An Ensemble Neural Architecture for Lung Diseases Prediction Using Chest X-rays

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Abstract: Accurate diagnostic tools for disease control and treatment options is of immense importance, specially during pandemics, Coronavirus (or COVID) that drew global attention in late 2019. Early detection and seclusion are the cornerstone effective ways to prevent virus spread. Artificial intelligence (AI)-based diagnostic tools for COVID detection have surged dramatically using various diagnostic imaging techniques, among which Chest X-ray (CXR) have been extensively investigated due to its fast acquisition coupled with its superior results. We propose a hybrid, automated, and efficient approach to detect COVID-19 at an early stage using CXRs. One of the main advantages of the proposed analysis is the development of a learnable input scaling module, which accommodates various CXR with different sizes with the ability to keep prominent CXRs features while filtering out noise. Additionally, the suggested method ensembles several learning modules to extract more discriminative representation of texture and appearance cues of CXRs, thereby facilitating more accurate classification. Particularly, we integrated two sets of features (texture descriptors and deeper features) representing a rich concentration of local and global features. In addition to learnable scaling and information-rich features, an ensemble classifier using various machine learning models is used for classification. Our classification module included support vector machine, XGBoost and extra trees modules. Extensive evaluation, supported by ablation and comparison studies, is conducted using two benchmark datasets to evaluate the model's performance in a cross-validation strategy. Using various metrics, the results document the robustness of our ensemble classification system with higher accuracy of 98.20% and 97.85% for the two data sets, respectively.

Keywords: Ensemble Classifier; Autoencoder; Artificial Intelligence; Feature Fusion

1. INTRODUCTION

Coronavirus (COVID-19) has spread at breakneck speed around the world since its discovery in late 2019. The worldwide pandemic caused by COVID-19 has resulted in a string of catastrophic losses, infecting over 287 million people and killing 5.4 million people. Since then, medical specialists from all over the world have been employed hard to find vaccines and medications for COVID-19 [1]. COVID-19 could be recognized in two distinct manners. The primary one is a real-time polymerase chain reaction (RT-PCR) nucleic identification testing. RT-PCR has aided in diagnostics, discharge evaluation, and recovery monitoring. Nevertheless, the RT-PCR sample sensitivity is restricted, and this may result in an increased false negatives. Medical imaging, i.e., chest X-ray (CXR) or computed tomography (CT), is the second technique for detecting COVID-19 [2]. CT scans have multiple cross sections, making diagnosis time-consuming and costly. Technicians must make numerous adjustments during the process. Inadequate disinfection between CT technicians

and patients can cause cross-contamination. Furthermore, in some areas, a shortage of radiologists poses a challenge [3]. Given the enormous impact of artificial intelligence (AI) methods for health-related imagery, a number of scientists have turned to these resources in the recent COVID-19 scenario more accurately, quickly, and affordably [4]. Deep learning (DL) is highly effective and produces better results for CXR image classification. It has made significant progress in feature learning and representing features [5]. In summary, early, accurate, and fast COVID-19 diagnosis is critical for timely quarantine and medical care. This is also important for patient diagnosis, epidemic prevention, and public preventive care.

In applications that use image-based data, AI approaches have consistently produced accurate and dependable results. In recent years, researchers have investigated and analyzed CXR images to identify COVID-19 using DL-based techniques (e.g., [6]–[12]). An automated technique for detecting COVID-19 was developed using extended

