International Research Journal of Multidisciplinary Scope (IRJMS), 2026; 7(1): 1613-1626

Original Article | ISSN (O): 2582-631X DOI: 10.47857/irjms.2026.v07i01.07770

Optimization Assisted Hybrid ResNet with YOLO Classifier for COVID-19 and Pneumonia Diagnosis from X-ray Images

AP Narmadha[1]*, N Gobalakrishnan[2]

[1]School of Computing, Sathyabama Institute of Science and Technology, Chennai, India, [2]Department of CSE, Saveetha Engineering College, Thandalam, Chennai, India. *Corresponding Author's Email: narmadhaparasuraman@gmail.com

Abstract

Due to the spread of the COVID-19 cases, medical experts are analyzing the automatic detection model for preventing the disease. In worldwide, there is more number of confirmed cases, but only a few CT scan images are available. The classes like COVID-19, normal and pneumonia images are collected from various benchmark databases. This work has the stages like pre-processing, data augmentation, feature extraction and classification. Initially, the image contrast is enhanced and Gaussian filtering is used for eliminating the noise. Then, the image augmentation techniques like image rotation; scaling, translation and flipping are applied on the original dataset. Then, the two stage hybrid deep learning (DL) model has been designed for the diagnosis of COVID-19 using the CXR images. The DL model hybrid ResNet with YOLO-V5 classifier is used for extracting the features and classifying the COVID-19 classes. Further, for optimizing the YOLO-V5 classifier, the met heuristic algorithm Capuchin Search Optimization (CaSO). The proposed ResNet with YOLO-V5-CaSO automatically classifies the normal, COVID-19 and Pneumonia cases. The outcomes provided by this model proved that this model can efficiently diagnose COVID-19 and Pneumonia using the CXR images. Further, the accuracy and TPR achieved are 99.3% and 1.108 for the proposed model and it shows that this model saves time and assists the early diagnosis.

Keywords: Capuchin Search Optimization, COVID-19, CXR Images, Deep Learning, Image Augmentation.

Introduction

Pneumonia is a common disorder and is affected due to various microbial organisms like fungi, bacteria and viruses. COVID-19 is an extremely infectious disorder and is affected due to SAR-CoV-2 (Severe Acute Respiratory Syndrome-Coronavirus-2). The first COVID-19 case was reported in December 31, 2019 in China and in March 11, 2020, world health organization (WHO) announced it as a pandemic. COVID-19 is transmitted by respiratory drops that are produced or exhaled by the affected people (1). There are various techniques are used for diagnosing pneumonia; some of them are chest X-rays, pleural fluid culture, blood gas analysis, and CT scan. Generally, pneumonia is cured on the basis of causative pathogen and antibiotics are utilized for treating bacterial pneumonia. Anti-viral drugs are utilized for treating viral pneumonia and for fungal pneumonia; anti-viral drugs are utilized (2). In most of the cases, this COVID-19 causes pneumonia and the infection characteristics are monitored with the help of radiologists. In addition, the deep learning (DL) models are useful to operate deep analysis on the radiograph images. Furthermore, Artificial intelligence (AI) plays major part in the detection and prevention of COVID-19 and efficient screening of this disease is complex process. One of the traditional screening kits Reverse Transcription (RT)-Polymerase Chain Reaction (PCR) is usually not available and these test are more sensitive (3-5). It has been found that for early diagnosis the Deep Learning (DL) based computerized tomography (CT) are more robust. Chest X-rays and CT images provide additional data to screen COVID-19. In China, AI technique is deployed for the examination of radiography. CT imaging has more radiation and it is time-consuming process than x- ray imaging. Further, the CT images are not available in most of the backward places, but the x- ray imaging is available in all places and cost-effective (6-8). It is more complex for detecting the nature of the diseases from x-ray images by visual analysis since both COVID-19 and pneumonia looks same. Due to the less number of a radiologist, the detection process

(Received 22nd August 2025; Accepted 08th January 2026; Published 31st January 2026)

well the treatment processes are slow (9-11). Hence, the AI (artificial intelligence) based automated models are attaining huge attention for detecting the COVID-19. Using better accuracy-based AI models in healthcare applications may improve comport of patient and minimize the workload of radiologists (12-14). During the last two decades, various research works influenced by the requirement for better detection using medical imaging with deep learning (DL) were published. DL models are the field of AI that mimics the human brain and it is the extended model of machine learning. These DL models are able to identify the hidden features which are not identified by the radiologists (15). The convolutional neural network (CNN) has the capacity for extracting the features and differentiates the classes like positive, negative, affected, healthy and non-healthy. Some of the CNN models utilized in the conventional research works are ResNet, AlexNet, InceptionV3, and Xception models (16, 17).

The requirement for the detection of COVID-19 is essential one due to more number of COVID cases. In the world, all medical experts are searching for the sophisticated models for correctly diagnosing the disease. At present, various models are utilized for detecting various kinds of pneumonia. But, the identification of various pathogen strains by molecular analysis doesn't meet the standard of the diagnosis process. Instead of that, the specimens are obtained and transmitted to the fully-equipped laboratory using Reverse Transcription-Polymerase Chain Reaction (RT-PCR) test. However, this test is high cost and sometimes generates error outcomes. Furthermore, the remote places and backward countries don't have the testing kit and also only less number of ventilators are available. Hence, there is a need for an alternative model which is reliable, simple and cost-effective. This can be achieved by computed aided model based DL models which are precise, fast and accurate. Further, most of the existing works focused on only two classes like normal and COVID-19. This work presents multi-classification of COVID-19 which classifies the COVID-19, viral, bacterial pneumonia and normal images.

The contributions of the work are: To present an automated hybrid deep learning (DL) model for the detection of COVID-19 using CXR images for overcoming the drawbacks of RT-PCR test. To present hybrid ResNet with YOLO-V5 classifier for extracting the features and classifying the COVID-19 classes. To optimize the hyper-parameters of YOLO-V5 classifier using the met heuristic algorithm CaSO. To compare the performance of the proposed disease detection model with other diseases on the basis of certain performance measures.

Literature works relevant to the proposed model based on the classification of various classes of COVID-19 is listed: The Pre-trained AlexNet model to classify the COVID-19, non-COVID-19, bacterial pneumonia and normal images. This method was trained for performing binary and multi-stage classifications. The accuracy, sensitivity and specificity attained for the muti-stage classification were 93.4%, 89.1% and 98.1% respectively was found in past research (18). CNN with TL (transfer learning) for the detection of COVID-19 and Pneumonia found in past research (19). Two datasets were utilized and it was obtained from the benchmark X-ray images. The experimentation proved that the DL model with X ray images extracts the essential biomarkers and attained better accuracy, sensitivity and specificity of 96.7%, 98.6% and 96.4%.

