture objects. Because there is so much training data, the hold-out method is preferred to cross-validation when using a CNN-based approach.

The algorithm is trained using a categorical log-loss function and fully linked layers to classify data. In this stage, research feeds the learned model with more training data. Last but not least, the dense layer is removed to provide a new training database for learning the gradient-boosting technique.

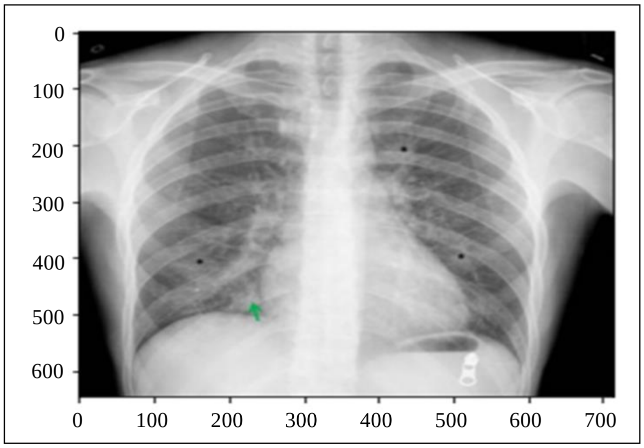
4. Result and Discussion

Pre-trained CNN models are used to evaluate the proposed study. From 20,000 pictures, 10,000 of which are of COVID-19 and 10,000 of which are of healthy chest X-rays, research evaluates the effectiveness of a newly updated deep learning approach designed to achieve optimal COVID-19 identification. Since the study aims to identify the best model, not only the suggested improved model but also VGG16, MobileNet, ResNet, InceptionV3, EfficientNetB0, and GoogleNet deep models were evaluated for performance and compilation time.

With a learning rate of 10^{-6}, the best 10 iterations were saved and evaluated after each model was fine-tuned using epochs (25-100) and optimizers (suggested by grid search). Images were downsampled to a 256 x 256 resolution before being fed into the neural network since this was shown to be the most effective size for the models. Only 20% of the information was used for actual testing, while the remaining 80% was used for actual training.



(a)



(b)

Fig. 5 (a) Normal, and (b) COVID image.

Figure 5 displays some data from chest X-rays taken from people with and without COVID-19. The improved classification accuracy was achieved by feeding this revised data into CNN models. To get started, a 10% subset of the training dataset was employed as the validation dataset. The technique obtained train accuracy and train loss values processes were then used on the dataset. The accuracy scores for the 100 observed iterations were calculated using the classification training and validation scores to evaluate the models' effectiveness. Training and validation accuracy of 98% and 97%, respectively, were attained by the modified model presented in the research, with the pre-trained model, InceptionV3 [23], coming in second.

Figure 6 shows the preprocessed image. When used with the data, the InceptionV3 model achieves an accuracy of 94% on the training set and 95% on the validation set. Test accuracy of 93% was attained by both the EfficientNetB0 [24] and GoogleNet [25] models. The 90%, 91%, and 91% accuracy rates attained by the VGG16, MobileNet, and ResNet models were equally impressive.

The loss value of a model reveals its performance quality after each epoch. A lower loss indicates better effectiveness unless a technique has been overfit to its train dataset. Figure 7 depicts and quantifies the loss the suggested models incur during the training and testing phases. As the no. of iterations rose, the mean rate of loss reduced. There was an extensive range in average loss from model to model. Figure 8 shows the validation and training accuracy of the proposed model. However, the proposed model has the most minor loss, at just 0.0549%. At 5% and 4% for the training and validation sets, correspondingly, InceptionV3 has the second-lowest loss rate.

Figure 9 visually represents the models' overall performance via the confusion matrices. There are 1063 samples in the test dataset; 497 are from the COVID-19 dataset, and 566 are from the healthy dataset. Labels' 1' and '0' designate COVID-19 infected and healthy instances, respectively. 563 healthy samples and 488 COVID-19 samples are correctly identified from the matrix using the improved model. The model successfully recognized 98% of the test data samples.