segmentation-based fractal texture analysis and the discrete wavelets [13]. The optimal features were selected and combined with an entropy-controlled genetic algorithm and a serial approach. To detect the chosen features, different ML classifiers were used. The naive Bayes classifier achieved 92.6% accuracy, compared to other ML algorithms. A hybrid shape-based (HOG-based) and convolutional neural network (CNN)-derived features was proposed by [14]. Integrated features improved overall performance by allowing classifiers to learn from the combined data. They used three CT datasets with three classes: 328 common pneumonia, 1,972 COVID-19, and 1,608 normal individuals. VGG-16 + HOG accomplished 99.4% accuracy using SVM. This suggests that the proposed combined feature can improve SVM accuracy in COVID19 diagnosis. Pre-trained CNNs were combined by [15] with a pyramid MLP-mixer module to classify 4,099 CXR images which contained 1,464 COVID-19, 1,294 pneumonia, and 1,341 normal patients. Their model achieved an accuracy of 98.3%. Singh et al. [6] utilized a modified stacked ensemble model with four CNN base-learners and Naive Bayes algorithm as meta-learner to classify CXR images. Their method scored an accuracy of 98.67%. Waisy et al. [16] applied a preprocessing step fusing 800 CXRs. They combined the weighted decisions of the two trained proposed models and achieved extremely high accuracy of 98%. The performance of seven different DL architectures for detecting COVID-19 in CXR images was introduced by El Asnaoui et al. [17]. In their study, Inception-ResNetV2 achieved an accuracy of 92.18%. A DL-based accurate and efficient ensemble model based on CNN for binary and multi-calss classification was proposed by Bhardwaj et al [9]. Their method provided 98.33% accuracy for binary class and 92.36% for multiclass. A similar approach was proposed in [10], where the experimental results showed that their model achieved an accuracy of 91.2% for the three-class problem. Although the used dataset was large and TL concept was applied, the overall accuracy wasn't high. A modified COVIDnet model for COVID-19 diagnosis, called EDL-net, was proposed by Tang et al. [12]. The proposed model achieved a detection accuracy of 95%. Balasubramaniam et al. [18] proposed a model based on ensemble learning technique for COVID-19 detection. They applied their method on a dataset consisted of 5000 CXR images. Their approach achieved an accuracy of 92.3%. COVID-19 identification was carried out using multiclass and hierarchical classification tasks in [19]. In the classification schema, both early- and late-fusion methods were used using texture features and CNN-extracted features. They used a dataset consisted seven classes with a total 1,144 CXR images. The evaluation results showed that the proposed approach was effective, with an F1-score of 0.89 for COVID-19 recognition. Hossain et al. [20] presented an AI-based solution for an fast and effective COVID-19 infection identifying technique. Their proposed method accomplished this by integrated a weighted CNN fusion strategy with an attention module. The former combined multiple base pretrained CNN models, such as ResNet50V3, VGG-16,

and InceptionV3 models. The attention module was utilized to extract important features resistant to overfitting and exploit an LC layer. The dataset used includes 1,848 CXR images with equal counts from the COVID-19, healthy, and pneumonia classes. The results of the experiments revealed that the fusion model scored an accuracy of 96.75%.

In sum, various studies have been conducted and demonstrated promising results. Most of the methods employed DL-based approaches; however, the overall accuracy still need improvement. Also, some studies have a small number of subjects to test. Traditionally, the original image is used as the input to the CNN, that might not be sufficient to give a high accuracy score. Furthermore, various studies have integrated CXR and CT data sets; however, higher-order texture features were not deeply investigated in addition to the deep features. This work aims to present a robust ensemble pipeline based on the feature fusion of higher-order texture feature and CNN-derived deep features in order to get high accuracy with minimum loss. Additional, our design is based on an ensemble classifier that integrates three ML algorithms with five fold cross-validation for evaluation. Our proposed model is hybrid and has been evaluated using two data sets and compared against of the shelf networks as well as recent COVID-19 detection methods.

2. ANALYSIS PIPELINE

Figure 1 illustrates the proposed analysis pipeline, comprising multiple analysis blocks: data preprocessing, the proposed deep feature extraction model, feature fusion, and ensemble classification. All stages are further detailed next.

A. Preprocessing and Learnable Input-Scaling

Before data analysis, a preprocessing stage is conducted, which is essential to improve the input data for subsequent processing operations. This stage is crucial as it ensures that a given model is generalizable, particularly when evaluated on data sets outside of the training cohort. Preprocessing step also minimizes data noises and/or deformations, allowing the deep architectures or hand-crafted features extraction to perform its tasks effectively and quickly.