DL models with chest X-ray images to detect the case of Pneumonia infection and also introduced health indicator to evaluate the detected case of Pneumonia infection and estimate the status of patients was introduced (20). The model Inceptio-ResNet-RNN attained better accuracy of 90.5%. COVID-19 Pneumonia using generalized CNN using chest X-ray images. Initially, pre-processing and augmentation were carried out. Pre-trained models like DenseNet-201, Squeeze net and ResNet18 were utilized. Finally, the binary classification was carried out for COVID-19 Pneumonia and other types of Pneumonia. Among the pre-trained models, DenseNet-201 attained better F1-measure and precision values of 92.1% and 94.9% on the Kaggle dataset.

Pre-trained CNN with optimization based capsule network (DN) for the diagnosis of COVID-19 using chest X–rays. Initially, the SMOTE was applied for generating the new samples and VGG-16 was used for extracting the features. Finally, the CN model with Gaussian optimization was used for the detection of COVID-19. The accuracy and precision achieved were 96.58% and 96.52% on the Kaggle dataset states in past study (21). Modified CNN to detect COVID-19 and pneumonia using chest X-ray images. Here, the network model utilized was the hybrid Xception and ResNet-50V2 models and the data utilized has 180 X ray images. The average accuracy achieved was 99.5% by using multi-features extracted by the hybrid Xception and ResNet-50V2 states in past study (22).

Four DL models like Inceptionv3, DenseNet121, Xception, and InceptionResNetv2 for the classification of COVID-19, pneumonia and normal images states in past study (23). For the binary and multi-class classification, the accuracy attained were 98.3% and 92.3% respectively. Multi-COVIDNet model for the diagnosis of COVID-19. Two pre-trained models like Inception-V3 and ResNet-50 were utilized and Multi Objective Grasshopper Optimizer (MOGO) was utilized for optimizing the weights of the pre-trained models. The accuracy and sensitivity values achieved were 98.2% and 99.6% states in past study (24). COVID-Deep-Net model for the detection of COVID-19 Pneumonia. Contrast of the images was enhanced and noise was eliminated; then, the convolutional-deep belief network (C-DBN) was used for disease classification. The detection accuracy and MSE achieved were 99% and 0.021. COVID-19 Pneumonia model using the CNN model and improved pre-trained AlexNet model. This pre-trained model was used for accelerating the speed of the process and for detecting COVID-19. The modified CNN and pre-trained models attained better accuracies of 94.1% and 98% states in past study (25).

Methodology

CXR test is regarded as major solution for detecting COVID-19 and it is cost effective. The hybrid DL models are very effective for solving various real-life applications like computer vision models and healthcare applications. Hence, this work uses the hybrid DL model ResNet with YOLO-V5-CaSO to carry out an automated classification of CXR images. This model ensures better performance and generalization than the single classifiers. Further, for optimizing the hyper-parameters, the algorithm CaSO is utilized to enhance the performance measures. Figure 1 delineates the proposed automated COVID-19 classification model and the following section defines the working of the proposed methodology.

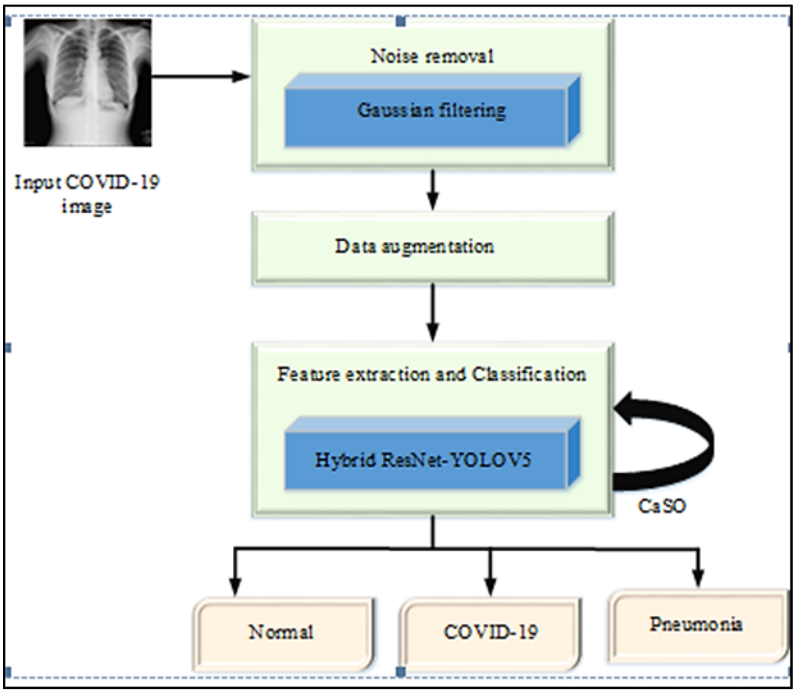

Figure 1: Proposed Automated COVID-19 Classification Model

Noise Removal

Generally, the COVID-19 images are affected by noise and due to this artifacts may form. Due to these artifacts, the classification accuracy may be degraded and causes incorrect detection outcomes. For the accurate detection of disease, the noise removal stage is an essential process before the segmentation process. In this work, for smoothening the image, the Gaussian filtering is used for removing the speckle noise. The coefficients of Gaussian kernels are sampled from the 2D Gaussian function and it is expressed as in Equation [1]:

$$G(y,z) = \frac{1}{\sqrt{2\pi\alpha^2}} \exp - \left(\frac{y^2 + z^2}{2\alpha^2} \right) \quad [1]$$

where α is the smoothing term.

Data Augmentation

Initially, the data augmentation process is provided to the dataset for reducing the over fitting problem and expands the volume of data. Because of the non-massive data, the new samples are generated for enriching the dataset using data-augmentation processes. The original data is elaborated by the python tool using random scaling, angle rotation, vertical flipping and horizontal flipping. During the generation of new samples, scaling, rotation and flipping are carried out by using random bound values. These values are set in the particular range, the range of rotation in 90^0 and 270^0, the shear range is 0.3 and the scale is varied from 0.8 to 1.2.

Feature Extraction and Classification Using Optimal ResNet- YOLOV5

After pre-processing and data augmentation process, the feature extraction and optimal classification are carried out by ResNet- YOLOV5. This network automatically classifies the disease as normal, COVID-19 and Pneumonia. The network YOLOV5 overcomes the issues of poor detection, but the accuracy in the identification of object position is not better. One of the major ways to enhance the accuracy is developing the network as deeper and also the network should overcome the gradient vanishing problem. The DL model ResNet overcomes the gradient vanishing during the network deepening. Hence, according to the DarkNet, the network ResNet is used to extract the features. DarkNet has 1x1 and 3x3 convolutional layers and considers stride 2 for reducing the dimension of the feature map for extracting the features. Then, this network is integrated with ResNet which extracts the features deeply. Finally, these two feature extracting models are averaged for reducing the dimension.