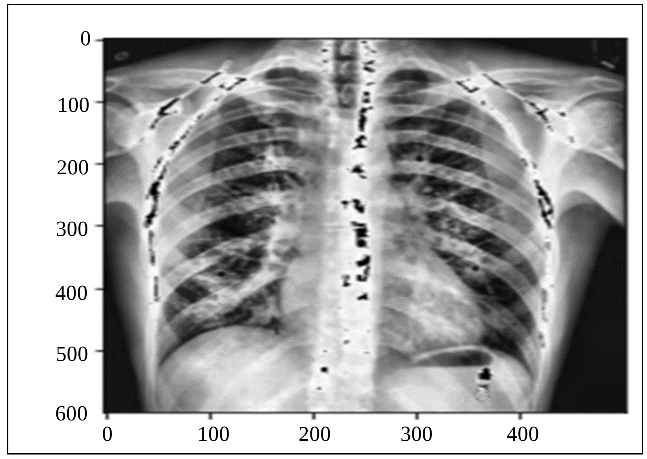
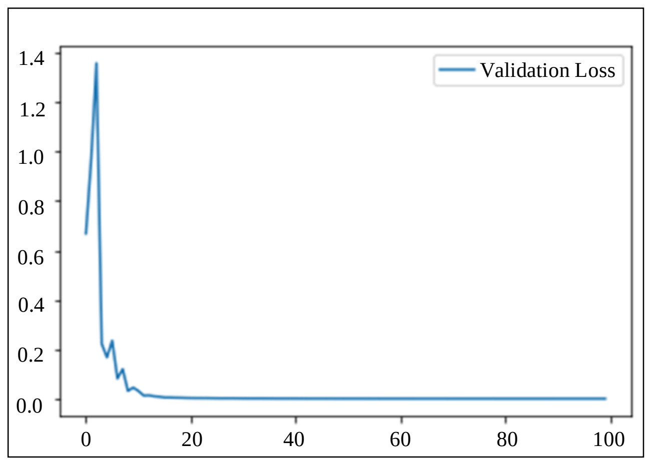
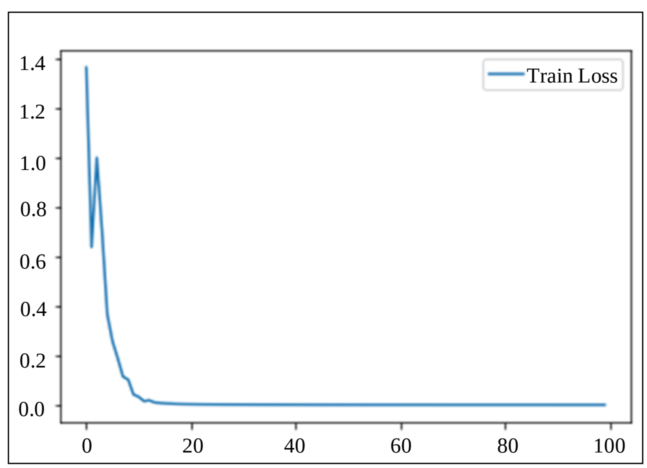


Fig. 6 Pre-processed image

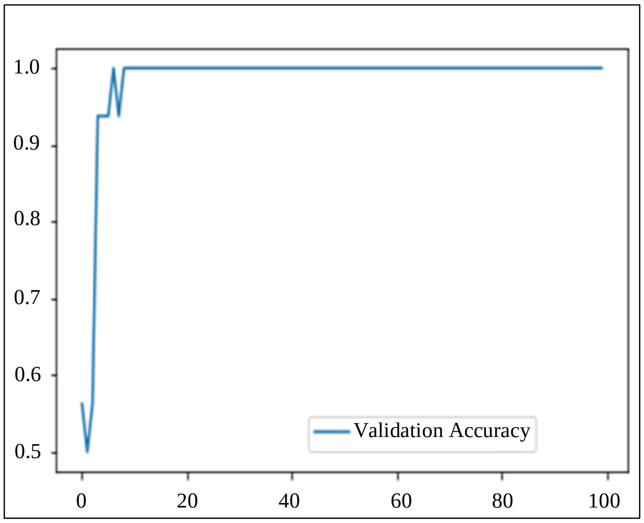


(a)