Since data collected from different sites and machines have different sizes, images have to be rescaled to fit a designed model's input. In our design the learnable input scaling module resize the CXRs to a fixed size of 224×224 using an auto-encoder structure with the block diagram depicted in Figure 2. The encoding path comprises successive convolutional and pooling layers to produce the feature map, AE_m. The latter has the size of 224×224, which subsequently undergoes convolution, transposed convolution, and reshaping to achieve dimensions of $224 \times 224 \times 4$. Both original and processed AE_ms are then combined via concatenation, generating high and low-resolution images. The former is utilized for preprocessing and feature extraction, while the latter aids in module training to minimize reconstruction error and learn crucial features while discarding redundancy and noise. Training
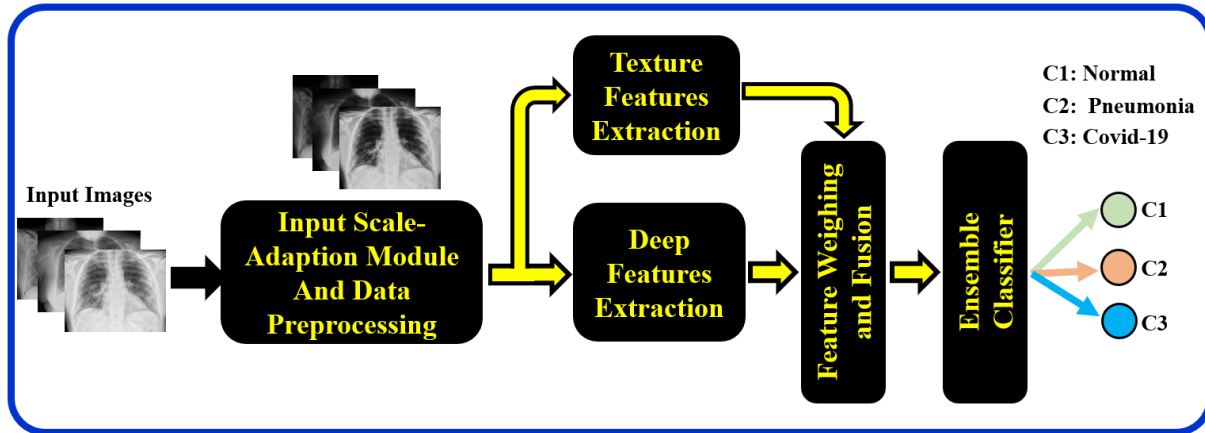
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Figure 1. Schematic of the developed pipeline for lung disease detection.

employs a hybrid loss function that incorporates pseudo-Huber and log-cosh loss functions [21], [22].

After resizing, multiple image preprocessing are conducted on the resized images. Image pre-processing is a vital process in the analysis of medical images tasks. This step range from simple task, such as noisy removal to more complicated tasks like, histogram equalization and data augmentation, which are for vital for enhanced and right classification. In this study, we used data normalization, in which all pixel values were rescaled to $[-1, 1]$ using $\left(\frac{1}{255}\right)$ as the pixel-wise multiplication. Given a grayscale image I with maximum (I_{max}) and minimum (I_{min}) values, the normalized image, $R = \frac{I - I_{min}}{I_{max} - I_{min}}$. After data normalization, we applied histogram equalization in order to increase the global contrast. This allows areas with low local contrast to gain contrast. Histogram equalization frequently produces artificial appearances in images; however, it is extremely useful for scientific images in nature such as thermal, satellite, or X-ray images [23].

B. Feature Extraction

In medical image classification problems, feature extraction and selection are critical. A number of images may be classified based on its primary distinguishing features, that are found using a suitable feature extraction technique [24]. To enhance the accuracy of CXR classification, in the proposed pipeline we integrated two types of CXR-derived information-rich features: deep CNN–derived along with texture, radiomic features. These feature-driving algorithms are well-known for their proficiency in medical image classification tasks. The extracted features are then integrated where the layers of these models are combined using the stacking method to create an ensemble classifier, resulting in a more robust classification.