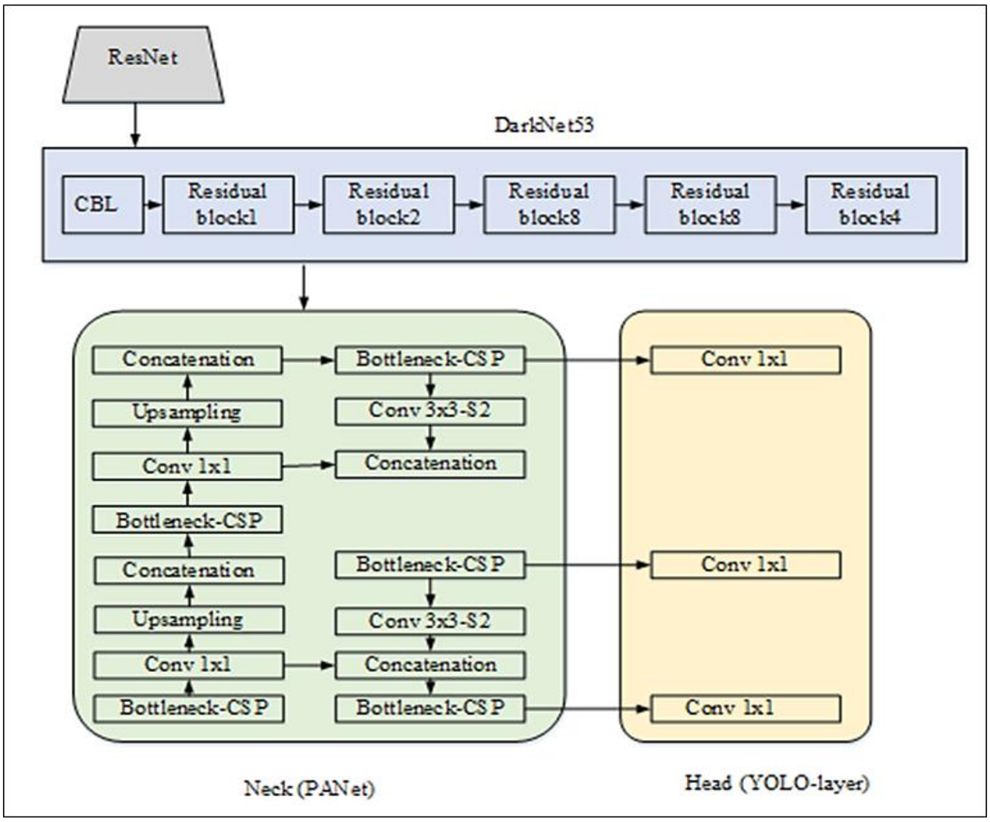

Figure 2: Structure of ResNet- YOLOV5

Figure 2 represents the structure of ResNet-YOLOV5. This model uses YOLOV5 and ResNet for extracting the features. The DarkNet has 2D-convolutional layer (C), batch normalization (B) and leaky-ReLU (L). Even though, YOLOV5 overcomes the issues of the disease detection, the performance of the model in disease detection is poor. Hence, according to the model of Darknet53, the model ResNet is hybrid in this work. Hence, the extraction of features is enhanced which attains better detection and also overcomes the degradation problem.

In the ResNet model, the input and the convoluted output are added for obtaining the last output. Let the function $H(z)$ is transformed to the $F(z)+z$ and when the entire parameters in $F(z)$ are set as zero, and then $H(z)$ is the identity mapping. Let the building block is given as in Equation [2]:

$$x = F(z, W_j) + z \qquad [2]$$

where x is the input vector, z is the output vector, and $F(z,W_j)$ is the residual mapping.
In Equation [2], the dimensions of F and the input vector x must be same. The linear function W_r is used for matching the dimension via shortcut connection (Equation [3]).

$$x = F(z, W_j) + W_r z \qquad [3]$$

The residual skip model disrupts the grouping that the results of the neural network $n-1$ is provided to n layer as the input. Hence, the output of these layers crosses different layers as the input of the following layer (26).
As shown in Figure 2, YOLOV5 has DarkNet (backbone model), PANet (neck) and the YOLO-layer (head). The features extracted by the DarkNet with ResNet are given to the bottleneck. This bottleneck forward the COVID features to the neck and SPP (special pyramid pooling). The neck has concatenated bottleneck-CSP and convolutional layers. Finally, the head is used for aggregating the COVID features for processing the prediction box.

This optimization aims to attain better accuracy and the fitness function and it is given as in Equation [4]:

Fitness= Maximize (A) [4]

Where A is the accuracy.
This section presents the mathematical modelling of capuchin monkey's during the food searching process. The swarm of m capuchins in the $d-$dimension search space is indicated using the matrix and it is represented as (Equation [5]):

$$z = \begin{bmatrix} z_1^1, & z_2^1 \ldots\ldots\ldots\ldots\ldots z_d^1 \\ z_2^1 & z_2^2 \ldots\ldots\ldots\ldots\ldots y_d^2 \\ \vdots & \\ z_1^m, & z_2^m \ldots\ldots\ldots\ldots\ldots z_d^m \end{bmatrix} \qquad [5]$$

Where z the capuchin is's position, d is the total parameters, m is total capuchins and z_d is the position dimension.
In the swarm, every capuchin is used for allocating the initial position and it is given as (Equation [6]):

$$z^j = ul_k + r(ul_k - ll_k) \qquad [6]$$

where r is the random number, ul_k and ll_k are the upper and lower limits of j^{th} capuchin at k^{th} dimension.

The evolutionary model of this optimization depends on the source of food (F_j) and best and present positions. All alpha capuchins jump from the branch to another branch or tree and in this situation the position of the capuchins are given as (Equation [7]):

$$z_j^k = F_j + \frac{\Pr_a (v_j^k)^2 \sin(2\theta)}{gr} \quad k < m/2; 0.1 < \delta \le 0.2 \qquad [7]$$

where z_j^k is the alpha capuchin's position, $\Pr_a$ is the probability of balancing ensured on the leap process, gr is the gravitational force and v_j^k is the velocity of j^{th} capuchin at k^{th} dimension.
The life-time of the capuchins is used for balancing between the exploitation and exploration and it is given as (Equation [8]):

$$\tau = \alpha_0 \exp - \alpha_1 \left(\frac{I_1}{I_2} \right)^{\alpha_2} \qquad [8]$$

where I_1 and I_2 are the present and next iterations, α_0, α_1 and α_2 are the random parameters.
The capuchins jump from one place to another for searching the food. In this situation, the positions of capuchins and leader are given by (Equation [9]):

$$z_j^k = F_j + \frac{\Pr_e \Pr_a (v_j^k)^2 \sin(2\theta)}{gr} \quad k < m/2; 0.2 < \delta \le 0.3 \qquad [9]$$

where $\Pr_e$ is the probability of elasticity of the capuchin's motion.
During the new position updation, the position of alpha capuchins is utilizing normal walk and it is given as (Equation [10]):

$$z_j^k = z_j^k + v_j^k \quad k < m/2; 0.3 < \delta \le 0.5 \qquad [10]$$

Capuchins utilize the swing process for finding the source of food on the two sides of the branch. In this situation, the positions of capuchins are given by (Equation [11]:

$$z_j^k = F_j + \tau \Pr_a \times \sin(2\theta) \quad k < m/2; 0.5 < \delta \le 0.75 \qquad [11]$$