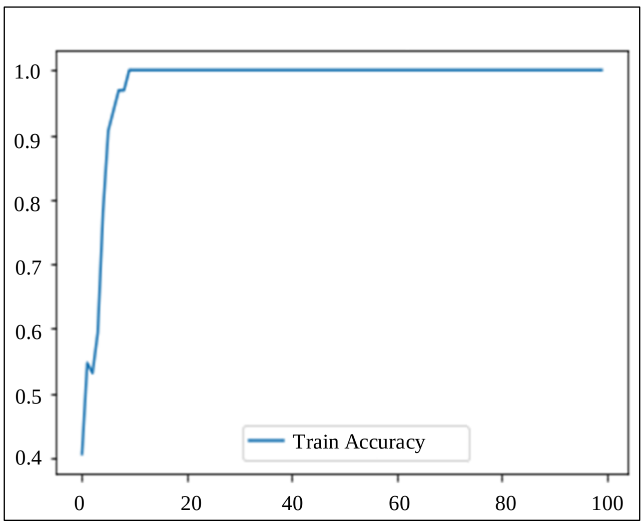


(b)

Fig. 7(a)Validation loss, and (b) Train loss of proposed model.

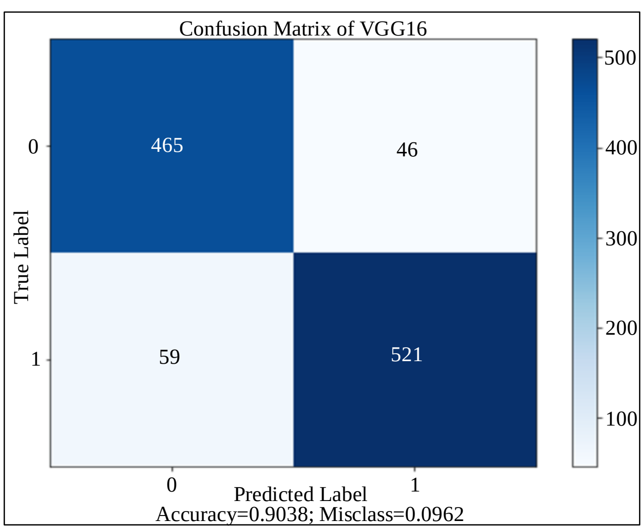


(a)

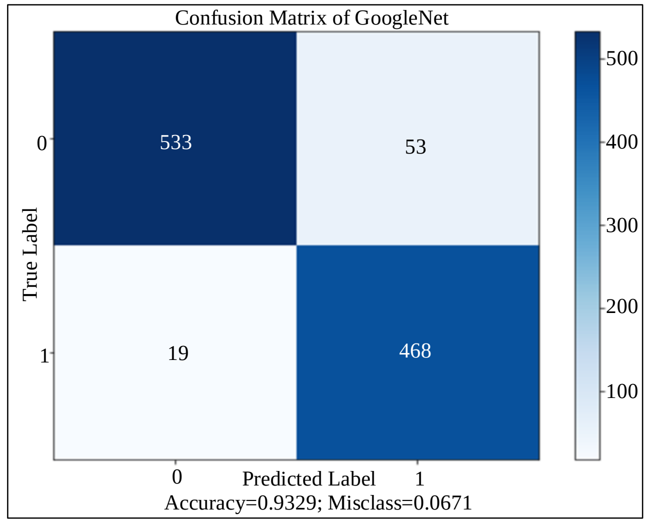


(b)