Firstly, deep features are extracted from the preprocessed image using pretrained neural network architecture. The goal of this stage is to diagnose COVID-19 (i.e., categorize an input CXR image to one of the three classes).

To attain the goal, we utilized ResNet50 pretrained on the ImageNet dataset [25]. ResNet is cutting-edge CNN architecture that presented an improvement over traditional CNN architectures due its ability to address the vanishing gradient problem often encountered by CNN modules, which is circumvented using the residual layers. The latter enable direct transfer of data from one layer to another, skipping some layers. By doing so, the network (with very deep architecture) to develop residual functions, that represent basically the variations between the desired output and the present result at the current layer. Thus, through intrgerating a pretrained ResNet50 into our ensemble architecture, we utilize its ability to learn detailed features and patterns from CXR images. The CXRs are resized to 224×224 using the learnable input scaling module and then we removed the final fully connected layer to get the feature vector. Obtaining these feature vectors required minimal computational capacity. We deployed pre-trained ImageNet dataset weights instead of fine-tuning ResNet50 for the data set, as it is able to offer features for most images.

Secondly, a set of texture features from the CXRs are also included to enhance disease differentiation by helping the proposed architecture to harness the spatial interactions between pixels' intensities. The features are computed using two higher-order texture feature descriptors. This set of features are derived from using GLCM based Haralick features and the gray-level run length matrix (GLRLM) features. GLCM produces a square matrix with the same dimension as the number of grey levels in the image. Each GLCM cell represents the total number of co-occurring associated grey levels in the image. The matrix must have a reasonably high occupancy level in order for the statistical estimate to be reliable. Thus, either the number of grey level values is reduced or a larger window should be used [26].
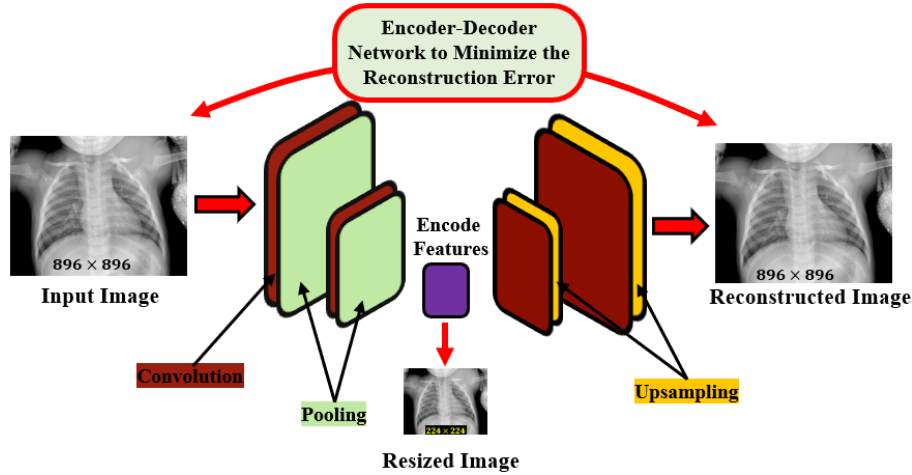
Figure 2. A schematic showing the structure of the learnable input scaling module.

The GLCM matrix, G, can be calculated as follows [27]:

$$G_{\Delta x,\Delta y}(i, j) = \sum_{x=1}^{K} \sum_{y=1}^{M} \begin{cases} 1, & R_i(x, y) = i, R_i(x + \Delta x, y + \Delta y) = j \\ 0, & \text{otherwise} \end{cases}$$

(1)

where $R_i(x, y)$, and $\{\Delta x, \Delta y\}$ are pre-processed data with $K \times M$ dimension at the spatial position $\{x, y\}$; and the spatial offset in the image I, respectively. The GLCM matrix's second-order statistical analysis yields various parameters that are widely used as texture features in medical data classification research [28]. In our work, we extracted the five most commonly used GLCM features from each image: energy, contrast, correlation, homogeneity and dissimilarity [29]. We statistically evaluated the GLCM features to select the most informative and distinctive ones.

