Multiclass Chest Disease Classification Using Deep CNNs with Bayesian Optimization

Maneet Kaur Bohmrah, Harjot Kaur
Department of Computer Science and Engineering
Guru Nanak Dev University
Amritsar, India, 143001

***Abstract*—Ever since its outbreak, numerous research studies have been initiated worldwide as an attempt for an accurate and efficient diagnosis of COVID-19. In the recent past, patients suffering from various chronic lung diseases, either passed away due to COVID-19 or Pneumonia. Both of these pulmonary diseases are strongly correlated as they share a common set of symptoms and even for medical professionals, it has been difficult to perform discerned diagnosis for both of these diseases. The dire need of the current scenario is a chest-disease diagnosis framework for accurate, precise, real-time and automatic detection of COVID-19 because of its mass fatality rate. The review of various contemporary and previous research works show that the currently available computer-aided diagnosis systems are insufficient for real-time implementation of COVID-19 prediction due to their long training time, substantial memory requirements and excessive computations. This work proposes an optimized hybrid DNN-ML framework by combining Deep Neural Networks' (DNNs) models and optimized Machine Learning (ML) classifiers along with an efficacious image preprocessing approach. For feature extraction, Deep learning (DL) models namely GoogleNet, EfficientNetB0, and ResNet50 have been deployed and extracted features have been further fed to Bayesian optimized ML classifiers. The two major contributions of this study are, Edge based Region of Interest (ROI) extraction and use of Bayesian optimization approach for configuring optimal architectures of ML classifiers. With extensive experimentation, it has been observed that the proposed optimized hybrid DNN-ML model with encapsulated image preprocessing techniques performed much better as compared to various previously existing ML-DNN models. Based on the promising results obtained from this proposed light weight hybrid framework, it has been concluded that, this model can facilitate radiologists, while functioning as an accurate disease diagnosis and support system for early detection of COVID-19 and Pneumonia.**

Keywords*—*Deep neural networks; machine learning; Bayesian optimization; image preprocessing; COVID-19; pneumonia

I. INTRODUCTION

Recently, a new virus known as **COVID-19** emerged in China and began to spread globally as an respiratory illness. Since its outburst, COVID-19 has contributed significantly to the economic crisis of numerous nations and adversely affected human life. Due to its transmissible characteristics, it can spread vigorously with uncertain transmission methods and co-exist for a longer duration of time [1]. According to statistics received from World Health Organization (WHO) [2], approximately six million people worldwide have died till date because of COVID-19 and over forty million cases have been reported so far. People who are older or have chronic health conditions seem to be more susceptible to contacting COVID-19 infection. Various symptoms of COVID-19 include high fever, coughing, anxiety and breathlessness. This virus spreads quickly via respiratory droplets produced by an infected person's cough or sneeze [3].

Numerous medical professionals globally, have been developing vaccines and researching on treatments to combat this virus. Moreover, many medical techniques and therapies have been developed and are currently under development for treatment and recovery of the affected individuals. Unfortunately, despite several protective measures, the available medical systems have failed to combat and control the virus, because it has been continuously undergoing several mutations [4]. This study requires advanced diagnosis and treatment methodologies to control its menace. Presently, COVID-19 has been diagnosed using time consuming primitive methods like, administering RT-PCR (Reverse Transcription - Polymerase Chain Reaction) examination. Another alternative is *Computed Tomography (CT) scan and Chest X-ray (CXR)* images, that have emerged as an robust imagery techniques for diagnosis of the same [5]

While investigating CXR and CT scan images, notable clinical findings that can be inferred are, ground glass opacities (GGO), thickening of intertobular septa and air branchogram sign, with or without increased broncho-vascular markings that lead to diagnosis of disparate lung diseases. Among these two medical imaging tools, CT scan images have been considered more reliable due to their high contrast image properties. And, they are more effective medical imaging system for diagnosis of the chest diseases. As compared, CXR images, have been widely recommended by doctors, because they are more economical as compared to CT scan image and easily accessible for patients too. For effective screening and diagnosis of COVID-19 and/or other chest infections, CXR and CT scan images have to be manually examined and then clinically correlated with patient's symptoms. Nevertheless, this manual screening is a very time consuming process and might not be feasible in emergency cases [6]. Therefore, an accurate, precise, real-time and automated COVID-19 diagnostic system is the dire need of the current scenario.

With the advent of prominent AI tools and medical imaging, researchers have started proposing novel solutions to develop automatic tools for accurate detection of COVID-19. AI based deep learning (DL) models, i.e., *Convolutional Neural Networks (CNNs)* excel in domain of image classification and provide extraordinary performance in medical image analysis. Due to their complex architecture, CNNs can be used for both feature extraction and classification tasks, which makes them distinguishable from rest of Machine Learning (ML) algorithms [7].

In medical imaging system, accurate and precise results, are always a major concern. For image classification task, a model should be well-versed with dominant features of an image. The ultimate motivating factor for the present study is that, all the image characteristics needed for feature extraction and classification should be noise free [8]. Henceforth, this study has focused more on image preprocessing techniques (segmentation, filtration and enhancement) in order to pertain the prominent features of the image. Afterwards, resultant segmented and enhanced image has been utilized by the pretrained CNN models for feature extraction. And finally, in order to classify the features, Bayesian optimized ML classifiers have been used in this work. Various innovative and novel contributions of the present study are as follows:

- Experimentation with the new enhanced model for the diagnosis of COVID-19 for two distinct types of COVID-19 images; the Chest X-ray and CT scan image datasets.
- Proposal of Edge based Adaptive Segmentation algorithms and their integration with image filtration and enhancement techniques for the preparation of enhanced dataset.
- Utilization of pretrained models and machine learning classifiers for feature extraction and classification process, respectively.
- Implementation of Bayesian optimization technique for disparate ML classifiers.
- Performance based comparative analysis of proposed DNN-ML models trained with and without image preprocessing techniques, thereby highlighting the advantages of latter.
- Comparative analysis based on classification accuracy of Bayesian optimized ML classifiers (BO-ML) with their non-optimized ML version, thereby investigating the significance of Bayesian optimization and deducing experimental insights on CXR and CT scan datasets.
- Comparison of the experimental findings with the other existing state-of-the-art models.

The remaining part of this article has been structured as follows, Section II highlights the state-of-the-art research studies conducted for automated diagnosis of COVID-19. Section III describes the datasets, the proposed framework, and methods used. Section IV presents various experiments performed along with the findings, discussions and comparative analysis. Finally, the conclusions and future work have been discussed in Section V.

II. LITERATURE REVIEW

In recent past, numerous research studies have been performed on automatic COVID-19 detection using disparate pretrained Deep Neural Networks (DNNs) and ML algorithms from lung images, in a stand-alone and hybrid mode. Kesav et al. [9] employed GoogleNet, a pretrained neural network for feature extraction and used different ML classifiers for performing the task of classification. On chest X-ray image dataset, Bayesian optimization has been utilized to optimize ML classifiers with accuracy score of 98.31% for binary and 98.60% for multi-class classification respectively.

Hamza et al. [10] proposed the use of Bayesian optimized neural networks and gradcam technique for visualization of chest x-rays to detect chest diseases. Arman et al. [11] designed modified Xception model based on Bayesian optimization and compared it with other DNN models such as VGG16, MobileNetV2 and InceptionV3. The proposed model achieved the highest value of classification accuracy, i.e., 99.4% to classify COVID-19, normal and pneumonia classes belonging to CXR image dataset. Canayaz et al. [12] presented a combination of ResNet50 and Bayesian optimized kNN to detect COVID-19 and this model accomplished an accuracy score of 96.42% when trained using CT scan dataset with 349 images for binary classification (COVID-19 and non COVID-19 categorization).

Awal et al. [13] experimented using various machine learning classifiers, i.e., Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Naive Bayes(NB), k-Nearest Neighbour (kNN), Decision Tree (DT), Random Forest (RF), extreme Gradient Boosting (XGBoost) for COVID-19 diagnosis. To optimize hyperparameters of aforementioned ML classifiers, Bayesian Optimization has been deployed and the results hence obtained showed that optimized XGBoost performed better as compared to other ML classifiers. Aslan et al. [14] utilized Artificial Neural Networks (ANN) based segmentation method for dataset enhancement and compared eight different pretrained DNNs. Further, three Bayesian optimized ML classifiers (i.e., SVM, kNN and NB) have been used in integration with these pretrained models. The results concluded that DenseNet201 and BO-SVM outperformed other competing models with 96.29% accuracy score. Nour et al. [15] proposed CNN for feature extraction and utilized Bayesian optimization based ML (SVM, kNN and DT) classifiers, achieving 98.97% accuracy.

Jaiswal et al. [16] deployed a pretrained DenseNet201 model to classify COVID-19 using CT scan images with an accuracy score of 96.25%. The combination of Bayes and SqueezeNet, has been utilized by Ucar et al [17] to detect COVID-19 using CXR images and the accuracy score accomplished was 98.30% . A Gravitational Search Algorithm (GSA) has been deployed to optimize hyperparameters of DenseNet121 (Ezzat et al.[18]) for classification of COVID-19 using CXR images and with the an accuracy value of 98.38%. Das et al. [19] presented a fully automated COVID-19 detection model. COVID-19 radiography dataset from Kaggle repository has been used that consisted of three classes: COVID-19 positive, pneumonia infection, and no infection. Two CNN models namely, VGG16 and ResNet50 have been implemented and compared in this work. With an accuracy score of 97.67%, VGG16 model provided the best performance in automated COVID-19 detection model.

According to Monshi et al. [20], the hyperparameter optimization of ML classifiers provided best results. The pretrained models have been implemented in this work to design a novel CovidXrayNet framework based on EfficientNet-B0 and Bayesian optimized ML classifiers. The testing accuracy value of this model on data generated from two distinct databases has been revealed as 95.82%.

To detect COVID-19, Panwar et al. [21] presented a Transfer Learning (TL) based nCOVnet Deep Learning approach and obtained an accuracy score of 88.10% in training and testing of the CT scan images. Asif et al. [22] designed CNN model to diagnose COVID-19 using CXR images. Without applying any preprocessing techniques, input images have been fed into the Inception-V3 model and accomplished classification accuracy score of 96%.

COVID-19 and Pneumonia detection has been performed using 3-stage model based on CXR images (Bhattacharya et al. [23]). To start with, the affected lung region has been separated from the CXR images by deploying the Conditional Generative Adversarial Network (C-GAN). The characteristics from segmented lung pictures have been extracted in the stage two by using DNN based feature extraction model. Afterwards, different ML classifiers have been deployed to categorize the CXR images according to the extracted features. The proposed combination of VGG19 with Binary Robust Invariant Scale Key-points (BRISK) yielded the best classification accuracy score of 96.6%.

Kaur et al. [24] proposed a classier fusion model using ResNet50 to diagnose COVID-19 using CXR images. Kumar et al. [25] designed a model with the blended features of MobileNetV2 and DarkNet19 model based on CT scan dataset. This was one of the earliest attempts of using open-source DNNs for COVID-19 detection from CXR images. An automated tool for COVID-19 diagnosis, COVID-Net (Linda Wang et al. [26]) has been proposed and testing of same along with VGG19 and ResNet50 has been performed on COVIDx (an open-access dataset formed from collection of five different datasets). This experimental setup attained 93.3% accuracy. The performance of seven deep learning models have been examined (Khalid El Asnaoui et al.[27]) in order to identify and categorize COVID-19 and Pneumonia. The process of image preprocessing has been applied on the raw CT and X-ray images to enhance their quality and an accuracy score of 92.18% has been obtained by using Inception-ResNetV2.