During the foraging process, the capuchins climb the tress and, in this situation, the positions of capuchins are given by (Equation [12]):

$$z_j^k = F_j + \tau \Pr_a (v_j^k - v_{j-1}^k) \quad k < m/2; 0.75 < \delta \le 1 \qquad [12]$$

In certain cases, the capuchins search the source of food randomly and this characteristic is performed on the foraging process. Then, it is expressed as (Equation [13]):

$$z_j^k = \tau \times [ul_k + \delta (ul_k - ll_k) \quad k < m/2; \delta \le Pc \qquad [13]$$

where τ is the life-time variable, δ is a constant parameter and Pc is the probability parameter.
The third law of motion is utilized for updating the follower's position by the following expression (Equation [14]):

$$z_f = z_j + v_0 t + \frac{1}{2} acc \times t^2 \qquad [14]$$

where z_j and z_f are the first and last migration, v_0 is an initial velocity, t is time and acc is the acceleration.

The hyper parameters of YOLOV5 like learning rate and momentum are optimized by the metaheuristic optimization CaSO (24). This optimization mimics the effective characteristics of the capuchin monkeys. This optimization states the foraging and wandering behaviour during the food search. General characteristics of the foraging process are climbing, leaping, swinging and jumping are explained in this work and the flowchart of the CaSO is presented in Figure 3.

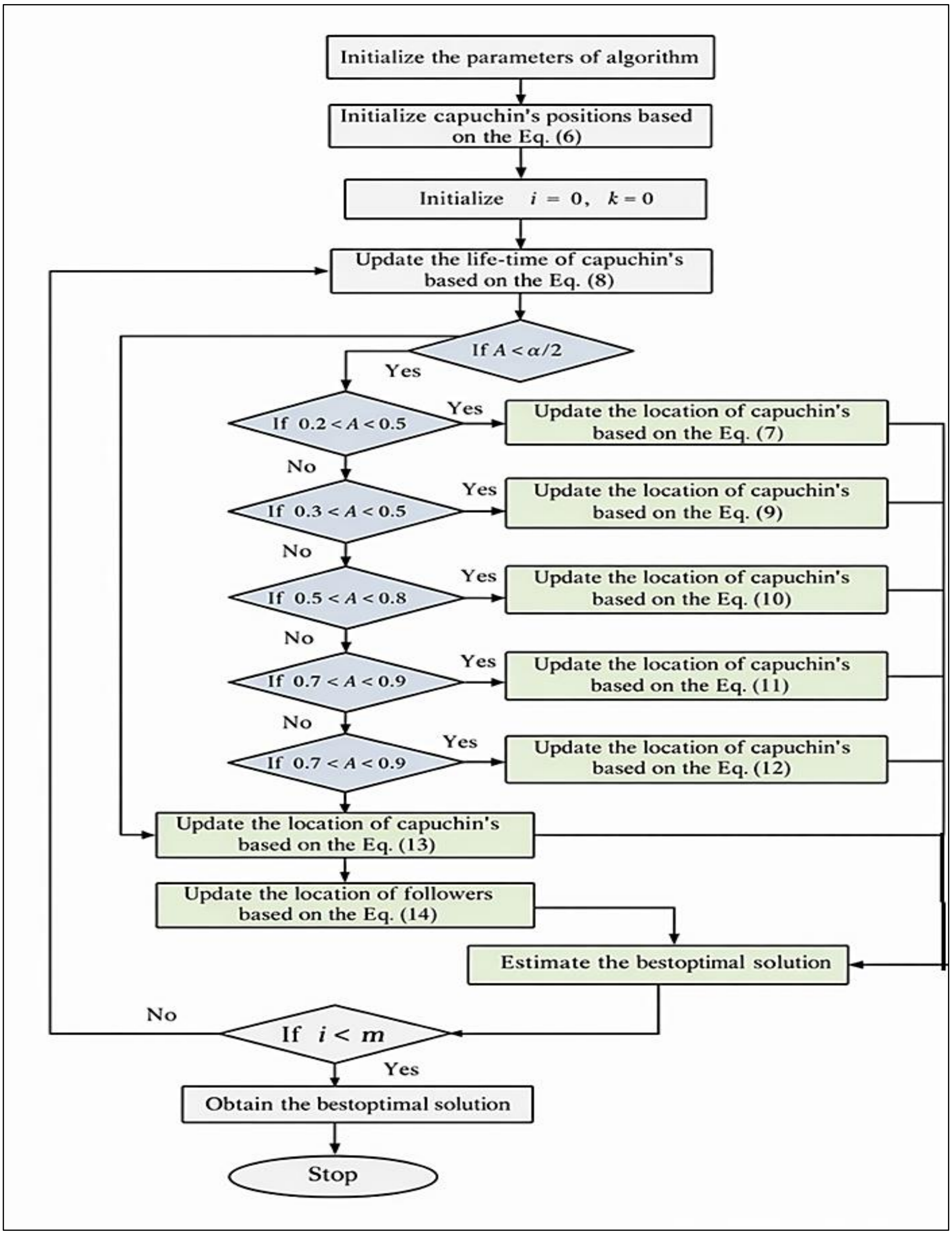

Figure 3: Flowchart of the CaSO

Results and Discussion

The proposed ResNet with YOLO-V5-CaSO is trained for detecting and classifying the three classes. The experimentation is carried out on 10-fold cross-validation. Then, Google collab is the online software utilized to simulate the Python libraries. Table 1 indicates the Hyper-parameters of ResNet with YOLO-V5-CaSO.

Table 1: Hyper-parameters of ResNet with YOLO-V5-CaSO

Hyper-parameters	ResNet	YOLO-V5
Learning rate	0.065	0.009
Momentum	0.750	0.952
Epoch	50	50
Size of batch	32	32
Optimizer	CaSO	CaSO

Evaluation Measures

The efficacy of the proposed model is presented on the basis of accuracy, precision, False positive rate (FPR) and true positive rate (TPR). Further, the performance of CM (confusion matrix) and ROC (receiver operating characteristics) are also plotted.

Accuracy: It is the ratio of truly predicted samples to the overall samples and it is expressed as (Equation [15]):

$$A = \frac{RP + RN}{RP + RN + WP + WN} \quad [15]$$

Precision: It is the ratio of truly predicted positive samples to the overall positively predicted samples and it is given as (Equation [16]):

$$P = \frac{RP}{RP + WP} \quad [16]$$

FPR: It is the ratio of a number of normal images that is incorrectly identified as positive and it is given as (Equation [17]):

$$FPR = \frac{WP}{RN + WP} \quad [17]$$

TPR: It is the ratio of the COVID-19 cases is tested as positive and it is given as (Equation [18]):

$$TPR = \frac{RP}{RP + RN} \quad [18]$$

F1-score: This measure balances the precision and recall and it is computed by (Equation [19]):

$$F1 - score = \frac{2(\Pr ecison \times \mathrm{Re}\, call)}{\Pr ecison + \mathrm{Re}\, call} \quad [19]$$

where RP is true positive in which the COVID images are correctly identified, WP is false positive in which normal images are in correctly identified as COVID, RN is true negative in which the normal images are correctly identified and WN is is false negative in which COVID images are in in correctly identified as normal images.