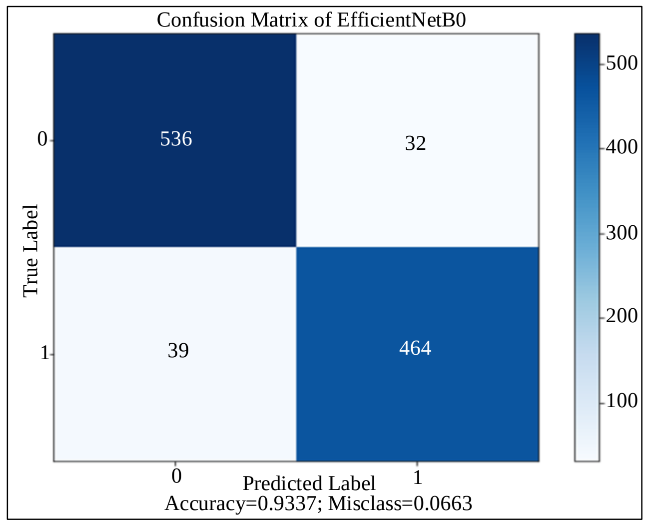
Fig. 8(a)Validation accuracy, and (b) Training accuracy of proposed model.



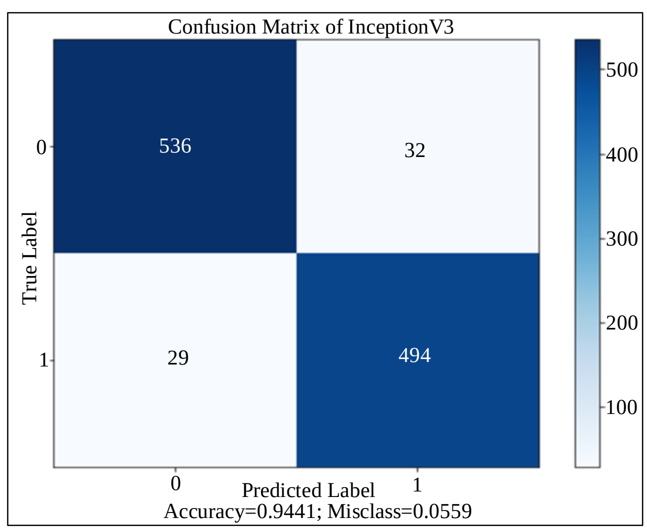
(a)



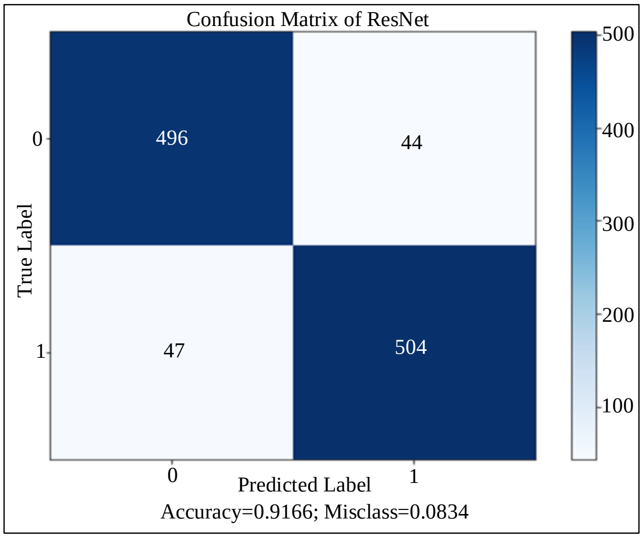
(b)



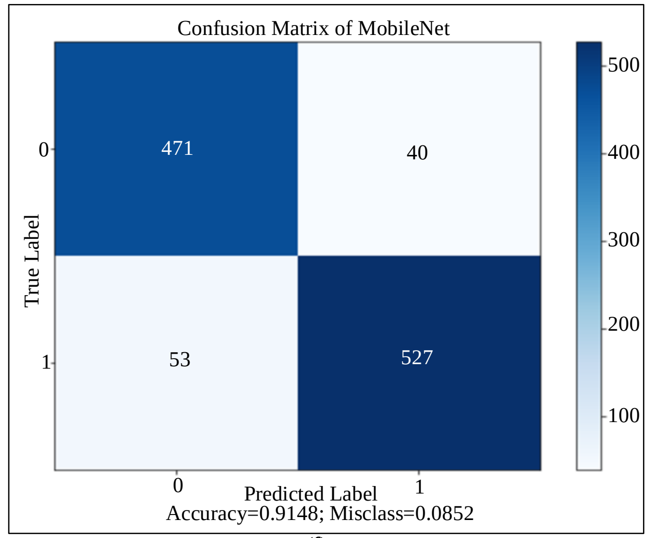
(c)