A transfer learning based COVID-19 detection from CXR and CT images has been proposed by Afshar Shamsi et al. [28]. To accomplish the classification objective, four different pre-trained models (namely, VGG16, ResNet50, DenseNet121 and InceptionResNet) have been used for feature extraction, and the extracted features were then fed into ML models. With an accuracy score of 87.9%, the combination of ResNet50 model and SVM classifier produced the best results. Arellano et al. [29] proposed a modified pretrained DenseNet121 model, with relearning of last layer for identification of COVID-19 from CXR images. A publicly available COVID-19 database has been used for training the model with an accuracy value of 94.7%.

Most of studies in the existing literature used raw images directly or combined with computationally intensive image preprocessing functions. The vital image features such as texture, color, shape, etc. play a significant role in the process of image classification, and it is performed by the DNN model. Henceforth, this tri-modular approach towards the proposal of optimized hybrid DNN-ML model encompasses first module for feature processing task, which includes the use of proposed image preprocessing techniques for image enhancement. Second module uses pretrained DNN models for feature extraction from enhanced images and third uses optimized ML for classification from the extracted image features.

III. Materials and Methods

This section provides details about various encompassing the proposed hybrid DNN-ML model. The datasets used for training of the proposed model have also been discussed in this section.

A. Description of the Dataset Used

For verification and validation of the proposed optimized hybrid DNN-ML framework, two different and original CXR (Chest X-Rays) and CT scan datasets have been utilized. The first dataset, i.e, CXR dataset, is a multiclass dataset, consists of COVID-19, viral pneumonia, and normal CXR image classes. The second dataset, comprises CT scan images, is a binary class dataset consisting of only COVID and non-COVID (COVID negative) image classes. First dataset in original form has been collected from different sources ([30], [31], [32]). The reason behind choosing these sources is as they contain original or non-processed CXR images. Because of continuous and ongoing research on COVID-19 disease, the newer version of this dataset may contain processed images which may lose their originality with the passage of time. The collected CXR image dataset is a balanced image repository containing 364 images for COVID-19 and other classes in order to avoid the problem of overfitting. Similarly, the second dataset related to lung disease patients comprises 349 CT scan images for both the classes (i.e., COVID-19 and non-COVID-19) [33].

The CXR images of patients suffering from COVID-19, Viral Pneumonia diseases, and Normal CXR images, and CT scan images of COVID-19 and COVID-19 negative patients have been presented in Fig. 1(a) and (b) respectively. CXR images of patients infected with COVID-19 show hyperlucent lung area denoting hyperinflation of lungs due to hindrance of small airways. CXR images with no abnormality detected show chest wall with normal shape and size plus trachea with normal appearance and zero opacity. CXR images of patients infected with viral pneumonia represent diffused bilateral GGO showing disperse alveolar. For training of the proposed hybrid model, enhanced version of both datasets have been prepared by using image preprocessing techniques, as presented in the next section. In order to study the effects of applied image preprocessing technique, results for the same have been verified using both original and enhanced CXR and CT scan image datasets.

B. Image Preprocessing

A variety of proficient and non-invasive medical imaging systems such as MRI, PET, Endoscopy, CT scan and X-Rays can be used to capture images internal infected parts of various organs in the human body. The two most commonly used medical imaging modalities for diagnosis of infectious lungs diseases are CT scan and CXR images. Both raw CXR and

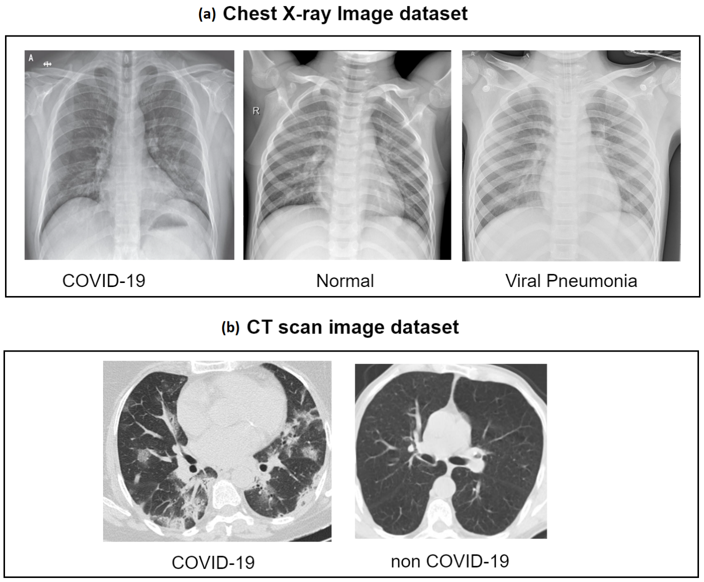

Fig. 1. Sample images from the original CXR and CT scan image datasets.

CT scan images can contain different types of noise patterns, including unrelated blobs, soft lung tissues and fine blood vessels. Henceforth, classification results can be misguided by soft lung tissues and minute blood vessels found in CXR images and CT scans. Thus, in order to improve the model accuracy, it is imperative to preprocess these medical images so that pertinent information can be extracted from the same after eliminating various types of noise patterns [34]. Also, to enhance the image quality of the raw medical data, image preprocessing can be applied to digitized images for enhancement of visual information contained in them [35].

The proposed image preprocessing approach applied to raw CXR images and CT scan images for the purpose of image enhancement comprises the following steps:

1) Image Segmentation (Using Edge Detection)
2) Image Filtration (Median filter)
3) Image Enhancement (Intensity improvement using CLAHE's method)

1) Proposed Image Segmentation Technique: **Image Segmentation** performs segmentation or masking of meaningful region or *Region of Interest (ROI)* area from an image so that there is no effect of noise patterns on the accuracy of image classification process [36].

For detection of COVID-19 using CXR images and CT scans, the target ROI is lungs (i.e. both left and right lung regions). The training of DNN model based on masked lung area, i.e., ROI will always provide with a more accurate disease prediction. The process of image segmentation used to perform ROI extraction from CXR and CT scan images is a very time-consuming and tedious process due to large size of COVID-19 image datasets; therefore, it can't be performed manually. It has been also shown in previous studies that, AI based U-NET model as the conditional Generative Adversial Networks (GANs) [14] [23] has been used for the extraction of ROI regions. The inclusion of DNNs for image segmentation process in various previous studies has contributed to additional overhead in terms of overall training time and computational complexity.

Originally, both CT scan and CXR images are *grayscale* in nature. But, the available CT scan and CXR images in the used dataset may contain some blue colored biomarkers. Therefore, for generation of accurate binary mask in the image segmentation step, it is important to convert these existing original images into grayscale. This study devises an *adaptive edge based image segmentation technique* has been devised as an intermediate and transitional solution for fast and accurate ROI extraction from the original images. This proposed technique uses *Canny Edge Detection* and a set of *Morphological operations* for automatic extraction of lungs ROI. It consists of three major steps.

1) *Image smoothing*, which is performed in the first step by using *Gaussian filter* function $G_f(x,y)$[1], (equation 1);
2) The second step involves calculation of *gradient magnitude* $G_m(x,y)$ and gradient direction $\theta(x,y)$ (equations 2 and 3);
3) Application of *edge point detection and connection* function $E_p(x,y)$ has been performed in step 3 (equation 4).

$$G_f(x,y) = [G_x(x,y) * \ G_y(x,y)] * \ I(x,y) \tag{1}$$

$$G_m(x,y) = \sqrt{G_x^2(x,y) + G_y^2(x,y)} \tag{2}$$

$$\theta(x,y) = arctan\left[\frac{G_y(x,y)}{G_x(x,y}\right] \tag{3}$$

where,

- $G_x(x,y) = (-P_1 + P_2 - P_3 + P_4)/2$;
- $G_y(x,y) = P_1 + P_2 - P_3 - P_4)/2$;
- $I(x,y)$ is an original grayscale CXR/CT scan image;
- P_1, P_2, P_3, P_4 are the pixel values of the coordinates (x,y), $(x{+}1,y)$, $(x,y{+}1)$, $(x{+}1,y{+}1)$, respectively of an original grayscale image;
- x and y represent the corresponding row and column of an original grayscale image.

The proposed image segmentation technique uses *canny edge detection method* combined with *Hough Transform (HT)* [37] for connection of edge points. Hough Transform method overcomes the boundary leakage problem that arises during the process of edge detection by finding all the collinear points (along the directions of an edge) by joining them as edge points, thereby producing efficient results for low intensity images as well.

[1]Gaussian filter is based on Gaussian function, and it can be defined as

$$G(x,y) = \frac{1}{2\pi\sigma^2}\exp\left[-\frac{(x)^2+(y)^2}{2\pi\sigma^2}\right]$$

$$E_p(x,y) = \begin{cases} \text{mark (x,y) as edge points in } G_f(x,y)^2 & \text{if } G_m(x.y) \geq t \\ \text{mark (x,y) as candidate edge points,} & \text{otherwise} \end{cases} \quad (4)$$

where, t is the threshold value, obtained by applying Ostu method [38]. The resultant HT Canny Edge-detected binary image $BM(x,y)$ is further preprocessed by using 3-step application of widely acceptable *dilation, fill and erosion* morphological operators. First step involves application of dilation operator(dil) for edge dilation to $BM(x,y)$ resulting in $BM_1(x,y)$ (Eq. 5) The second step comprises use of fill operation ($fill$) (Eq. 6) on dilated image $BM1(x,y)$ for filling the holes based object intensity of displayed region resulting in a filled image $BM_2(x,y)$. The third and final step deploys the erosion operator ($erode$) (Eq. 7) on $BM_2(x,y)$ for removal of the connected components on the edge boundary resulting in computation of a final binary image $BM_{final}(x,y)$.

$$BM_1(x,y) = dil(G_f(x,y)); \quad (5)$$

$$BM_2(x,y) = fill(BM_1(x,y)); \quad (6)$$

$$BM_{final}(x,y) = erode(BM_2(x,y)); \quad (7)$$

$$I_s(x,y) = BM_{final}(x,y) * \ I(x,y) \quad (8)$$

where

- $BM_1(x,y)$- A binary mask obtained after edge detection;
- $BM_2(x,y)$- A binary mask obtained after edge dilation;
- $BM_{final}(x,y)$- The final binary mask obtained after removal of connected components;
- $I_s(x,y)$ - The final segmented image.

The final segmented image $I_s(x,y)$ with the extracted ROI is procured by segmenting an original grayscale image with the computed binary image $BM_{final}(x,y)$ mask, resulting from the application of edge detection and morphological operators as a binary mask (Eq. 8).

2) Image Filtration Methodology: **Image filtration** is responsible for modification or enhancement of image modification by removing different types of noise[3] existing in them. *Noise* can be classified as *Gaussian, Salt and Pepper, Poisson, impulsive and speckle noise*. The CXR and CT scan images which have been used to validate proposed model are mostly subject to Gaussian, Salt and Pepper, and Poisson noise. *Gaussian noise* can be eliminated by using a *Gaussian filter* (as described in image segmentation phase). And, for the removal of *Salt and Pepper, and Poisson noise* from CXR and CT images, *median filter* has been applied to segmented image that includes the extracted ROI (for lungs region).

$$I_f(x,y) = Med(I_s(x,y)) \quad (9)$$

where, Med is a median filter and $I_f(x,y)$ is a filtered and sharpened image[4] obtained after application of median filter to segmented image $I_s(x,y)$.