Dataset Details

Although, there is a greater number of COVID-19 cases worldwide, there is only a limited number of CT images. The following websites are used for obtaining the datasets. Nearly, 1036 images are collected for the cases like normal, COVID-19 and pneumonia. Total of 153 images are collected from the Github and 137 (normal) and 100 (COVID-19) images are collected from the Kaggle repository. Then, a Chest X-ray of 646 images is collected from (27). Figure 4(A-D) represents the sample images obtained from the dataset.

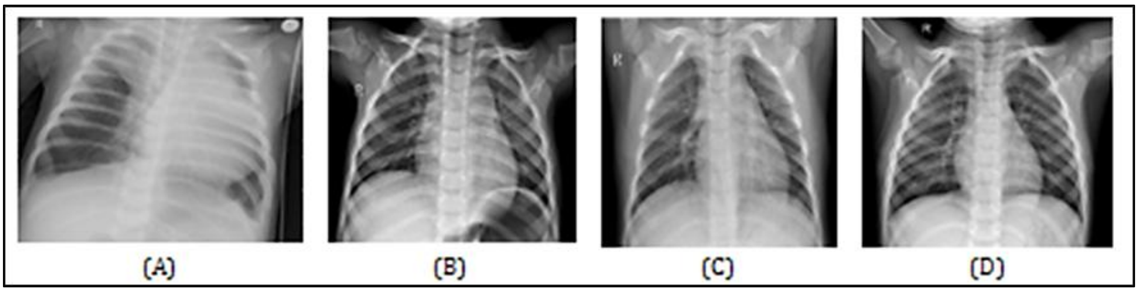

Figure 4 (A-D): Sample Images Obtained from the Dataset

Qualitative Analysis

This section presents the qualitative analysis of the proposed ResNet with YOLO-V5-CaSO COVID-19 classification model. The input images are shown in Figure 5(A), while the pre-processed images (after applying Gaussian filtering) are presented in Figure 5(B). The augmented images generated through flipping, rotation, translation and scaling are illustrated in Figure 5(C) to Figure 5(E). Before the augmentation process, there are 1036 images and after the augmentation process, there are 5, images.

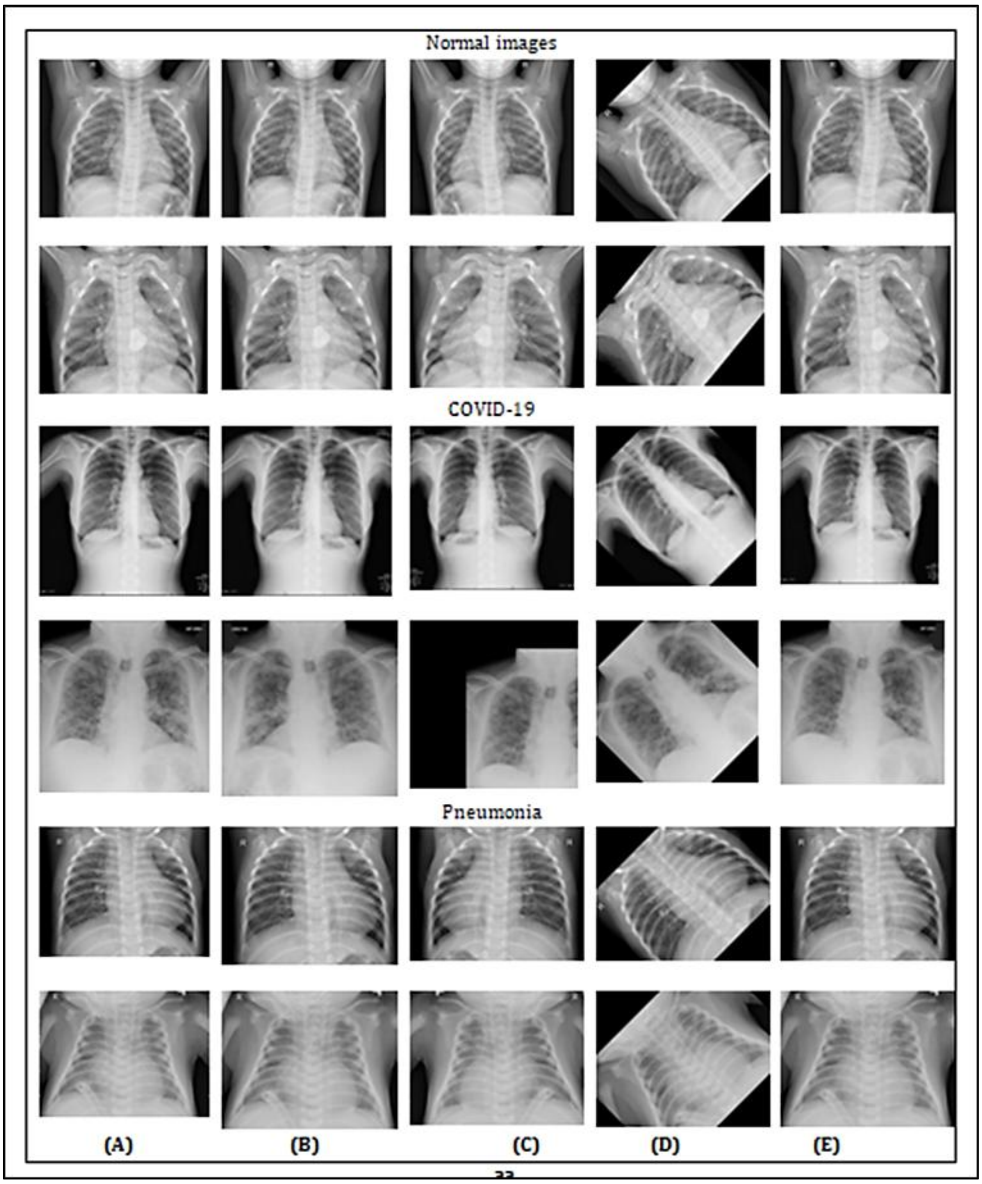

Figure 5: Qualitative Analysis (A) Input Images, (B) Pre-Processed Images and (C-E) Augmented Images

Figure 6 represents the performance of the methods like ResNet, YOLOv5 and the DenseNet networks are compared with the proposed ResNet with YOLO-V5-CaSO. The performance measures like accuracy, precision, FPR, F1-score and TPR are considered. The accuracy achieved by the ResNet, YOLOv5, DenseNet and the proposed ResNet with YOLO-V5-CaSO are 96.97%, 98.06%, 97.94% and 99.35% respectively. Similarly, the TPR values achieved by the ResNet, YOLOv5, DenseNet and the proposed ResNet with YOLO-V5-CaSO are 4.70, 1.93, 2.21 and 1.10 respectively. This measure show that the proposed model has very less TPR and shown a better performance. Hence, it is proved that the optimal hybrid DL model perform better than the single classifiers.