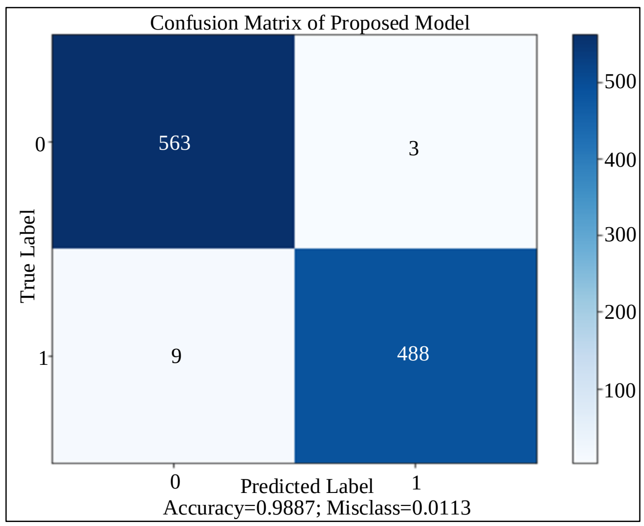
(d)



(e)



(f)



(g)

Fig. 9 Confusion matrix of different models

Model performance metrics such as accuracy, precision, recall, and F1 score. Table 1 displays the results of the calculations for the performance indicators. The table shows that the suggested model outperforms its competitors across the board, with an accuracy score of 98%, recall of 97%, and specificity of 99%. Figures 10 and 11 show the accuracy and specificity comparison of various models. Furthermore, the study evaluates the compilation times of the models, recognizing that an ideal model should exhibit high accuracy while maintaining a short computation time. Table 2 illustrates each model's total compilation time in seconds, calculated by multiplying the epoch time by the number of epochs. Notably, VGG16 demonstrates the least efficiency, requiring the longest completion time at 1028 seconds. MobileNet, despite having shorter compilation times per epoch, ranks second in overall compilation time due to its need for a relatively sizeable total epoch count for optimal predictions. In contrast, the proposed model boasts the shortest compilation time and the swiftest overall completion time, even with the highest number of iterations.

This signifies that the enhanced proposed model achieves the optimal balance between prediction accuracy and computational efficiency. Sensitivity comparisons and computation time analyses of different models are depicted in Figures 12 and 13.

Table 2 compares the computational times of several models, such as GoogleNet, EfficientNetB0, InceptionV3, ResNet, MobileNet, VGG16, and the suggested approach. Remarkably, the proposed technique outperforms well-known models such as VGG16 (1028 sec), ResNet (992 sec), and InceptionV3 (995 sec) with a calculation time of only 698 seconds.

The suggested method's better computational efficiency highlights how new it is in maximizing resource utilization while preserving high diagnostic accuracy. A novel approach to rapid and efficient COVID-19 detection from X-ray images, combining Hybrid Convolutional Neural Networks, Gradient Boosting Classifier, and Differential Algorithm, improves detection performance and demonstrates a notable computational advantage.

Table 1. Performance matrix of different models

Model	Precision	Sensitivity	Specificity	Accuracy
VGG16	0.91	0.92	0.90	0.90
MobileNet	0.90	0.91	0.91	0.91
ResNet	0.92	0.90	0.91	0.91
InceptionV3	0.95	0.93	0.92	0.94
Efficient Net B0	0.93	0.93	0.91	0.93
GoogleNet	0.94	0.93	0.90	0.93
Proposed	0.98	0.97	0.99	0.98