The proposed image filtration technique uses a median filter to generate a low-frequency image by replacing the pixel value with a median pixel value in an image, computed over a square area of 8×8 pixels centered at the pixel locations.

3) Proposed Image Enhancement: **Image enhancement** enhances the contrast value of grayscale and colored images, and plays a vital role in medical imaging for improvement of visual perception quality. In case of CXR and CT scan images, the strong contrast in the white area washes out the vital information saved in white pixels of an image [8]. The proposed image enhancement methodology, applies improved version of *AHE (Adaptive Histogram Equalization)*, termed as *CLAHE (Contrast Limited Adaptive Histogram Equalization)* [39] to filtered images (Eq. 10) for *intensity enhancement, improvement of local contrast and edge definitions;* and produces final enhanced images used for training the proposed hybrid DNN-ML framework.

$$I_e(x,y) = Clahe(I_f(x,y)) \quad (10)$$

where $I_e(x,y)$ is a final enhanced image and $CLAHE$ is an image enhancement technique that enhances images by evenly spreading intensity level in small regions throughout the images and setting up the maximum contrast limit [40].

The step-wise functional implementation for preprocessing of CXR and CT scan images has been presented as Algorithm 1 and the corresponding set of transformations have been demonstrated graphically as in Fig. 2(a)-2(h) and Fig. 3(a)-3(h), respectively.

Algorithm 1 The Proposed Image Preprocessing Methodology

Input: Infolder $\Leftarrow$ Original Grayscale Image Repository
Output: Outfolder $\Leftarrow$ Enhanced Image Repository
$N \Leftarrow$ Length of Infolder
for each image I in Infolder $= 1$ to N **do**
  $IR \Leftarrow imread(infolder(I))$ $\triangleright$ imread is a function used to read images from Original Grayscale Image Repository
  $IG \Leftarrow im2gray(IR)$ $\triangleright$ Convert retrieved image (IR) into a grayscale image (IG)
  $BM \Leftarrow Cannyedge(IG)$ $\triangleright$ Canny edge detection and morphological operator to obtain a Binary mask (BM)
  $maskIG \Leftarrow cast(IG, BM)$ $\triangleright$ Apply BM on original grayscale image to obtain segmented image ($maskIG$)
  $FIG \Leftarrow medfilt2(maskIG)$ $\triangleright$ Apply median filter to segmented image to obtain filtered image FIG
  $CIG \Leftarrow CLAHE(FIG)$ $\triangleright$ Apply CLAHE on filtered image to obtain final image CIG
  $Outfolder \Leftarrow Save(CIG)$ $\triangleright$ Save final image in an Enhanced Image Repository
end for

[3]Noise refers to errors occurring at the time of image acquisition process and in case of CXR, imaging of ribs can be considered as noise

[4]The process of median filtering improves the sharpness of CXR and CT scan images by eliminating the impacts of noise and blurriness during image acquisition.

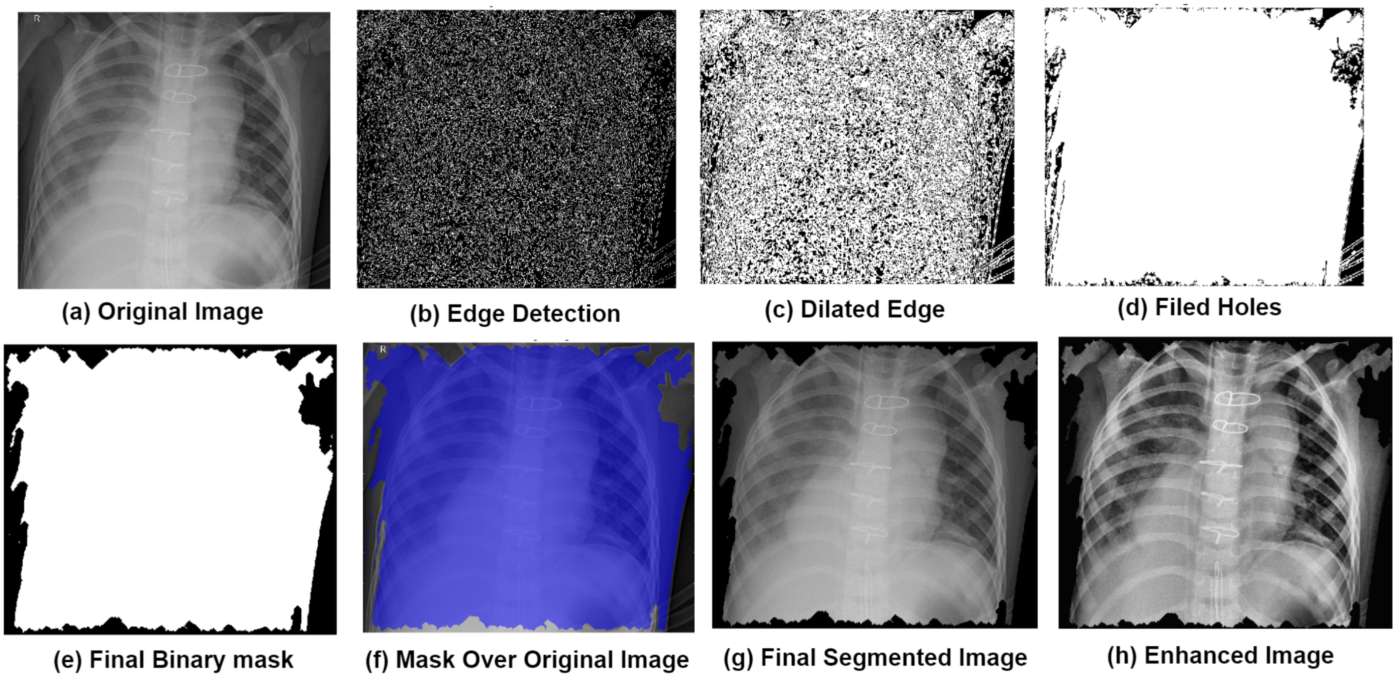

Fig. 2. Application of the proposed segmentation and image enhancement technique on Chest X-ray images.

C. Feature Extraction Process

After the feature enhancement phase (which includes image segmentation, filtration and intensification steps), **feature extraction** process is applied on the processed, enhanced and obtained segmented CXR and CT scan images, from the previous step. Feature extraction is the typical and challenging task, which involves capturing of various significant attributes of an image such as *texture, color, intensity, edge information* etc. This work uses advanced *Deep Neural Networks (DNNs)* to extract features of enhanced images.

Convolutional Neural networks (CNNs) are a sub-type of DNNs, widely used in the domain of computer vision, such as object detection and image classification etc. CNNs consist of input, convolution, max/average pooling, fully connected and classification layers. The combination of these layers with *different techniques and topologies* has resulted in various variations of CNNs such as VGG19, ResNet50, GoogleNet and many more. The layers used by the proposed model for performing the process of feature extraction can be summarized as follows. Firstly, input images are loaded into image / input layer and further fed to convolutional layers for convolution operation and for production of the final output feature map. The pooling layer also called down sampling downsizes the feature map, i.e, reduces the feature map without any signification feature loss related to input image. Lastly, a fully connected layer collects the final output comprising features extracted by CNN model and passes them to classification layer.

This work uses three pretrained DNN models namely, *GoogleNet, ResNet50 and EfficientNetB0* as a feature extractor tool to extract various significant characteristics from CXR and CT scan images. These prominent extracted features are further used by the feature classifiers in order to classify COVID-19 images. Each of these models has a different architecture and specific input/image layer size. It is important to resize the input image according to the input layer size for each model and this study uses data augmentation approach for image resizing.

1) GoogleNet: GoogleNet is a pretrained CNN consisting of 144 layers including convolution, ReLU, average and max pooling, concatenation and fully connected. Inception modules are the building blocks of GoogleNet which comprises convolution with filters in vary size (1×1, 3×3 and 5×5) and *performs convolution operation in parallel*. Each inception block contains max pooling layer which reduces feature dimensions while retaining most significant features simultaneously [41]. The fully connected layer in GoogleNet called "loss3-classifier", performs storage and retrieval of extracted features, and it extracted almost 1000 features in this work.

2) EfficientNetB0: EfficientNetB0 is based on the principle of compound scaling which balances the network length, width and resolution to increase the feature extraction efficiency. It consists of convolution layers, 2D global average pooling layer, batch normalization , fully connected layer, and sixteen depth separable *convolutional blocks (mobile inverted bottleneck convolution)* [42]. The "$dense \mid matmul$" layer has been used in this work for performing feature extraction process, and it extracted almost 1000 significant features.

3) ResNet50: ResNet50 is a variant of ResNet model also called "Residual Network" with deep 50 layers. And, the residual connection existing in this network can be termed as distinguishable feature which helps grasping residual functions and mapping the input with desired output. The two major components of ResNet50 are *convolutional and identity blocks* that further comprise several convolutional layers followed by *batch normalization and activation function (ReLU)*. These

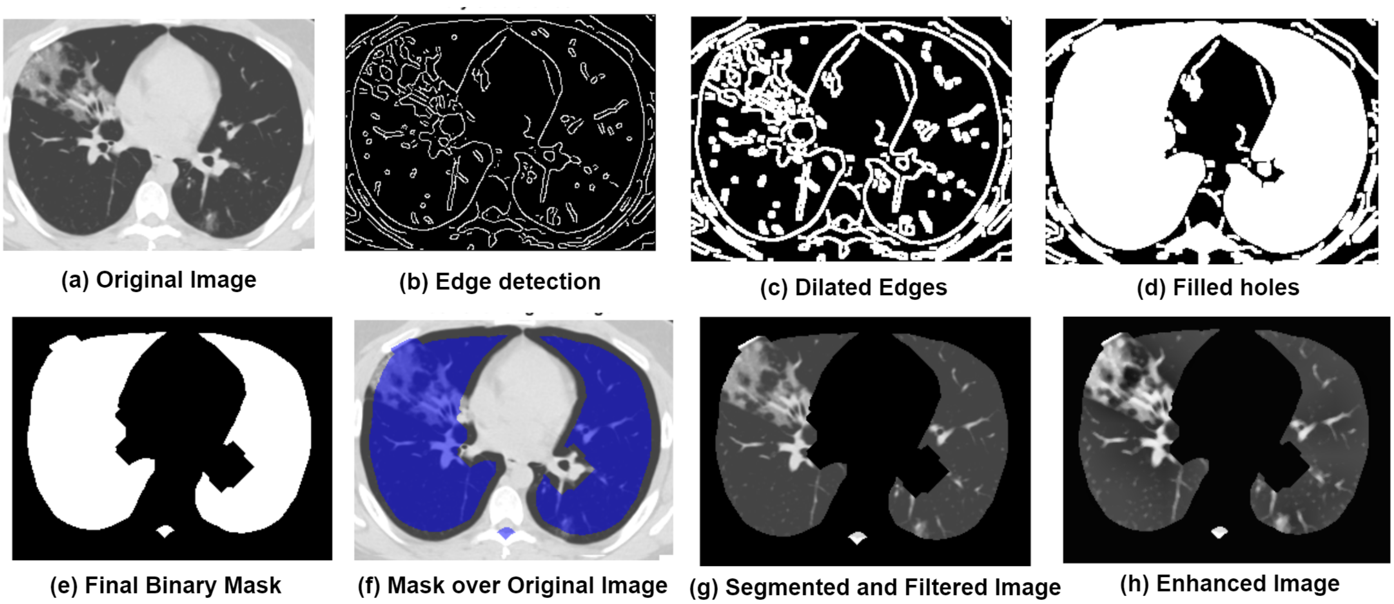

Fig. 3. Application of the proposed segmentation and image enhancement technique on CT scan images.

layers are responsible for capturing the features such as color, shape, texture and edge information [43]. This work uses ResNet50 with “fc1000” fully connected layer for extraction of 1000 features.