Furthermore, the GLRLM texture features are utilized in the method we employ as a higher-order statistical texture feature set. GLRLM investigation, like GLCM, commonly herbal extracts the spatial plane features of pixels based on the high-order statistics of their immediate neighbors [30]. Thus, GLRLM features texture patterns assessment deliver discriminative power for image classification and supplement other features such as color, shape, and intensity for comprehensive representations and better performance. The technique generates a normalized 2D feature matrix, with each component representing the overall number of occurrences of the graylevel in the given direction [31]. Typically, GLRLM extractor captured information of pixel pairs at angels 0, 45, 90, and 135°. Mathematically, each element $L(i, j|\theta)$ of the run length matrix L, represents the number of runs with pixels of graylevel intensity and length of run equal to i and j,respectively along a specific orientation, $i, j \in [0, 255], \theta \in \{0, 45, 90, 135\}$. From L for an input image of size $N \times M$, many features including short/long run emphasis (SRE/LRE), greyLevel/run Length non-uniformity (GLN/RLN), run percentage (RP), low/high gray level run emphasis (LGRE/HGRE) for a given θ can

be calculated using the number of greylevel (g) and number of discrete run lengths (r) of a given image as as follows:

$$SRE = \sum_{i=1}^{g} \sum_{j=1}^{r} \frac{L(i, j)}{j2}$$

(2)

$$LRE = \sum_{i=1}^{g} \sum_{j=1}^{r} j^2 L(i, j)$$

(3)

$$GLN = \sum_{i=1}^{g} \left(\sum_{j=1}^{r} L(i, j) \right)^2$$

(4)

$$RLN = \sum_{i=1}^{r} \left(\sum_{j=1}^{g} L(i, j) \right)^2$$

(5)

$$RP = \frac{1}{N \times M} \sum_{i=1}^{g} \sum_{j=1}^{r} P(i, j)$$

(6)

$$LGRE = \sum_{i=1}^{g} \sum_{j=1}^{r} \frac{L(i, j)}{i^2}$$

(7)

$$HGRE = \sum_{i=1}^{g} \sum_{j=1}^{r} i^2 L(i, j)$$

(8)

C. Feature Fusion and Ensemble Classification

Following feature extraction, we used a feature fusion approach for combining derived CXR features for classification. This technique usually enhances the discriminative classification power of a given system by delivering

comprehensive representations of information-rich features. Finally, the fused CXR features are provided as input to a ML classifier for prediction. Our design is based on an ensemble classifier that integrates three ML algorithms: SVM, XGBoost, extra trees. Also, five fold cross-validation technique was used for training the ensemble models on the CXRs datasets. **The SVM** is the first ML algorithm that is employed in our design. SVM is a supervised ML technique that creates a hyperplane that separates two input classes with the largest margin. The margin indicates the difference between the support vectors and the hyperplane [32]. The main advantage of SVM lies in the fact that it powerfulness ability to handle high-dimensional data and non-linear classification using kernel functions, while being effective with limited training samples. In addition to SVM, **XGBoost** is also included in our ensemble model. It has gradient boosting at its core. The XGBoost algorithm differs from simple gradient boosting in that it uses a multi-threaded approach to add weak learners, rather than adding them sequentially. The XGBoost algorithm differs from simple gradient boosting in that it adds weak learners in a multi-threaded approach, utilizing the machine's CPU cores for faster and better performance. Sparse aware implementation includes automatic handling of missing data values, a block structure for parallel tree design, and ongoing training to improve an existing model on new data [33]. Finally, **Extra tree**, an extremely randomized classifier, is integrated in our ensemble model [34]. It is built differently than traditional decision trees. Random splits are utilized to determine the best way to divide a node's samples into two separate sets. The best split will be determined based on randomly selected features, specifically max features. Its averages out the variance problems of a single decision tree method, making it suitable for multiple sub samples of a dataset. This improves predictive accuracy and prevents overfitting [35].