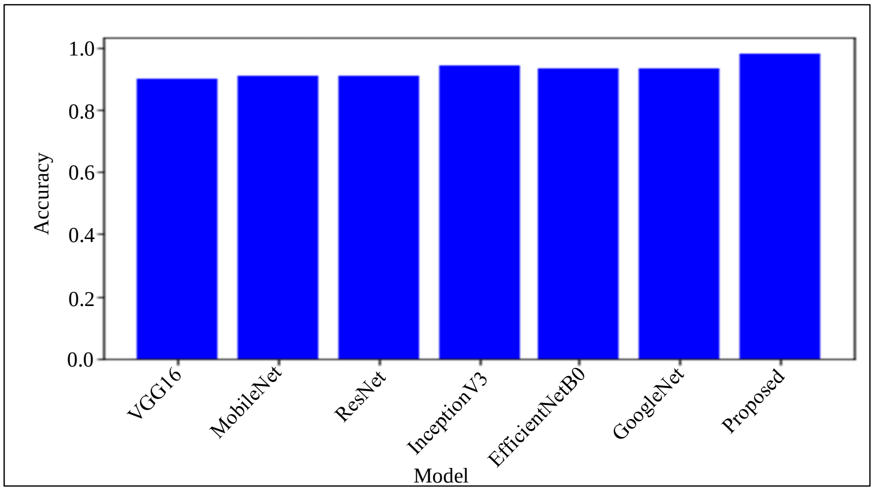


Fig. 10 Accuracy comparison of different models

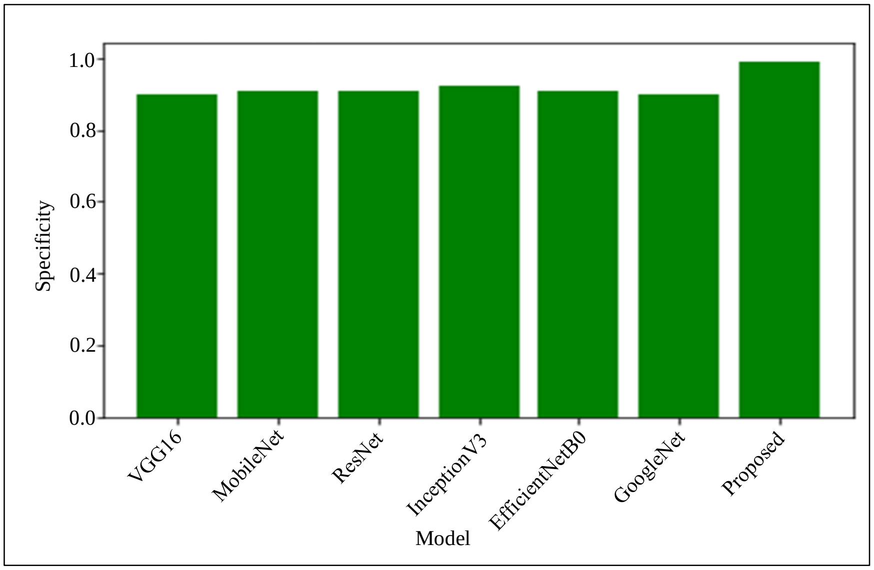


Fig. 11 Specificity comparison of different models

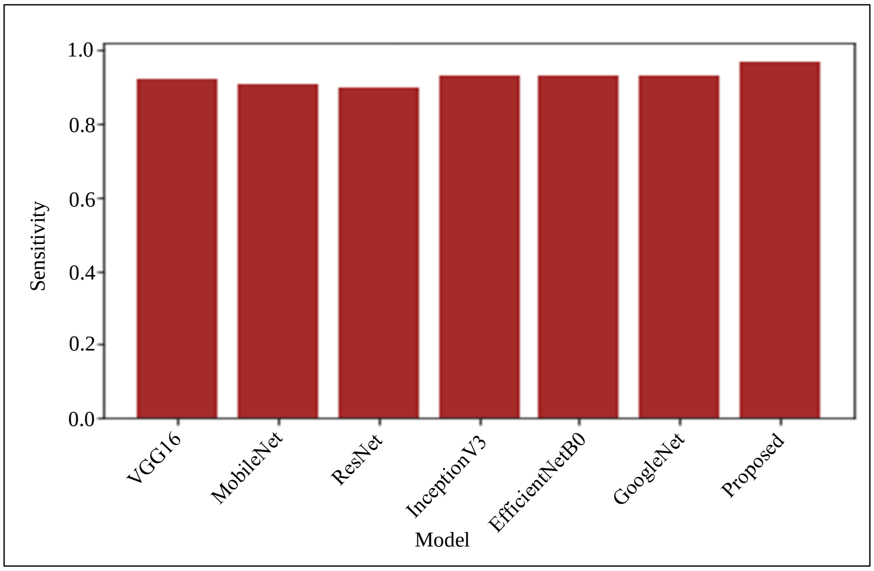


Fig. 12 Sensitivity comparison of different models

Table 2. Computational time of multiple models

Model	Computation Time (sec)
VGG16	1028
MobileNet	890
ResNet	992
InceptionV3	995
EfficientNetB0	893
GoogleNet	794
Proposed	698