For the purpose of validation and benchmarking, all these three pretrained DNN architectures have been trained using enhanced CXR dataset. Each model has been initially operated for 30 epochs and each epoch further consists of 330 iterations, with batchsize of 64 and learning rate of 0.0001. For the training of aforementioned pretrained CNN models the enhanced CXR dataset has been splitted into training and testing set ratio of 70:30 respectively. It has been observed that when these three DNNs, i.e., GoogleNet, EfficientNetB0 and ResNet50 trained on enhanced CXR dataset have been compared for accuracy, they performed with 96.94%, 95.72% and 92.97% respectively. The performance metrics for all three implemented pretrained networks have been shown in Table I. *The highest accuracy has been achieved by ResNet50 (96.94%) with total training time of 514 minute*s, which outperformed the other implemented models to detect COVID-19 using enhanced CXR dataset. GoogleNet stayed close with 95.72% accuracy, but training time (612 min) taken to achieve the same has been more as compared. The training time (674 min.) taken by EfficientNetB0 and achieve accuracy (92.97%). Henceforth, for performing feature extraction in this work, ResNet50 can serve as the best choice. The sequential process of feature extraction has been mentioned in Algorithm 2.

TABLE I. RESULTS OBTAINED FOR PRETRAINED DNNS USING ENHANCED CXR DATASET

DNN model	Accuracy (%)	Recall (%)	Precision (%)	F-Score (%)	Time (min)
GoogleNet	95.72%	95.2	95.8	95.75	612
EfficientNetB0	92.97%	93.4	93.1	92.96	674
ResNet50	96.94%	96.92	96.93	96.92	514

Algorithm 2 FEATURE EXTRACTOR

Input: EDS ← Image Repository for Enhanced images
Output: f_{ext} ← Set of extracted features

1: IMD ⇐ Load(EDS) ▷ Retrieve images from the enhanced image data store
2: Net=ResNet50 or GoogleNet or EfficientNetB0 ▷ Call to pretrained CNN model and initialize as Net
3: COVNET ⇐ Train(Net, IMD) ▷ Train proposed COVNET with network training options and enhanced dataset
4: Calculate and compare the classification accuracy of pretrained models ▷ trained on CXR and CT datasets
5: Select the model with maximum accuracy, $COVNET_{max}$ ▷ as Feature Extractor (FE)
6: $f_{ext} \Leftarrow COVNET_{max}(FC_{layer})$ ▷ Extract set of features from fully connected layer FC_{layer} of extractor

D. Feature Classification Process

The features extracted by the “fc” fully connected feature layer of ResNet50 model are fed to ML classifiers for performing **feature classification**. This study utilizes Bayesian optimized ML classifiers(i.e, *Decision Tree (DT), K-Nearest Neighbor (kNN), Naive Bayes (NB), Discriminant Analysis (DA) and Support Vector Machine (SVM)*) for *feature-based image classification* from CXR and CT scan image datasets.

- *Decision Tree (DT)* classifier [44] is a tree based decision-making model for classification of image features where internal nodes and branches of a tree represent and rules, respectively. DT classifier works on *entropy and information gain* parameters (Eq. 11).

$$entropy(D) = \sum_{i=1}^{|c|} P_r(C_i) log_2 P_r(C_i),\ where\ \sum_{i=1}^{|c|} P_r(C_i = 1) \tag{11}$$

On the basis of these parameters, each node of DT is further splitted until the traversal of final leaf node, which represents the final output class. The vital *hyperparameters* that can be considered for fine tuning of DT classifier are *maximum number of splits* and *maximum depth*.

- *K-Nearest Neighbor (kNN)* [45] classifies the new data point according to similarity with its neighboring points. To find similarity, distance between the new and neighboring data points is computed using various methods (i.e., Euclidean, Manhattan, Spearman, Murkowski, etc.), This study computes *euclidean distance D* (equation 12) with k-NN for image classification.

$$D = \sqrt{(x - x_i)^2 - y - y_i)^2} \tag{12}$$

k-NN classifier can be refined by optimal values of *neighbor size (k)* and *distance method* as vital hyperparameters for accurate results.

- *Naive Bayes(NB)* [46] is a simple probabilistic algorithm based on *Bayes' theorem* (Eq. 16) and it classifies images identical to the corresponding disease type (COVID-19, Viral Pneumonia, Normal images) with the largest posterior probability. The objective function $O(x)$ of NB can be defined as (Eq. 13)

$$\widehat{y} = argmax_y P(y) \pi_{i=1}^{n} P(x_i \mid y) \tag{13}$$

where, $P(x_i \mid y)$ is the posterior probability of x_i for given values of y.
In NB classifier, the smoothing hyperparameter (α), which is continuous in nature is the only one that needs to be fine-tuned for refinement of the former.

- *Discriminant Analysis (DA)* [47] is a statistical approach based on Bayes' theorem (16) and estimates the probability of new data point with respect to each class. And, the class having highest probability will be the class for a new point. The objective function $O(x)$ for DA can be defined by (Eq. 14)

$$\widehat{y} = argmax_{y=1\ldots k} \sum_{k=1}^{k} \widehat{P}(k \mid x) C(y \mid k) \tag{14}$$

- *Support vector machine (SVM)* [48], is a prominent nonlinear classifier which divides the dataset into two parts by using a hyperplane. It can efficiently handle both linear and non-linear data. Hyperplane learning is facilitated by Kernel function f(x) (where type of kernel functions are Linear, Polynomial, Radial Basis Function(RBF), Sigmoid). The objective function $O(x)$ for SVM can be defined by Eq. 15.

$$argmin(\frac{1}{n} \sum_{i=1}^{n} max(0, 1 - y_i f(x_i) + E w^T . w)) \tag{15}$$

where, w denotes normalization vector and E represents classification error rate. The most crucial hyperparameter which can be optimized for best results in SVM model is *kernel type*.

1) Hyperparameter Tuning process for ML Classifiers: **Hyperparameter Optimization (HPO)** [49] process involves finding the most appropriate set of hyperparameter values before training phase of ML classifier that results in the best performance in a finite duration of time for a particular dataset. The major objective of HPO is to obtain optimal performance for ML models by finetuning their hyperparameters under time constraints. Since, *training time* is one of the crucial factors for HPO of ML models, therefore, for every new set of hyperparameter values, the entire model is retrained and performance of the latter is evaluated [50], [51]. It is important to determine the optimal values for the relevant hyperparameters in a ML classifier, in order to maximize the value of classification accuracy. Most commonly used hyperparameter tuning methods are *Grid Search (GS), Random Search (RS),* and *Bayesian optimization (BO)* .

Grid search is a time-consuming optimization technique, as it iterates for all the possible values of the selected hyperparameters and henceforth,is an infeasible approach. On the other hand, random search, randomly selects various possible values for the selected set of hyperparameters and computes the results, and may miss the best suitable combination for set of hyperparameter values, concluding it to be an inefficient approach. As compared to GS and RS, BO, is a probabilistic optimization technique that uses prior information (previous outcomes) of various experimented hyperparameter values to compute the next ones and avoids unnecessary iterations. This increases the computational power of BO, and it finds optimal hyperparameter values using fewer iterations as compared [52]. Therefore, this study has adopted BO as a hyperparameter tuning method that makes it as heart and soul of the proposed hybrid DNN-ML model for chest disease diagnosis. The implementation of BO along with its various outcomes, has been discussed in the upcoming sections.

2) Bayesian Optimization: Bayesian optimization (BO) [53] has been derived from Bayes' theorem. And, it states that for a given information I, the posterior probability ($P(M|I)$) of a given model M is directly proportional to to the product of likelihood $P(I|M)$ and marginal or prior probability $P(M)$ defined in Equation 16.

$$P(M|I) = P(I|M) \times\ P(M) \tag{16}$$

Bayesian approach uses the information retrieved from data(considered as prior knowledge) along with the factors that improve existing knowledge from the derived posterior knowledge. BO based Hyperparameter optimization problem can be defined as in equation 17) and its goal is to obtain maximize or minimize the value of objective function $O(x)$.

$$x^* = argmin_{x \in X}\ O(x),\ or\ argmax_{x \in X}\ O(x) \tag{17}$$

where,

- X denotes the search space comprising x samples, expressed as x_1, x_2, x_3,.........x_n with size of search space $= n$.
- x^* represents hyperparameter configuration that generates the maximum/minimum value of $O(x)$.

The values of x_1, x_2,.........x_n can be estimated using the objective function $O(x)$. The sequential combination of these samples and their evaluations forms a set S expressed as $S = x_1, O(x_1), ...x_n, O(x_n)$. The set S is further used to define the surrogate model (SM) for generating the value of posterior probability.

This study uses Gaussian Process (GP) as a surrogate model because of its stochastic behavior and normal distribution property. GP is defined as the function of mean $\mu(x)$ and a covariance matrix $K(x, x')$ (Eq. 18).

$$O \sim GP(\mu(x), K(x, x')) \tag{18}$$

The optimal values for $O(x)$ can be determined using the posterior probability value, according to the acquisition function(α). The minimum value of Bayesian optimized objective function $O(x)$ can be derived by from set X selected on the basis of α.

$$x^+ = argmin_{x \in X}\ \alpha(x \mid X),\ or\ argmin_{x_i \in X1:t}\ O(x_i) \tag{19}$$

where, x^+ represent the position for which objective function $O(x)$ obtains maximum value after t sample points. Acquisition function uses Expected improvement (EI) method (equation 20), to evaluate the degree of improvement for the objective function $O(x)$.

$$EI(x) = max\{0, O_{t+1}(x) - O(x^+)\} \tag{20}$$

The step-wise implementation of proposed Bayesian Optimization for hyperparameter optimization of ML classifiers has been shown as Algorithm 3. The set of computed hyperparameters using BO with ML classifiers, for chest disease diagnosis from CXR and CT scan image datasets are shown in Table II.