3. EXPERIMENTAL RESULTS

The primary objective for developing the proposed AI-pipeline is to create a robust classification model that will perform well regardless of the domain in which it can be used. System evaluation and assessment is based on two publicly-available chest x-ray datasets with compromising a total CXRs of 13,830 images [36]–[40]. The datasets consist of three classes: normal, pneumonia, and COVID-19 and are summarized in Table I. For experimental and training settings, the system was built with the TensorFlow framework and Keras as the backend using the Python programming language. All experiments are conducted using a windows machine with 32GB of RAM, 4GB NVIDIA graphics card, and a 12 core i7-processor. we employed Adam optimizer [41] and set the learning rate at 10^{-4} due to its effective hyperparameters' selection. Furthermore, the batch size was fine-tuned to 32, epochs are tuned at 50, and categorical loss function was used.

The overall accuracy for the proposed method is summarized in Table II. Quantitative performance evaluation is

TABLE I. Per-class distribution for the public datasets.

	Dataset		
	First	Second	Total
Normal	4,200	1,751	5,951
Pneumonia	4,273	4,273	8,546
COVID-19	4,195	1,371	5,566
Total	12,668	7,395	20,063

conducted mainly using accuracy, recall, precision, and F1-Score indexes. The accuracy (AC) represents the ratio of correctly categorized labels to the total number of tested ones. Recall (RC, specificity) is a representation of the fraction of correctly identified positive (or negative) class. Further, correctly predicted positive samples out of the total predicted patterns in the positive class is referred to as precision (PR). Finally, the F1-Score indicates the harmonic mean between RC and PR. At first, we investigated the importance of the ensemble classifier on the overall system performance. Thus, we evaluated the classification process using different single ML models and Table II represents the summary of the accuracy of the tested models. It observed that most of the single classifier have lower performance and the extra tress achieved the highest accuracy when tested on the extracted features. However, individual classifiers are all less than the ensemble model of the fused features.

TABLE II. Multi-class accuracy of comparing the ensemble classifier against various machine learning models. AC: accuracy, PR: precision, RC: recall.

	Evaluation Metrics (%)			
Classifier	AC	PR	RC	F1-Score
XGBoost	78.23	80.64	76.51	77.15
RF	81.13	82.36	82.56	82.42
SVM	85.39	83.03	84.25	83.87
Extra Trees	88.10	87.18	86.08	86.73
Our (dataset1)	98.20	97.91	98.18	96.43
Our (dataset2)	97.85	97.33	95.67	96.67