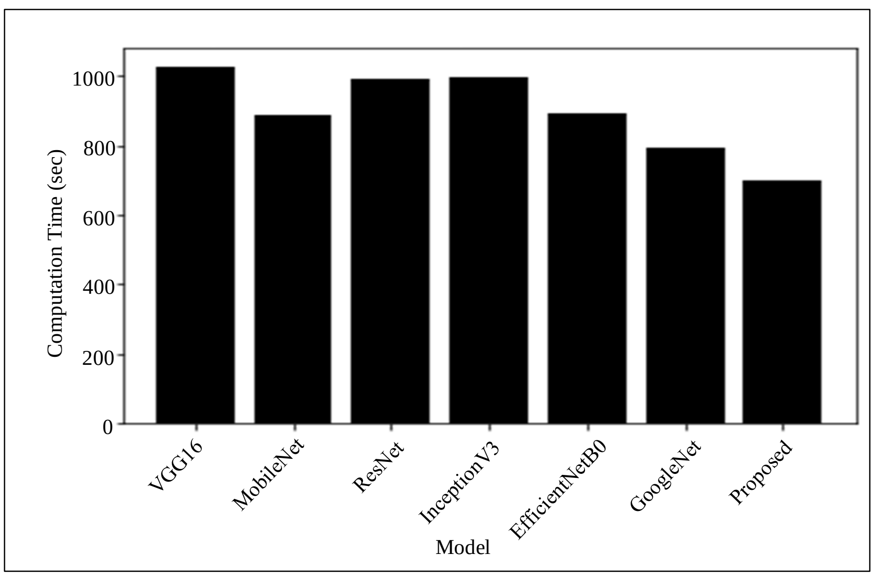


Fig. 13 Computation time comparison of different models

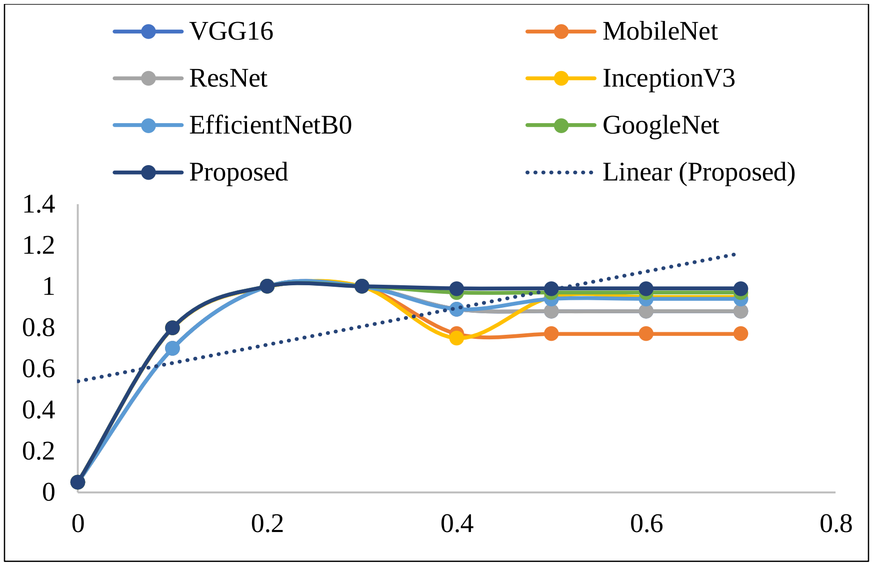


Fig. 14 ROC curve

Figure 14 shows the performance metrics supplied; the Proposed approach regularly beats the other models, including VGG16, MobileNet, ResNet, InceptionV3, EfficientNetB0, GoogleNet, and the Proposed method, across all evaluation criteria. Although precise numerical numbers are not provided, it is clear from the continuously high scores that the accuracy, recall, and precision of the Proposed technique are excellent. This superiority highlights the efficacy of the suggested technique and establishes it as the most stable and dependable solution out of all the models taken into consideration.

4.1. Discussion

By overcoming some of the shortcomings noted in other investigations, the research presented makes a substantial contribution to the changing field of COVID-19 detection techniques. In real-world circumstances, quick, non-invasive diagnostic tools are needed. A "COVID cough" detection system and a face mask recognition model are prioritized. The need for effective detection and containment of COVID-19 dissemination worldwide aligns with these advancements. Incorporating deep learning algorithms into the processing of CT scans and chest X-rays further demonstrates how artificial intelligence might improve diagnostic effectiveness, especially when more conventional techniques could result in false positives or negatives.

Nonetheless, a typical flaw in these techniques is their reliance on specific datasets, which may restrict their applicability. In addition to addressing this drawback, the hybrid strategy suggested for COVID-19 identification from X-ray pictures also shows better computing efficiency compared to existing models. Gradient Boosting Classifier, Differential Algorithm, and Hybrid Convolutional Neural Networks are combined to reduce computation time and improve diagnostic accuracy.

Further chapters, including Background and Preliminaries, Algorithm Steps, Detection Rate Analysis, Feature Set Visualization, and ROC-based Analysis, promise a more thorough examination of the suggested technique. The innovative aspect of state-of-the-art hybrid methodologies is their comprehensive integration, which uses optimization tactics, deep learning, and ensemble learning.