E. Evaluation Metrics

The four major performance metrics, i.e., *Accuracy, Precision, Recall* and *F-Score* have been utilized in this study to assess the effectiveness of proposed optimized hybrid DNN-ML model.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \tag{21}$$

$$Precision = \frac{TP}{TP + FP} \times 100\% \tag{22}$$

$$Recall = \frac{TP}{TP + FN} \times 100\% \tag{23}$$

TABLE II. THE SET OF OPTIMAL HYPERPARAMETER VALUES FOR DEPLOYED BO-ML CLASSIFIERS

ML classifier	Hyperparameters	CXR images	CT scan images
DT	Minimum leaf Size	1	10
	Maximum Splits	287	13
	Split Criteria	deviance	deviance
	TET(s)[1]	41.58	26.9735
	TOFET(s)[2]	27.523	13.3903
kNN	Neighbors size	8	9
	Distance	euclidean	spearman
	Distance weight	inverse	squaredinverse
	TET(s)	38.9375	32.7209
	TOFET(s)	19.011	17.1105
NB	Distribution Nature	Kernel	Kernel
	Kernel width	1.0826	0.322
	Kernel Type	Normal	Normal
	TET(s)	2338.4096	1150.12
	TOFET(s)	2324.1023	1136.294
DA	Delta	0.01723	0.0188
	Gamma	0.5991	0.8467
	Discriminant type	Linear	Linear
	TET(s)	59.7759	39.8835
	TOFET(s)	41.4394	22.867
SVM	Box Constraint	1.2984	0.1012
	Kernel Scale	92.227	91.017
	Kernel Function	Gaussian	linear
	Coding technique	onevsall	onevsone
	TET(s)	1317.2887	
	TOFET(s)	1285.26	

Algorithm 3 Psuedocode for applied Bayesian optimization technique

Input: X ← Hyperparameter Space of size n, O(x)← Objective function
Output: $x_{optimal}$ ← optimal hyperparameter configuration, $y_{optimal}$ ← optimal objective function value

```
Assign initial value x_0 and calculate objective function value y_0 = O(x_0)  ▷ initial hyperparameter configuration
Set x_optimal = x_0 and y_optimal = y_0 with Training set T_0 = x_0, y_0
for i in range n do
    Obtain new values for hyperparameter configuration by optimizing acquisition function α_i
    x_i = argmin_{x∈X} α(x | T_{i−1})
    Calculate objective value y_i = O(x_i)
    Update the training set T_i = T_{i−1} ∪ {x_i, y_i}
    Update the surrogate model
    if y_i < y_optimal then
        {x_optimal, y_optimal} = {x_i, y_i}
    end if
end for
return {x_optimal, y_optimal} ⇐ optimal set of hyperparameter configuration and objective function value
```

$$F - score = \frac{2TP}{2TP + FP + FN} \times 100\% \tag{24}$$

where, *TP, TN, FP, FN* are values of *True Positive, True Negative, False Positive and False Negative* scores, respectively. These values can be calculated from the resultant confusion matrix.

F. Proposed Framework

This section describes the proposed framework for classification of COVID-19 images using two different datasets that vary according to size, mode and labels. This work proposes a *three-layered optimized hybrid DNN-ML framework*. The three different layers are, feature enhancement, feature extraction and classification layer performing three distinguished tasks. The framework of proposed approach has been presented in Fig. 4. *Phase-I* (feature enhancement layer) performs the image preprocessing task for enhancing the image quality and ROI extraction with significant features of an image. This Phase comprises the proposed image segmentation, median filter and CLAHE methods for capturing image features that denote abnormal/disease region, for passing to Phase-II (feature extraction layer). *Phase-II* has deployed ResNet50 as a feature extractor tool because of its strengths such as lesser training time and higher classification accuracy. A sum total of almost 1000 distinguishable features has been extracted by the Phase-II, further dividing them into training and testing feature set in ratio 70:30. The training features have been given to *Phase-III* (Feature classification layer) as an input for training of ML classifiers. And, the test features have been employed to validate the classification accuracy of Bayesian optimized ML classifiers for CXR and CT scan image datasets. The Algorithm with all sub-procedures for the proposed hybrid BO DNN-ML model has been presented as 4.

Algorithm 4 Sequential Implementation for the proposed hybrid BO DNN-ML model

Input: DS← Image repository
Output: Image classification and accuracy using proposed model

```
procedure IMAGE PREPROCESSING(DS)    ▷ Apply various Image Preprocessing techniques
    N ← Number of images in each class
    for i in range N do
        EDS ← IMAGE PREPROCESSING(DS_i)    ▷ call image preprocessing method
        return EDS    ▷ returns enhanced CXR dataset
    end for
end procedure
procedure FEATURE EXTRACTION AND CLASSIFICATION(EDS)
    f_ext ← FEATURE EXTRACTOR(EDS)    ▷ call feature extractor for EDS
    return f_ext    ▷ return extracted features
    BO_ML ← BAYESIAN OPTIMIZATION(f_ext)    ▷ Call optimization to hyperoptimize the ML classifiers
    f_c, Accuracy ← FEATURE CLASSIFIER(BO_ML, f_ext)
end procedure
return Image class ← f_c with associated accuracy score ← Accuracy
```

IV. Experimental Results

In this study, three experiments have been conducted for the performance analysis of the proposed approach to detect COVID-19 on two different types of datasets: Chest Xray and CT scan image dateset. Firstly, the images have been segmented and enhanced with the proposed adaptive edge based segmentation algorithm. Afterwards, the proposed hybrid model described in Section 3 has been applied to enhance images for the next processes of feature extraction and classification. This section presents experimental specifications and results obtained in detail.

A. Experimental Setup

The hardware and software specifications of experimental setup include a computer system with 8 GB RAM, 7th Generation Intel Corei7 processor, Windows 10 as an operating system and MATLAB R2023b installed on it. The experiments have been carried out using two different datasets (CXR & CT scan images) and preprocessing applied to them before training of the proposed model. Various Morphological operators predefined in MATLAB [54] have been used for preparation of an enhanced dataset.

B. Experiment 1: Performance Evaluation of ResNet50 using Original CXR and CT Scan Datasets

The experiment 1 investigates the impact of image preprocessing for the improvement of *classification accuracy*. Numerous research studies have shown disease detection models with high classification accuracy but all of them used computationally intensive pretrained models to perform image preprocessing. Moreover, some research studies also utilized ANN models to perform image segmentation which introduces an additional overhead in overall computational time. This experiment illustrates the use of edge detection technique for image segmentation which improves both classification accuracy and efficiency of light weight ResNet50 model. Various performance metrics used for performance evaluation and comparison of ResNet50 with both original and enhanced datasets have been mentioned in Eq. 21, 22, 23 and 24. A summary of comparative results (Table III) show that ResNet50 achieved highest accuracy values of 96.94% and 96.67% with enhanced CXR and CT scan datasets. These results depict that no matter what type of images have been used for the training of DNN model, *feature enhancement always leads to the accuracy improvement*.

TABLE III. Performance Metrics for Comparison of Original and Enhanced Image Datasets with ResNet50

Dataset Modality	Dataset Type	Accuracy (%)	Class	Recall (%)	Precision (%)	F−Score (%)
CXR	Original	95.11%	COVID-19	95.4	100	95.04
			Normal	93.6	91.9	
			Pneumonia	96.3	93.8	
	Enhanced	96.94%	COVID-19	99.08	99.08	96.99
			Normal	99.08	93.10	
			Pneumonia	99.01	92.66	
CT	Original	95.71%	COVID-19	97.1	94.4	95.77
			Non COVID-19	94.3	97.1	
	Enhanced	96.67%	COVID-19	97.1	96.2	96.7
			Non COVID-19	96.2	97.1	

C. Experiment 2: Performance Analysis of the Proposed hybrid DNN-ML Model

Firstly, the proposed hybrid DNN-ML model has been trained and evaluated for CXR images dataset. ResNet50 has been employed as a feature extractor for the proposed model in experiment 2 and features extracted served as a input to disparate ML classifiers(viz., SVM, KNN, NB, DT, and DA). SVM classifier has been able to achieve the highest accuracy value of 97.25% with AUC value as 99.27% (Table IV). The

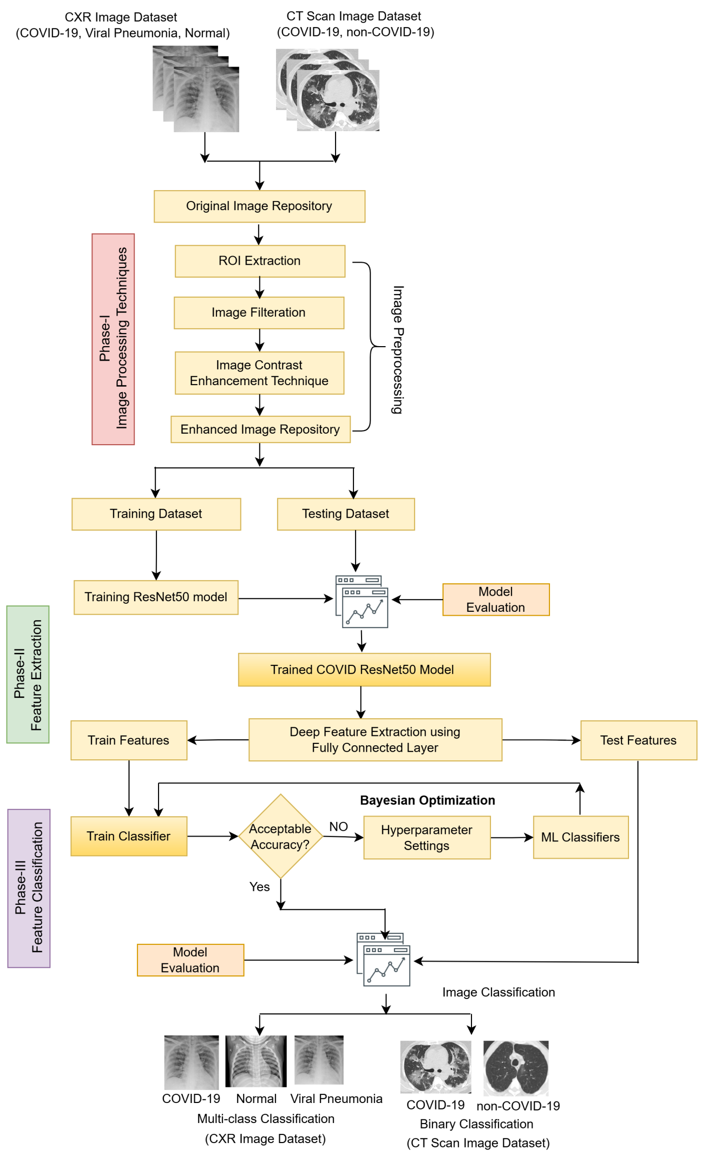

Fig. 4. Conceptual framework of the proposed optimized hybrid DNN-ML model.

confusion matrix obtained for various ML classifiers that have been trained using features extracted by ResNet50 has been shown in Fig. 5.

The same experiment is repeated CT scan dataset and as mentioned before, SVM outshined the rest of ML classifiers by achieving highest accuracy value 97.62% with AUC value as 99.84%. All the performance metrics and confusion matrix related to same have been presented as Table V and Fig. 6, respectively.