Besides quantitative indexes, the architecture performance is investigated using the confusion matrices (CM) and the receiver operating characteristics (ROC) curve, which are powerful tools for the evaluation and comparison of classification models. On the first hand, CM is an extremely useful tool for determining which classes, if any, were misclassified the most. On the other hand, the ROC of analysis tool is used to validate/support the reliability (and accuracy) of classification pipelines by analyzing models' output based on the relation between false and true positive rates assessed at various thresholds. The area under the curve (AUC) of a ROC can be utilized in quantitative classification models to demonstrate how well the model discriminates between classes. The last column of Figures 3 and 4, demonstrates the CM and the ROC curve for the proposed ensemble model evelaued on the first data set, respectively. Additionally, Figures 5 shows CM and the ROC curve for the proposed ensemble model tested on the
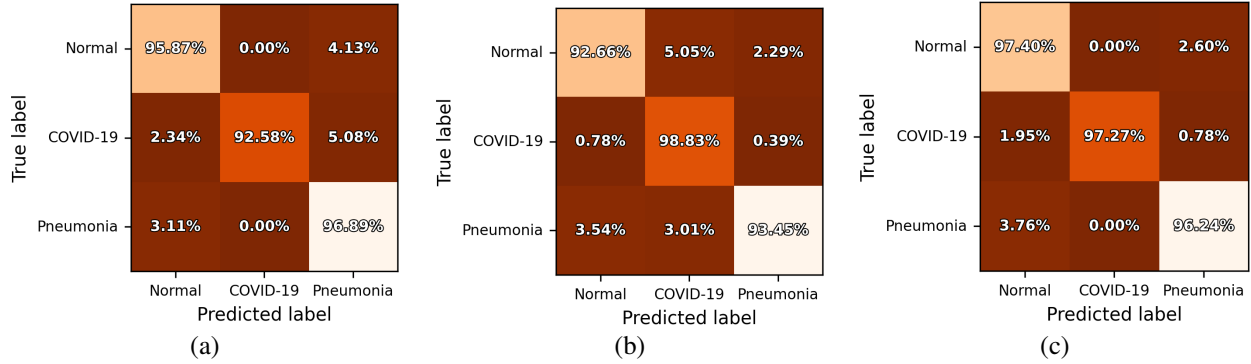
Figure 3. Visualization of confusion matrices of individual feature sets and the proposed method: (a) higher-order features; (b) CNN-derived features, and (c) their fusion (the proposed) on the first data set.
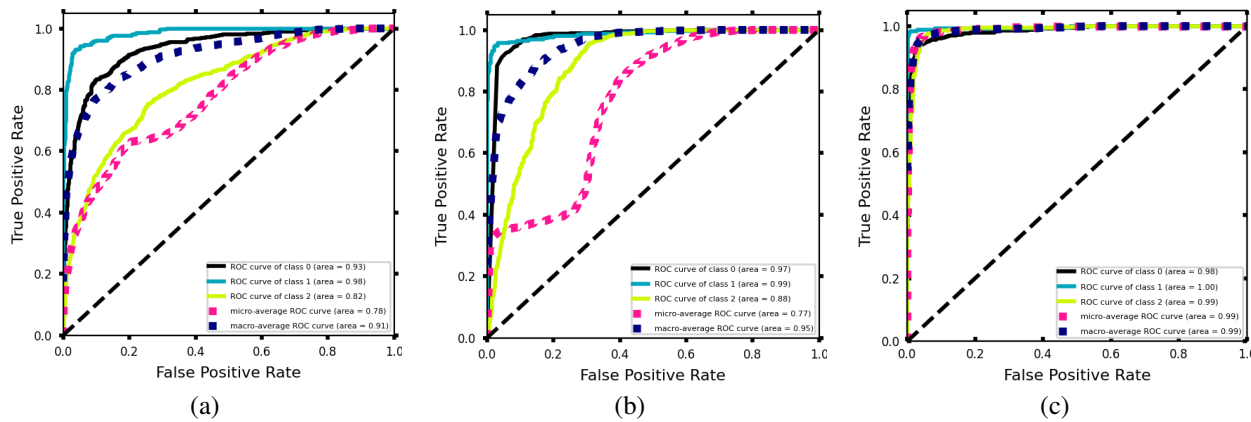

Figure 4. Visualization of the ROC curves of individual feature sets and the proposed method: (a) higher-order features; (b) CNN-derived features, and (c) their fusion (the proposed) on the first data set.

second data set.

For the second evaluation phase, we investigated the importance of features fusion. Thus, we conducted an ablation study where we test the system accuracy using each type of the features separately. Table III represents the summary of the obtained accuracy. As demonstrated, the proposed model's performance is highly enhanced using the fused features compared to individual features and reached to an accuracy of 98.20% and 97.85% for the first and second data sets, respectively.

TABLE III. Overall performance for the proposed model. HaC: Handcrafted Features; CNN: convolutional neural network.