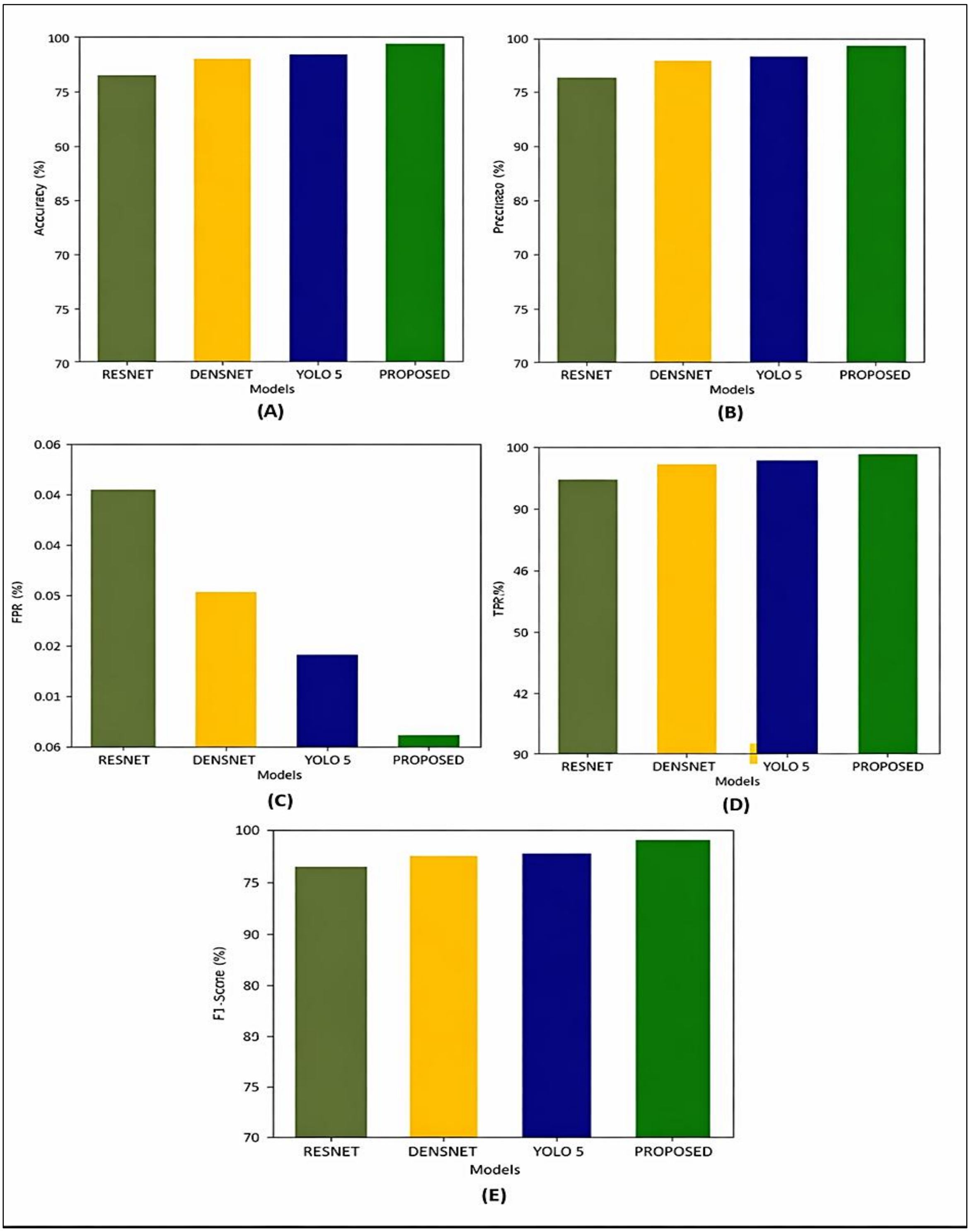

Figure 6: Performance of (A) Accuracy, (B) Precision, (C) FPR, (D) TPR, and (E) F1-Score

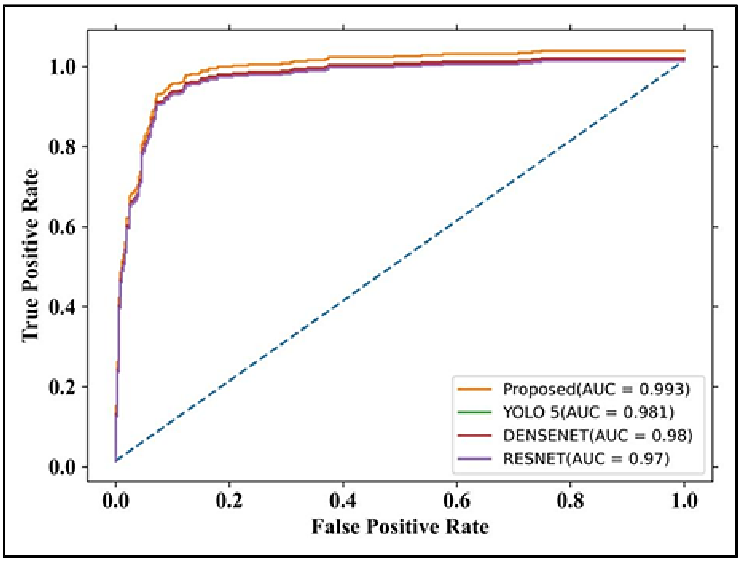

Figure 7: ROC Curve

ROC curve is the graphical illustration for showing the classifier's capacity of the model. When the curve is close to the top-left corner of ROC, then the outcomes are more correct. Figure 7 presents the AUC values of the ResNet, YOLOv5, DenseNet and the proposed ResNet with YOLO-V5-CaSO. The AUC values achieved by the ResNet, YOLOv5, DenseNet and the proposed ResNet with YOLO-V5-CaSO are 0.97, 0.98, 0.981 and 0.993.