D. Experiment 3: Performance Analysis of BO based hybrid DNN-ML Model

This experiment involves training, validation and evaluation of the proposed Bayesian optimized hybrid DNN-ML model using enhanced CXR and CT scan datasets. The results obtained have been shown in Tables VI and VII. The maximum values of classification accuracy when the proposed Bayesian

TABLE IV. Results of Various Performance Metrics for a Combination of ResNet50 and ML Classifiers for an Enhanced CXR Dataset

Model	Accuracy (%)	Class	Recall (%)	Precision (%)	F−Score (%)	AUC (%)
DT	88.07%	COVID-19	82.6	92.8	88.01	92.15
		Normal	98.2	89.2		
		Viral Pneumonia	83.5	82.7		
k-NN	94.5%	COVID-19	100	97.3	94.4	99.31
		Normal	100	87.9		
		viral pneumonia	83.5	100		
NB	91.13%	COVID-19	82.6	98.9	91.16	99.28
		Normal	98.2	93.9		
		Viral Pneumonia	92.7	82.8		
DA	97.86%	COVID-19	99.1	100	97.87	99.95
		Normal	100	94.0		
		Viral Pneumonia	94.5	100		
SVM	**97.25**%	COVID-19	100	99.1	97.23	99.27
		Normal	100	93.2		
		Viral Pneumonia	91.7	100		

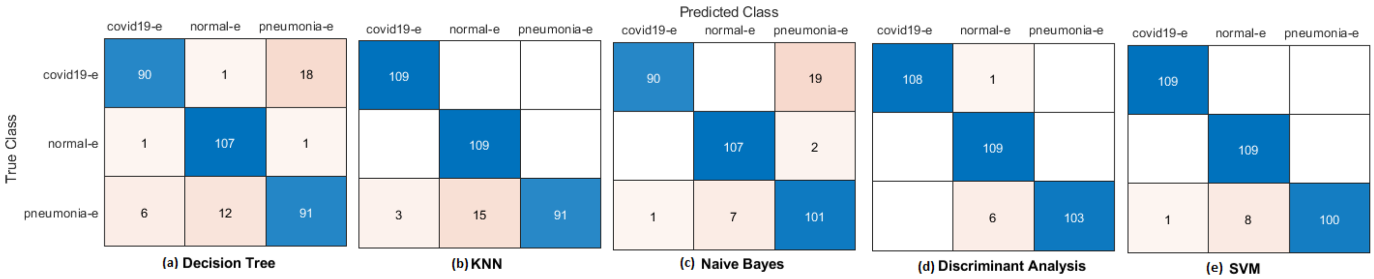

Fig. 5. Confusion matrix obtained with a combination of ResNet50 and ML classifiers for an enhanced CXR dataset.

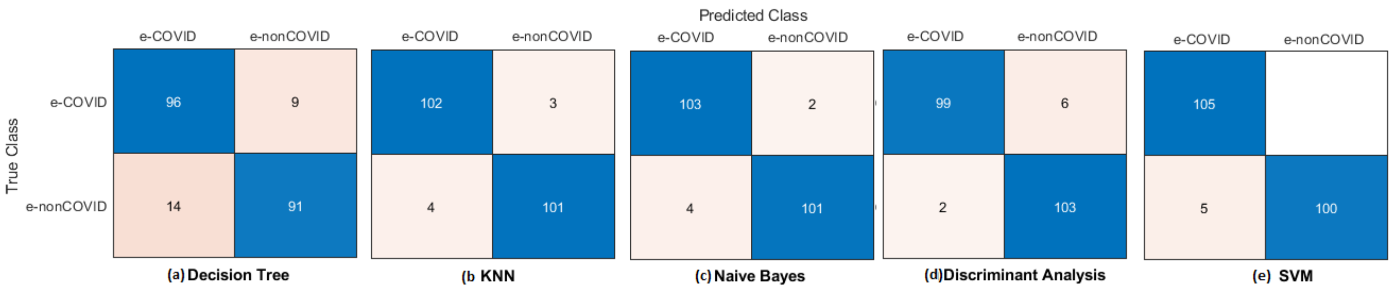

Fig. 6. Confusion matrix obtained with a combination of Resnet50 and ML classifiers for an enhanced CT scan dataset.

TABLE V. Results for Various Performance Metrics Obtained for ResNet50 and ML Classifiers for an Enhanced CT Scan Dataset

Model	Accuracy (%)	Class	Recall (%)	Precision (%)	F−Score (%)	AUC (%)
DT	89.05%	COVID-19	91.4	87.3	88.97	89.05
		Non COVID-19	86.4	91.0		
k-NN	96.67%	COVID-19	97.1	96.2	96.64	96.67
		Non COVID-19	96.2	97.1		
NB	97.14%	COVID-19	98.1	96.3	97.19	98.98
		Non COVID-19	96.2	98.1		
DA	96.19%	COVID-19	94.3	98.0	96.19	98.49
		Non COVID-19	98.1	94.5		
SVM	**97.62**%	COVID-19	100	95.5	97.62	99.84
		Non COVID-19	95.2	100		

optimized hybrid model has been trained with SVM for CXR and kNN classifier for CT scan image dataset, are 98.78% and 99.05% respectively. The confusion matrix and ROC curve after combining ResNet50 with the proposed BO-ML classifiers using CXR images have been presented in Fig. 7 and 8, respectively. Similarly, the confusion matrix and ROC curve for the proposed ResNet50 based BO-hybrid model trained on CT scan dataset have been presented in Fig. 9 and 10 respectively. The objective function presenting number of evaluations for BO-SVM validated with CXR and BO-KNN for CT scan image datasets have been presented in Fig. 8 and 10, respectively.

The performance comparison of ResNet50 model on original dataset containing raw images and enhanced dataset (using proposed image preprocessing methods) for CXR and CT scan images has been shown in Fig. 11. It can be concluded from the results, that image preprocessing techniques, i.e., primarily image segmentation and enhancement has helped in

TABLE VI. Results of Various Performance Metrics Obtained using ResNet50 Features and BO-ML Classifiers for an Enhanced CXR Dataset

Model	Accuracy (%)	Class	Recall (%)	Precision (%)	F−Score (%)	AUC (%)
DT	88.38%	COVID-19	86.2	93.1	88.3	93.59
		Normal	96.3	86.1		
		Viral Pneumonia	82.6	86.5		
k-NN	95.72%	COVID-19	96.3	98.1	95.1	99.47
		Normal	100	90.8		
		Viral Pneumonia	90.8	99.0		
NB	95.41%	COVID-19	97.2	96.4	95.37	99.73
		Normal	99.1	92.3		
		Viral Pneumonia	89.9	98.0		
DA	98.17%	COVID-19	96.3	100	98.16	99.95
		Normal	100	98.2		
		Viral Pneumonia	98.2	0.964		
SVM	**98.78**%	COVID-19	99.1	100	98.77	99.97
		Normal	100	97.3		
		Viral Pneumonia	97.2	99.1		

TABLE VII. Results of Various Performance Metrics Obtained using ResNet50 Features and BO-ML Classifiers for an Enhanced CT Scan Dataset

Model	Accuracy (%)	Class	Recall (%)	Precision (%)	F−Score (%)	AUC (%)
DT	85.71%	COVID-19	86.7	85.0	85.72	90.80
		Non COVID-19	84.8	86.4		
k-NN	**99.05%**	COVID-19	99.0	98.9	99.01	99.92
		Non COVID-19	90	98.9	99.0	
NB	97.14%	COVID-19	98.1	96.3	98.58	97.97
		Non COVID-19	96.2	98.1		
DA	98.54%	COVID-19	99.0	98.1	98.51	99.7
		Non COVID-19	98.1	99.0		
SVM	98.57%	COVID-19	99.1	98.12	98.55	99.83
		Non COVID-19	98.12	99.1		

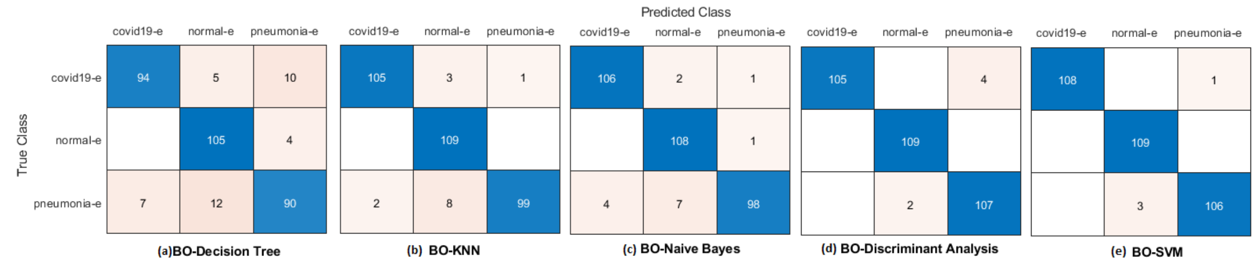

Fig. 7. Confusion matrix obtained by using combination of ResNet50 and BO-ML classifiers for an enhanced CXR dataset.

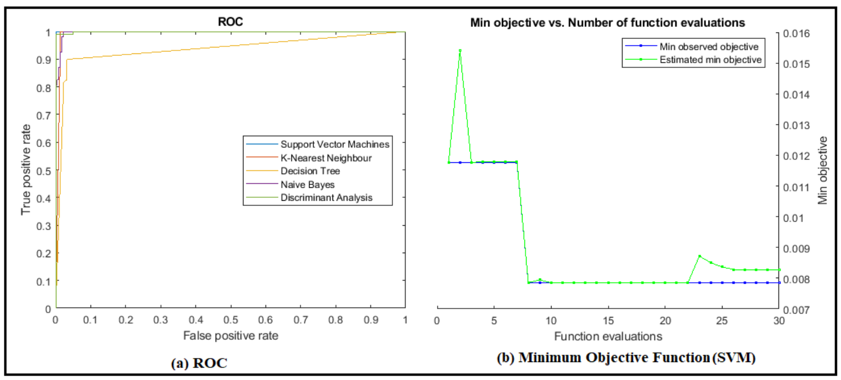

Fig. 8. ROC and Expected Improvement function(BO-SVM) for the proposed optimized hybrid DNN-ML model for CXR images.

tremendous improvement of ResNet50 model's performance for COVID-19 detection. And, it has considerable affect on classification accuracy score. The performance of Bayesian optimized ML classifiers combined with ResNet50 (DNN) is much better in terms of classification accuracy score as compared to non-optimized versions (Fig. 12). The final output in the form of tuple (image class, accuracy score) for CT scan images using the proposed hybrid BO DNN-ML model has been presented in Fig. 13.

E. Discussions

The work presented in this article has been compared with various contemporary and previous research studies for COVID -19 diagnosis using disparate medical imaging datasets. The *comparative analysis* includes parameters such as type of *dataset, classification genre, applied image pre-processing, classification techniques and performance metrics (Accuracy)* as discussed in Table VIII. The research studies that have specifically utilized CXR and CT scan image datasets for the validation of the proposed and deployed COVID-19 diagnosis framework, have only been considered in this comparative analysis. Arman et al. 2022 [13] had utilized a hybrid model that showed higher value of classification accuracy for CXR images but it used complex combination of Bayesian optimization and Xception model resulting in higher training time value. As compared to the proposed study, that used both CXR and CT scan datasets for training and testing of the optimized hybrid model, all the contemporary and previous studies have only focused on the use of single dataset, i.e., either CXR [9], [11], [14], [18], [23] or CT scan datasets [12], [24] for the training and testing of the applied ML models. Moreover, none of these have used adaptive edge based segmentation and devised image preprocessing techniques for image enhancement that contributes to a more accurate and efficient feature extraction process.