Method	Metrics, (%)			
	AC	PR	RC	F1-score
HaC Features	90.15	88.63	89.28	89.46
CNN Features	93.29	91.33	90.00	90.67
Proposed (dataset1)	98.20	97.91	98.18	96.43
Proposed (dataset2)	97.85	97.33	95.67	96.67

Moreover, evaluation of well-known pretrained backbone CNNs and recent literature work developed for COVID-19 detection are also conducted. For pretrained

CNNs, we tested various architectures including VGG19, Inception, DenseNet121, and Xception and the average accuracies were 71.36%, 78.50% , 80.00%, and 86.92%, respectively. Table IV summarizes the results of other literature work compared with the proposed model, which have been applied on the employed datasets. From the table, its readily seen that the proposed model scored higher accuracy accuracy compared to others. The reported results emphasis the idea that feature fusion coupled with ensemble ML classifier enhances the overall performance.

TABLE IV. Multi-class accuracy of recent work for COVID-19 detection. AC: Accuracy, PR: Precision, RC: Recall.

Model	Evaluation Metrics (%)			
	AC	PR	RC	F1-Score
Ismael et al. [42]	94.7	91.0	98.9	94.8
Horry et al. [43]	—	83.0	81.0	81.0
Abbas et al. [44]	95.1	97.9	91.87	93.36
Li et al. [45]	99.6	—	99.4	—
Medeiros et al. [46]	95.47	94.71	96.18	95.44

4. CONCLUSIONS AND FUTURE WORK

A hybrid pipeline incorporating ensemble feature fusion concept has been developed for distinguishing COVID-19
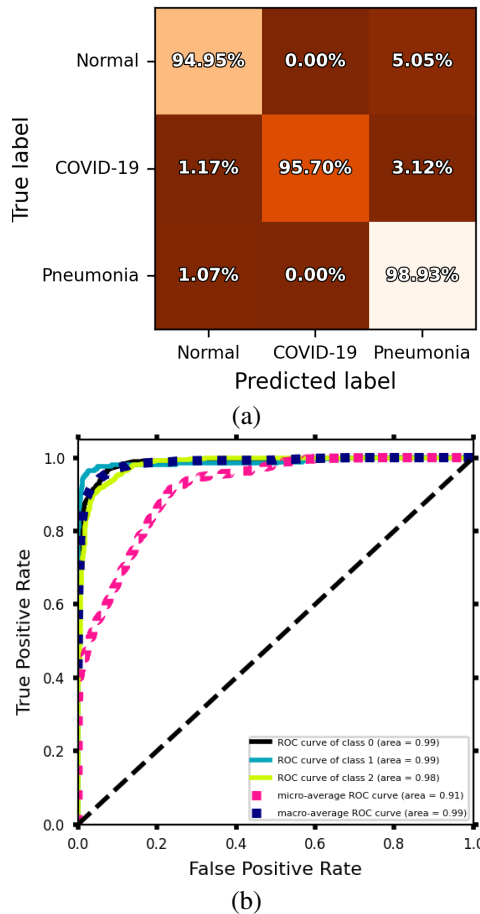
(a)

(b)

Figure 5. Visualization of confusion matrices and ROC curve of our ensemble model for the second data set.

from normal and pneumonia cases CXRs images through multi-classification. Particularly, an AI-based combining high-level features with higher-order texture ones has been developed. The potentials of the developed feature fusion architecture is supported by the presented results using two cohorts of CXR images. The experimental findings reveal in which the improved fusion approach combined with ensemble classifier outperformed the single prediction models and achieved overall accuracy of 98.20% and 97.85%. The suggested method has a high potential for clinical application and has the possibility to reduce both pollutants and hospital burden by preventing unnecessary hospital visits. In future work, we will create a multi-level classification framework that mimic physicians diagnosis of separating groups by providing global screening then performing micro classification of the potential instances. We will also investigate ensemble learning of multi-scale images. Although we have introduced a feature fusion approach, our future work will be dedicated to multi-modal features fusion. Integration between CXR-based features and CT in conjunction with using transformer-based architectures will be another research venue.

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7

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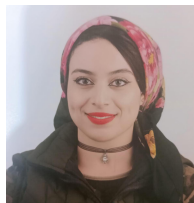
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9

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