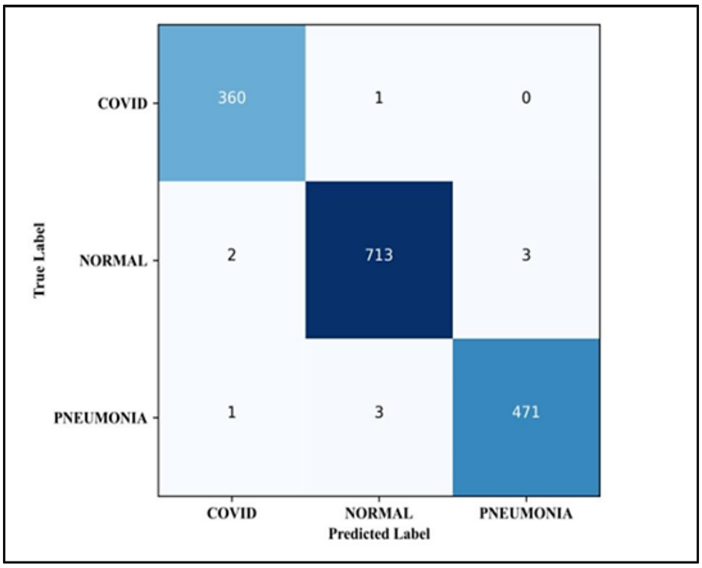

Figure 8: CM of the Proposed ResNet with YOLO-V5-CaSO

Figure 8 illustrates the CM of the proposed ResNet with YOLO-V5-CaSO which presents the three classes like COVID-19, normal and pneumonia. It is observed from the figure that 360 samples are classified as COVID-19 and 1 sample is misclassified. Then, 713 samples are classified as normal and 5 samples are misclassified. Finally, 471 samples are classified as pneumonia and 4 samples are misclassified.

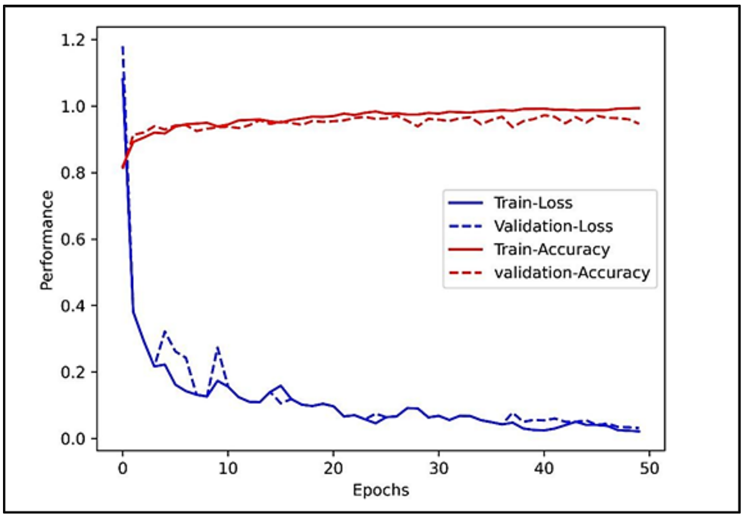

Figure 9: Accuracy and Loss Curve of the Proposed ResNet with YOLO-V5-CaSO

Figure 9 illustrates the accuracy and loss curve of the proposed ResNet with YOLO-V5-CaSO. The accuracy and loss are measured for the training and validation set. The epoch is varied from 0 to 50 and the graphs are mapped. It is observed that the loss is very less after the 10^{th} epoch; similarly, the accuracy is high after the 10^{th} epoch. Hence, it is proved that these two curves better consistency on the process of training and validation.

Table 2: Comparative Analysis of the Various Techniques

Methods	Accuracy (%)	Precision (%)
Ensemble model (28)	92.3	87.72
Multi-COVID-Net (29)	98.2	95.3
EfficientNet-B0 (30)	95.3	92.2
Pre-trained CNN (31)	98.9	96.72
YOLO (32)	87.02	89.71
Proposed	99.3	99.04

Table 2 presents the comparative analysis of the various techniques like Ensemble model (29), Multi-COVID-Net, EfficientNet-B0, Pre-trained CNN, YOLO and the proposed ResNet with YOLO-V5-CaSO. It is observed from the graph that the proposed model attained better accuracy and precision. This betterment is due to the optimal weight selection by CaSO and the hybrid nature of the ResNet with YOLO-V5.

Statistical Analysis

The statistical analysis in this study was conducted using Python (version 3.x) on Google Colab. The statistical analyses, including the Friedman Ranking (FR) and Wilcoxon Signed-Rank Test (WT), were conducted utilising Python libraries like SciPy and NumPy. The methods were employed to perform non-parametric statistical validation of the suggested model's efficacy at a 95% confidence level.

The performance of the model must be analyzed statistically, hence in this work Friedman ranking (FR) and wilcoxon test (WT) are carried out. The WT is carried out by 95% (confidence level) and 5% (significant level). FR is used non-parametric analysis used for ranking the model's performance. Table 3 provides the analysis of WT and FR, in which the value of $\rho < 0.05$ for the proposed model. Similarly, the proposed covid classification model attained best rank when compared to the existing methods.

Table 3: Analysis of WT and FR

Methods	WT ($\rho-$ value)	FR
ResNet	0.05	5.2
YOLOv5	0.12	4.5
DenseNet	0.08	2.4
proposed	0.01	1.1

Conclusion

This paper presented a hybrid DL based ResNet with YOLO-V5-CaSO model for diagnosing the COVID-19 using the CXR images. To overcome the drawbacks of the over fitting issues, the data augmentation procedure was carried out. Further, to overcome the feature extraction by the handcrafted features, this work utilized a hybrid DL model for the extraction and classification of features. Finally, the hyper-parameters of the network were fine-tuned by the CaSO. The performance was validated on the various benchmark datasets obtained from the various repositories which have the classes like normal, COVID-19 and pneumonia. The overall accuracy (99.3%), precision (99.04%), TPR (1.10) and FPR (0.99) were attained by the ResNet with YOLO-V5-CaSO model. The experimental findings proved that the mis-diagnosing rate will be minimized and COVID-19 cases will be identified efficiently. Further, this model is utilized for assisting radiologists, physicians and specialists in decision making process. In the future, this model will be utilized in remote places for overcoming the shortage of the medical experts. Further, this model can be able to diagnose the diseases like tuberculosis.

Abbreviations

CaSO: Capuchin Search Optimization, DL: Deep Learning, RT-PCR: Reverse Transcription-Polymerase Chain Reaction, SAR-CoV-2: Severe Acute Respiratory Syndrome-Coronavirus-2.

Acknowledgement

The author would like to appreciate the effort of the editors and reviewers.

Author Contributions

All the authors are equally contributed.

Conflict of Interest

The authors declare that they have no conflicts of interest.

Declaration of Artificial Intelligence (AI) Assistance

The authors declare that no generative AI or AI-assisted technologies were used in the writing, editing, or preparation of this manuscript.