V. Conclusions and Future Work

This work has presented the utilization of image pre-processing techniques for dataset enhancement without any additional overhead in computation cost for automated chest disease diagnosis. The proposed image preprocessing technique has used HT-Canny based edge detection method with morphological operators(dilation, fill and erosion) for image segmentation and median filter with CLAHE construct for noise removal respectively. As shown in experimental results of this article, there has been significant improvement in classification accuracy because of image segmentation, filtration and enhancement of CXR(Accuracy score = 96.94%) and CT scan (Accuracy score = 96.67%) images. While comparing the performance of three DNN models, namely, ResNet50, GoogleNet and EfficientNetB0 for feature extraction using CXR dataset, ResNet50 dominated in performance as compared to the rest of models by expending least training time(514 minutes) and best accuracy score(96.94%). Furthermore, the present study combined disparate ML classifers(namely DT, kNN, NB, DA and SVM models) with ResNet50 to formulate the proposed hybrid DNN-ML model. The proposed model showed that SVM classifier outperformed the rest of ML classifiers with an accuracy score of 97.25% and 97.62% for enhanced CXR and CT scan images respectively. Whereas, when Resnet50 was combined with Bayesian optimized ML classifiers to formulate the optimized hybrid DNN-ML model, BO-SVM(Accuracy

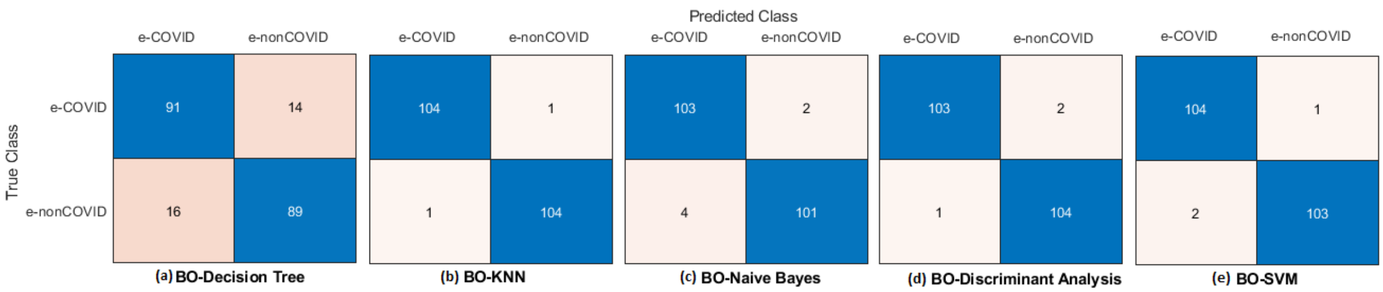

Fig. 9. Confusion matrix generated with ResNet50 and BO-ML classifiers for an enhanced CT scan dataset.

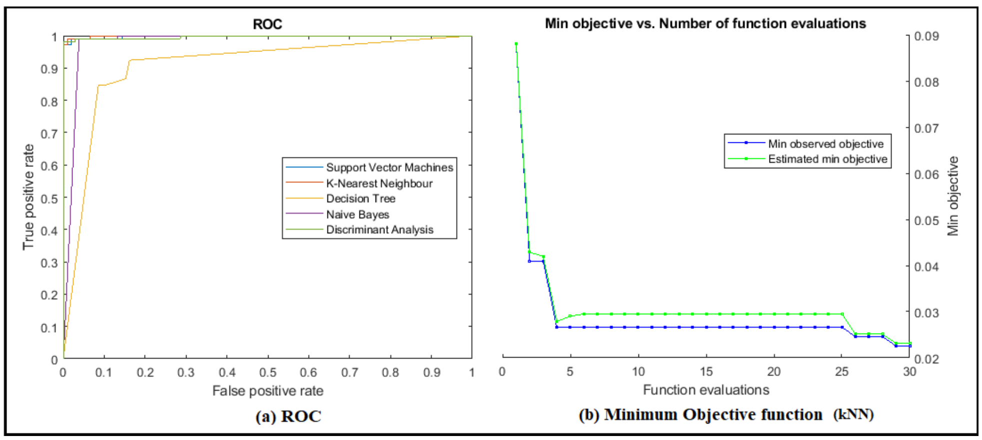

Fig. 10. ROC and Expected Improvement function (BO-kNN) for the proposed optimized hybrid DNN-ML model using CT scan image dataset.

TABLE VIII. Comparison of the Proposed Bayesian Optmized Hybrid DNN-ML Approach with Previous Studies for COVID-19 Detection

Author (Year)	Image type	Classification Count	Image Preprocessing technique used	Implemented Approach	Accuracy
Kesav et al.,2023 [9]	CXR images	Multiclass	Image resizing	GoogleNet and Bayesian optimized SVM classifier	98.31%
Arman et al.,2022 [11]	CXR images	Multiclass	Image resizing	Bayesian optimized Xception model	99.4%
Canayaz et al.,2022 [12]	CT scan images	Binary	Image resizing	Bayesian optimized kNN with ResNet50	96.42%
Aslan et al.,2022 [14]	CXR images	Multiclass	ANN based Image segmentation	DenseNet and Bayesian optimized SVM classifier	96.29%
Ezzat et al.,2021 [18]	CXR images	Multiclass	Image Augmentation	GSA based DenseNet	98.38%
Bhattacharya et al.,2022 [23]	CXR images	Multiclass	Image segmentation using GAN	VGG-19 with BRISK	96.6%
Kaur et al.,2022 [24]	CT scan images	Binary	Image resizing	Classifier fusion with ResNet50	98.35%
The Proposed Optimized hybrid DNN-ML model	CXR images & CT scan images	Multiclass, Binary	Image segmentation, filtration and CLAHE enhancement	BO-hybrid model	98.78%(CXR), 99.05%(CT)

score = 98.78 %) and BO-kNN (Accuracy score = 99.05 %), outperformed their non-optimized versions, when trained with CXR and CT scan images respectively. It can also be noticed from the experimental results that, the proposed Bayesian optimized hybrid DNN-ML model performed much better when trained and tested on CT scan images than on the CXR dataset. As a future research direction, the use of meta-heuristic algorithms has been proposed to perform feature selection, so as size of feature dimension set can be reduced. This will help in minimizing computation time and improve accuracy score. Also, the proposed Bayesian optimized hybrid DNN-ML approach can be validated using other medical imaging datasets.

References

[1] European Centre for Disease Prevention and Control. (2020). COVID-19 situation update worldwide. European Centre for Disease Prevention and Control.

[2] COVID, W. (19). Coronavirus Pandemic: https://www. worldometers. info/coronavirus/(2020). Accessed on December, 12, 2020.

[3] R. Singh, "Corona Virus (COVID-19) Symptoms Prevention and Treatment: A Short Review", JDDT, vol. 11, no. 2-S, pp. 118-120, Apr. 2021.

[4] A.M Al-Awadhi, K. Alsaifi, A. Al-Awadhi, & S. Alhammadi, "Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns", Journal of behavioral and experimental finance, 27, 100326,2020.

[5] M.Y. Ng, E.Y. Lee, J. Yang, F. Yang, X. Li, Wang, & M.D Kuo, "Imaging profile of the COVID-19 infection: radiologic findings and

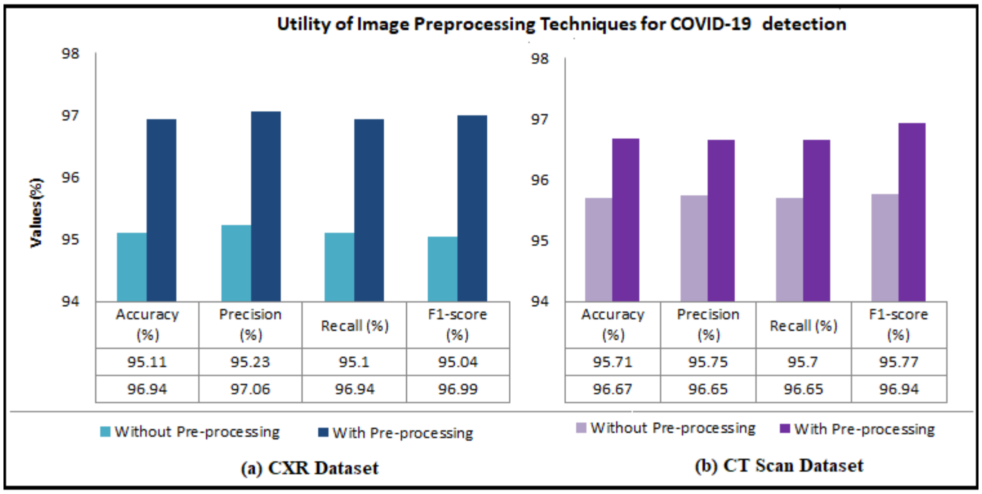

Fig. 11. Performance analysis of ResNet50 with image preprocessing techniques used in proposed approach on COVID-19 detection (CXR images).

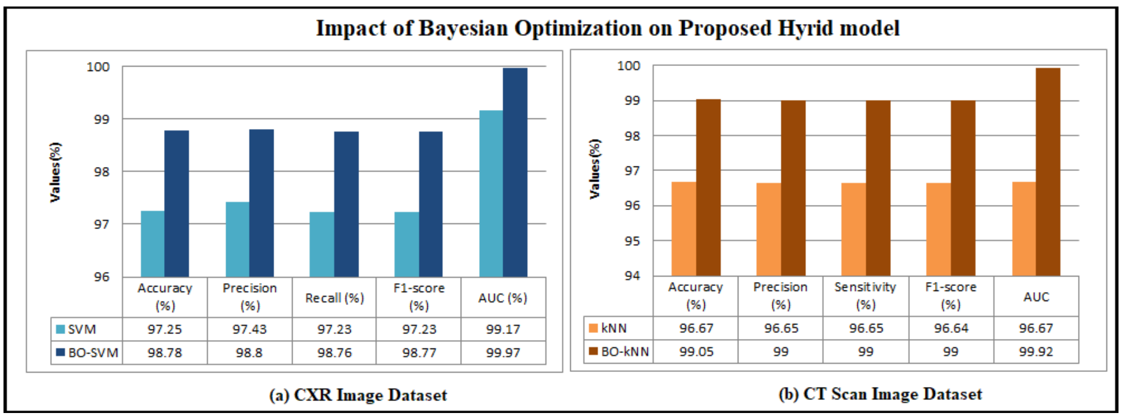

Fig. 12. Impact of bayesian optimization on SVM in the proposed approach for COVID-19 detection (CXR images).

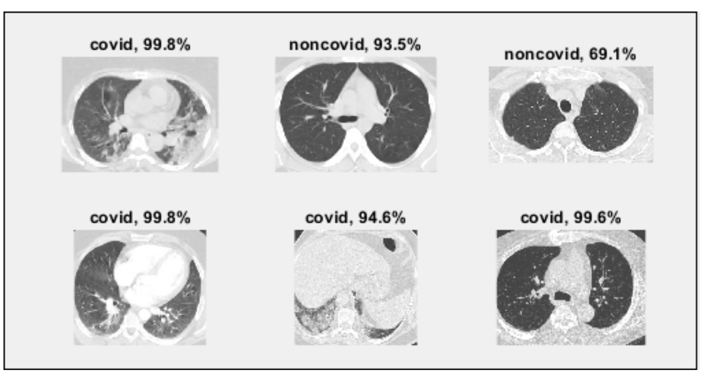

Fig. 13. Final output for classification (Image class, Accuracy) of CT scan images with the proposed hybrid DNN-ML model.

literature review", Radiology: Cardiothoracic Imaging, 2(1), e200034, 2020.