In contrast to single-model methods, this hybrid framework uses each component's advantages to improve computing efficiency, sensitivity, and specificity. To maximize its practical utility, the suggested solution attempts to be adaptable and deployable at important access points such as campuses, airports, and healthcare facilities.

The proposed methodology presents a promising development that is well-positioned to have a significant impact on the quick and precise identification of COVID-19 from X-ray images, addressing the urgent need for efficient diagnostic instruments in the ongoing fight against the virus as the world's medical system struggles with the challenges presented by the pandemic.

5. Conclusion and Future Works

COVID-19 infections have skyrocketed in recent years. Disease diagnosis and treatment rely heavily on machine vision and AI approaches. This research aimed to suggest a solution to the "COVID-19" problem by using a database of lung scans classified into two groups: COVID-19 and healthy.

Research presented a Gradient Boosting (GB) based approach for training Convolutional Neural Networks (CNNs) and Deep Neural Networks. Features of interest were chosen, and irrelevant ones were discarded using the binary differential metaheuristic approach. The suggested model has a 98% success rate regarding categorization.

The model has a 97% F1 score, 98% recall, 99% sensitivity, and 99% accuracy. When comparing current models to the proposed model, InceptionV3 has the best results. Classifying COVID-19 from healthy chest X-rays with the current InceptionV3 model is successful 94% of the time. This model has a 95% accuracy rate, 92% recall rate, 93% sensitivity, and 92% F1 score. The proposed strategy might be used for a dataset with more types of lung illnesses in future studies. The literature analysis also revealed that research has room to develop more refined techniques for extracting useful features from images. Therefore, in further efforts, a feature extraction method will be integrated. The classification accuracy rate may be increased by using an ensemble of deep learning and machine learning models.

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