Ethics Approval

There are no human subjects in this article and informed consent is not applicable.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

References

1. Kansal K, Chandra TB, Singh A. Advancing differential diagnosis: A comprehensive review of deep learning approaches for differentiating tuberculosis, pneumonia, and COVID-19. Multimedia Tools and Applications. 2025;84(13):11871-906
2. Chakraborty S, Paul S, Hasan KMA. A Transfer Learning-Based Approach with Deep CNN for COVID-19-and pneumonia-affected chest X-ray image classification. SN Computer Science. 2022;3(1):17. https://link.springer.com/article/10.1007/s42979-021-00881-5
3. Nikolaou V, Massaro S, Fakhimi M, *et al*. COVID-19 diagnosis from chest x-rays: developing a simple, fast, and accurate neural network. Health Information Science and Systems. 2021;9(1):36.
4. Jain R, Gupta M, Taneja S, *et al*. Deep learning based detection and analysis of COVID-19 on chest X-ray images. Applied Intelligence. 2021;51(3):1690-700.
5. Madaan V, Roy A, Gupta C, *et al*. XCOVNet: Chest X-ray image classification for COVID-19 early detection using convolutional neural networks. New Generation Computing. 2021;39(3):583-97.
6. Wang Z, Xiao Y, Li Y, *et al*. Automatically discriminating and localizing COVID-19 from community-acquired pneumonia on chest X-rays. Pattern Recognition. 2021; 110:107613
7. Singh K, Gaur A, Kumar S, *et al*. Deep CP-CXR: A deep learning model for classification of Covid-19 and pneumonia disease using chest X-Ray images. Annals of Data Science. 2025:1-24. doi: 10.1007/s40745-025-00601-3
8. Benmalek E, Elmhamdi J, Jilbab A. Comparing CT scan and chest X-ray imaging for COVID-19 diagnosis. Biomedical Engineering Advances. 2021; 1:100003.
9. Zhou T, Peng C, Guo Y, *et al*. Identity-mapping ResFormer: a computer-aided diagnosis model for pneumonia X-ray images. IEEE Transactions on Instrumentation and Measurement. 2025. doi: 10.1109/tim.2025.3534218
10. Gaurkhede S, Shendre S, Izankar S, *et al*. Detection and classification of pneumonia, Covid-19 and tuberculosis using deep learning methods. 4th International Conference on Sentiment Analysis and Deep Learning (ICSADL). IEEE. 2025:1637-43. doi:10.1109/ICSADL65848.2025.10933488
11. Signoroni A, Savardi M, Benini S, *et al*. BS-Net: Learning COVID-19 pneumonia severity on a large chest X-ray dataset. Medical Image Analysis. 2021; 71:102046.
12. Rajpal S, Lakhyani N, Singh AK, *et al*. Using handpicked features in conjunction with ResNet-50

for improved detection of COVID-19 from chest X-ray images. Chaos, Solitons & Fractals. 2021; 145:110749.

13. Gayathri JL, Abraham B, Sujarani MS, *et al*. A computer-aided diagnosis system for the classification of COVID-19 and non-COVID-19 pneumonia on chest X-ray images by integrating CNN with sparse autoencoder and feed forward neural network. Computers in Biology and Medicine. 2022; 141:105134.
14. Showkat S, Qureshi S. Efficacy of tansfer learning-based ResNet models in chest X-ray image classification for detecting COVID-19 pneumonia. Chemometrics and Intelligent Laboratory Systems. 2022; 224:104534.
15. Mahbub MK, Biswas M, Gaur L, *et al*. Deep features to detect pulmonary abnormalities in chest X-rays due to infectious diseaseX: Covid-19, pneumonia, and tuberculosis. Information Sciences. 2022; 592:389-401.
16. Vyas R, Khadatkar DR. Ensemble of deep learning architectures with machine learning for pneumonia classification using chest X-rays. Journal of Imaging Informatics in Medicine. 2025;38(2):727-46.
17. Yadav S, Rizvi SA, Agarwal P. Advancing pulmonary infection diagnosis: A comprehensive review of deep learning approaches in radiological data analysis. Archives of Computational Methods in Engineering. 2025; 32:3759-3786. https://doi.org/10.1007/s11831-025-10253-4
18. Hammoudi K, Benhabiles H, Melkemi M, *et al*. Deep learning on chest X-ray images to detect and evaluate pneumonia cases at the era of COVID-19. Journal of Medical Systems. 2021;45(7):75.
19. Alhudhaif A, Polat K, Karaman O. Determination of COVID-19 pneumonia based on generalized convolutional neural network model from chest X-ray images. Expert Systems with Applications. 2021; 180:115141.
20. AbouEl-Magd LM, Darwish A, Snasel V, *et al*. A pre-trained convolutional neural network with optimized capsule networks for chest X-rays COVID-19 diagnosis. Cluster Computing. 2023;26(2):1389-403.
21. Pavithra AC, Manjunath K, Kusuma HK, *et al*. Analysis of chest X-Rays based on MobileNetV2 models for the diagnosis of symptoms of pneumonia using ML. International Conference on Artificial Intelligence and Smart Energy. Cham: Springer Nature Switzerland. 2025:535-47. doi: 10.1007/978-3-031-90478-3_43
22. Wang D, Ru B, Lee EYP, *et al*. Validation of a deep learning model for classification of pediatric pneumonia in Hong Kong. Vaccine. 2024;42(26):126370.
23. Goel T, Murugan R, Mirjalili S, *et al*. Multi-COVID-Net: Multi-objective optimized network for COVID-19 diagnosis from chest X-ray images. Applied Soft Computing. 2022; 115:108250.
24. Al-Waisy AS, Mohammed MA, Al-Fahdawi S, *et al*. COVID-DeepNet: Hybrid multimodal deep learning system for improving COVID-19 pneumonia detection in chest X-ray images. Computers, Materials and Continua. 2021;67(2):2409-29.
25. Aslani S, Jacob J. Utilisation of deep learning for COVID-19 diagnosis. Clinical Radiology. 2023;78(2):150-7.
26. Braik M, Sheta A, Al-Hiary H. A novel meta-heuristic search algorithm for solving optimization problems: capuchin search algorithm. Neural Computing and Applications. 2021;33(7):2515-47.
27. Cohen JP. COVID chest x-ray dataset. Github; 2020. https://github.com/ieee8023/covid-chestxray-dataset
28. Chaurasia S, Gupta AK, Tiwari PP, *et al*. DSENetk: An efficient deep stacking ensemble approach for COVID-19 induced pneumonia prediction using radiograph images. SN Computer Science. 2025;6(1):68.
29. Rabbah J, Ridouani M, Hassouni L. Improving pneumonia diagnosis with high-accuracy CNN-Based chest X-ray image classification and integrated gradient. Biomedical Signal Processing and Control. 2025; 101:107239.
30. Deepak GD, Bhat SK. A multi-stage deep learning approach for comprehensive lung disease classification from x-ray images. Expert Systems with Applications. 2025; 277:127220.
31. Zhu J, Al-qaness MA, Dalal ALA, *et al*. Multiple lung diseases detection using advanced deep learning model with attention mechanisms and upsampling features. Engineering Applications of Artificial Intelligence. 2025; 156:111038.
32. Goyal S, Singh R. Detection and classification of lung diseases for pneumonia and COVID-19 using machine and deep learning techniques. Journal of Ambient Intelligence and Humanized Computing. 2023;14(4):3239-59.

How to Cite: Narmadha AP, Gobalakrishnan N. Optimization Assisted Hybrid ResNet with YOLO Classifier for COVID -19 and Pneumonia Diagnosis from X-ray Images. Int Res J Multidiscip Scope. 2026; 7(1): 1613-1626. DOI: 10.47857/irjms.2026.v07i01.07770