[6] H. Y. F. Wong, H. Y. S. Lam, & A. H. Fong, "Frequency and distribution of chest radiographic finding and distribution in COVID-19 positive patients", Radiology, 296, E72-E78, 2019.

[7] R. Yamashita, M. Nishio, R. K. G. Do, & K. Togashi, "Convolutional neural networks: an overview and application in radiology", Insights into imaging, vol. 9, pp. 611-629,2018.

[8] K. U. Ahamed, M. Islam, A. Uddin, A. Akhter, B.K. Paul, M. A. Yousuf & M. A. Moni, "A deep learning approach using effective preprocessing techniques to detect COVID-19 from chest CT-scan and X-ray images", Computers in biology and medicine, 139, 105014, 2021.

[9] N. Kesav & J. MG, "A deep learning approach with Bayesian optimized Kernel support vector machine for COVID-19 diagnosis", Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization, Vol.11, No. 3, pp 623-637, 2023.

[10] A. Hamza, M. Attique Khan, S. H. Wang, M. Alhaisoni, M. Alharbi, H. S. Hussein, & J. Cha, "COVID-19 classification using chest X-ray images based on fusion-assisted deep Bayesian optimization and Grad-CAM visualization", Frontiers in Public Health, 10, 1046296, 2022.

[11] S. E. Arman, S. Rahman, & S. A. Deowan, "COVIDXception-Net: A Bayesian optimization-based deep learning approach to diagnose COVID-19 from X-Ray images", SN Computer Science, Vol. 3, No. 2, 115, 2022.

[12] M. Canayaz, S. Sehribanoglu, R. Ozdag, & M. Demir, "COVID-19 diagnosis on CT images with Bayes optimization-based deep neural networks and machine learning algorithms", Neural Computing and Applications, Vol. 34, No. 7, 5349-5365, 2022.

[13] M. A. Awal, M. Masud, M. S. Hossain, A. A. M. Bulbul, S. H. Mahmud & A. K. Bairagi, "A novel bayesian optimization-based machine learning framework for COVID-19 detection from inpatient facility data" IEEE Access, 9, 10263-10281, 2021.

[14] M. F. Aslan, K. Sabanci, A. Durdu, & M. F. Unlersen "COVID-19 diagnosis using state-of-the-art CNN architecture features and Bayesian Optimization", Computers in biology and medicine, 142, 105244, 2022.

[15] M. Nour, Z. Comert, & K. Polat, "A novel medical diagnosis model for COVID-19 infection detection based on deep features and Bayesian optimization", Applied Soft Computing, 97, 106580, 2020.

[16] A. Jaiswal, N. Gianchandani, D. Singh, V. Kumar, & M. Kaur, "Classification of the COVID-19 infected patients using DenseNet201 based deep transfer learning", Journal of Biomolecular Structure and Dynamics, 39(15), 5682-5689, 2021.

[17] F. Ucar, & D. Korkmaz, "COVIDiagnosis-Net: Deep Bayes-SqueezeNet based diagnosis of the coronavirus disease 2019 (COVID-19) from X-ray images", Medical hypotheses, 140, 109761, 2020.

[18] D. Ezzat, A. E. Hassanien, & H. A. Ella, "An optimized deep learning architecture for the diagnosis of COVID-19 disease based on gravitational search optimization" Applied Soft Computing, 98, 106742, 2021.

[19] A. K. Das, S. Kalam, C. Kumar, & D. Sinha, "TLCoV-An automated COVID-19 screening model using Transfer Learning from chest X-ray images", Chaos, Solitons & Fractals, 144, 110713, 2021.

[20] M. M. A. Monshi, J. Poon, V. Chung, & F. M. Monshi, "CovidXrayNet: Optimizing data augmentation and CNN hyper-parameters for improved COVID-19 detection from CXR", Computers in biology and medicine, 133, 104375, 2021.

[21] H. Panwar, P. K. Gupta, M. K. Siddiqui, R. Morales-Menendez, & V. Singh, "Application of deep learning for fast detection of COVID-19 in X-Rays using nCOVnet", Chaos, Solitons & Fractals, 138, 109944, 2020.

[22] S. Asif, Y. Wenhui, H. Jin, Y. Tao, & S. Jinhai, "Automatic detection of COVID-19 using X-ray images with deep convolutional neural networks and machine learning", 2020

[23] A. Bhattacharyya, D. Bhaik, S. Kumar, P. Thakur, R. Sharma, & R. B. Pachori, "A deep learning based approach for automatic detection of COVID-19 cases using chest X-ray images", Biomedical Signal Processing and Control, 71, 103182, 2022.

[24] T. Kaur & T. K. Gandhi, "Classifier fusion for detection of COVID-19 from CT scans", Circuits, systems, and signal processing, 41(6), 3397-3414, 2022.

[25] N. Kumar, M. Gupta, D. Gupta, & S. Tiwari, "Novel deep transfer learning model for COVID-19 patient detection using X-ray chest images", Journal of ambient intelligence and humanized computing, 14(1), 469-478, 2023.

[26] L. Wang, Z. Q. Lin, & A. Wong, "Covid-net: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest x-ray images", Scientific reports, 10(1), 19549, 2020.

[27] K. El Asnaoui, & Y. Chawki, "Using X-ray images and deep learning for automated detection of coronavirus disease", Journal of Biomolecular Structure and Dynamics, 39(10), 3615-3626, 2021.

[28] A. Shamsi, H. Asgharnezhad, S. S. Jokandan, A. Khosravi, P. M. Kebria, D. Nahavandi, & D. Srinivasan, (2021), "An uncertainty-aware transfer learning-based framework for COVID-19 diagnosis", IEEE transactions on neural networks and learning systems, 32(4), 1408-1417, 2021.

[29] M. C. Arellano & O. E. Ramos, "Deep learning model to identify COVID-19 cases from chest radiographs" in 2020 IEEE XXVII International Conference on Electronics, Electrical Engineering and Computing (INTERCON) (pp. 1-4). IEEE, 2020.

[30] J.P. Cohen, P. Morrison, L. Dao, COVID-19 image data collection, (2020) arXiv: 2003.11597.

[31] M.E.H. Chowdhury, T. Rahman, A. Khandakar, R. Mazhar, M.A. Kadir, Z. B. Mahbub, K.R. Islam, M.S. Khan, A. Iqbal, N. Al-Emadi, M.B.I. Reaz, Can AI help in screening viral and COVID-19 pneumonia? IEEE Access 8, 2020.

[32] D. Kermany, K. Zhang, M. Goldbaum, Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification, Mendeley Data, 2018, p. v2,

[33] Zhao J, Zhang Y, He X, Xie P (2020) COVID-CT-Dataset: a CT scan dataset about COVID-19.

[34] T. Rahman, A. Khandakar, Y. Qiblawey, A. Tahir, S. Kiranyaz, S. B. A. Kashem, & M. E. Chowdhury, "Exploring the effect of image enhancement techniques on COVID-19 detection using chest X-ray images", Computers in biology and medicine, 132, 104319, 2021.

[35] S. M. Islam & H. S. Mondal, "Image enhancement based medical image analysis" in 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT) (pp. 1-5). IEEE,2019.

[36] L. O. Teixeira, R. M. Pereira, D. Bertolini, L. S. Oliveira, L. Nanni, G. D. Cavalcanti, & Y. M. Costa, "Impact of lung segmentation on the diagnosis and explanation of COVID-19 in chest X-ray images", Sensors, 21(21), 7116, 2021.

[37] E. A. Murillo-Bracamontes, M. E. Martinez-Rosas, M. M. Miranda-Velasco, H. L. Martinez-Reyes, J. R. Martinez-Sandoval & H. Cervantes-de-Avila, "Implementation of Hough transform for fruit image segmentation. Procedia Engineering", 35, 230-239, 2012.

[38] M. Huang, W. Yu, & D. Zhu, "An improved image segmentation algorithm based on the Otsu method", in 2012 13th ACIS International Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing pp. 135-139, IEEE, 2012.

[39] R. A. Manju, , G. Koshy, , & P. Simon, "Improved method for enhancing dark images based on CLAHE and morphological reconstruction", Procedia Computer Science, 165, 391-398, 2019.

[40] Laksmi, T. V., Madhu, T., Kavya, K., & Basha, S. E. Novel image enhancement technique using CLAHE and wavelet transforms. International Journal of Scientific Engineering and Technology, 5(11), 507-511, 2016.

[41] R. Anand, T. Shanthi, M.S. Nithish, & S. Lakshman, "Face recognition and classification using GoogleNET architecture" in Soft Computing for Problem Solving: SocProS 2018, Volume 1 (pp. 261-269), Springer Singapore, 2020.

[42] X. Chen, X. Pu, Z. Chen, L. Li, K. N. Zhao, H. Liu, & H. Zhu, "Application of EfficientNetB0 and GRU based deep learning on classifying the colposcopy diagnosis of precancerous cervical lesions", Cancer Medicine, 12(7), 8690-8699, 2023.

[43] K. He, X. Zhang, S. Ren & J. Sun, "Deep residual learning for image recognition" In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778), 2016.

[44] De Ville, B. Decision trees. Wiley Interdisciplinary Reviews: Computational Statistics, 5(6), 448-455, 2013.

[45] W. Zuo, D. Zhang, & K. Wang, "On kernel difference-weighted k-nearest neighbor classification. Pattern Analysis and Applications", 11, 247-257, 2008.

[46] I. Rish, I. "An empirical study of the naive Bayes classifier", In IJCAI 2001 workshop on empirical methods in artificial intelligence, Vol. 3, No. 22, pp. 41-46, 2001.

[47] A. J. Izenman, "Linear discriminant analysis. In Modern multivariate statistical techniques: regression, classification, and manifold learning" (pp. 237-280). New York, NY: Springer New York, 2013.

[48] Suthaharan, S., & Suthaharan, S. Support vector machine. Machine learning models and algorithms for big data classification: thinking with examples for effective learning, 207-235, 2016.

[49] J. Bergstra, R. Bardenet, Y. Bengio, & B. Kegl, "Algorithms for hyper-parameter optimization"' Advances in neural information processing systems, 24, 2011.

[50] J. Wu, X. Y. Chen, H. Zhang, L. D. Xiong, H. Lei, & S. H. Deng, "Hyperparameter optimization for machine learning models based on Bayesian optimization", Journal of Electronic Science and Technology, 17(1), 26-40, 2019.

[51] J. Snoek, H. Larochelle & R. P. Adams, "Practical bayesian optimization of machine learning algorithms", Advances in neural information processing systems, 25, 2012.

[52] L. Zahedi, F. G. Mohammadi, S. Rezapour, M. W. Ohland & M. H. Amini, "Search algorithms for automated hyper-parameter tuning"' arXiv preprint arXiv:2104.14677, 2021.

[53] P. I. Frazier, "Bayesian optimization"' in Recent advances in optimization and modeling of contemporary problems (pp. 255-278). Informs, 2018.

[54] A. McAndrew, "An introduction to digital image processing with MATLAB", Course Technology Press, 2004.