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RESEARCH ARTICLE

An Automated Chest X-Ray Image Analysis for Covid-19 and Pneumonia Diagnosis Using Deep Ensemble Strategy

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ABSTRACT Precise and timely diagnosis of Covid-19 and pneumonia is crucial for effective treatment. However, the traditional RT-PCR method is time-consuming, costly, and prone to incorrect results. To address these limitations, a deep ensemble strategy is proposed as a promising alternative to provide more accurate and reliable outcomes. The strategy comprises three main stages: i) pre-processing, ii) salient feature extraction, and iii) training and classification. In the pre-processing step, the authors resize the images to the desired input shape. Data augmentation techniques, such as zooming, nearest full mode, rotation, and flipping, are employed to augment the dataset, thereby improving the training accuracy of the proposed approach. Additionally, the proposed method leverages the capabilities of VGG-16, DenseNet-201, and Efficient-B0 models using transfer-learning techniques to extract deep features from the images. These salient features are then passed through proposed fully connected layers and ensemble classifiers to predict the probability of the given classes. Extensive experiments were conducted on a chest X-ray image dataset, demonstrating that the proposed system outperforms contemporary techniques in terms of precision, recall, F1-score, and accuracy (acc). The proposed method obtained 97% of acc, while 96%, 95%, and 97% pre, rec, and F1-score respectively. In conclusion, this study presents a valuable contribution to medical image diagnosis using an AI-based deep ensemble strategy. The proposed approach offers a promising solution for accurate and efficient diagnosis of Covid-19 and pneumonia, assisting healthcare professionals in making informed decisions for optimal treatment outcomes.

INDEX TERMS Chest X-ray images, covid-19 and pneumonia diagnosis, ensemble learning, fine-tuning, pattern recognition, transfer learning.

I. INTRODUCTION

Covid-19 is the latest viral epidemic that initially originated in Wuhan City, China. It rapidly spread to nearly every country globally [1]. It is a highly transmissible disease that is primarily spread through the inhalation of droplets. The rapid spread of this highly infectious virus caused a worldwide health emergency. Covid-19 is officially referred to as Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2), and it falls under the category of Coronaviridae virus family [2]. Statistics show that within two months of the World Health Organization (WHO) labelling Covid-19 as

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a pandemic, the virus claimed the lives of over 300,000 people globally [3]. As of December 8, 2021, Over 5.2 million people died because of Covid-19, while it infected over 267 million people across the globe. Government-implemented strategies to control the transmission of Covid-19 have substantially impacted all sectors of life worldwide [4]. COVID-19 can cause various illnesses, changing from temperate to intense and even critical. The SARS-CoV-2 virus produces viral proteins named antigens, intended to be found by the Rapid Diagnostic Test (RDT) in a person's respiratory system. The RDT typically determines if a sufficient amount of SARS-CoV-2 antigen exists in the sample taken; it can often bind to many antibodies on a piece of paper in a plastic container within 30 minutes. It produces a signal that is simple to detect. As these antigens are only produced during effective viral replication, these RDT tests are useful in identifying severe or preliminary SARS-CoV-2 infections. Pneumonia is one of the most severe intricacies due to Covid-19 [5]. The Greek term "Pneumon", meaning lung, gave its name to the word pneumonia. So, lung disease and pneumonia are related. The lung inflammation caused by pneumonia makes it difficult to breathe [6]. Other causes of pneumonia include aspiration of food and chemical exposure. As stated earlier, pneumonia causes lung inflammation, causing the alveoli to fill with fluid (i.e. pus). This sticky fluid prevents the proper transfer of oxygen and carbon dioxide between the blood and lungs, resulting in impeded breathing [7]. The diagnosis of pneumonia involves a range of methods, including CT scans, sputum analyses, chest radiography, blood gas analysis, and CBCs, albeit with inherent limitations. Among these, RT-PCR (Reverse Transcription Polymerase Chain Reaction) tests are widely considered to be the most reliable means of detecting Covid-19, as they allow for the retrieval of genetic information of SARS-CoV-2 from the upper respiratory tract [8]. In addition, the prolonged diagnostic procedure relying on RT-PCR kits impedes many patients from receiving a timely Covid-19 diagnosis and adequate treatment. The scarcity of RT-PCR kits exacerbates the situation, making it difficult for patients to access this crucial diagnostic tool. The extended wait time for test results, combined with inadequate hospital care and the highly contagious nature of the virus, can have fatal consequences for some patients [9]. Moreover, Chest X-ray examination offers a safer option for nurses in terms of avoiding viral infections compared to RT-PCR kits. Chest X-rays can help physicians to detect not only Covid-19 but also other viral and bacterial diseases. However, these X-ray images also have some limitations, such as low contrast, blurred borders, and overlapping organs, making it more difficult to diagnose pneumonia accurately [10]. These factors are currently leading to increasing interest in the automated diagnosis of viral species, including coronavirus, based on chest radiographs. Artificial intelligence (AI) has recently been used in many initiatives to assist physicians in accurately identifying diseases and determining the severity of those diseases [11]. Recent advancements in AI research have been driven by the use of Machine Learning (ML) and Deep Learning (DL) methods. DL utilizes neural networks with multiple layers and has proven to be more effective than traditional ML techniques [12], [13]. In situations where promising results are obtained, the models from DL are of great importance. Recently, different techniques have been employed to detect different diseases, and the techniques from DL have proven to be highly effective [14]. However, training DL networks requires training on extensive datasets, which is a limitation [15], [16]. For example, the absence of enough training examples in the dataset compromises the performance of the Convolution Neural Network (CNN). Transfer learning [17] can help to overcome this critical limitation where a model originally trained for one task is utilized for a second related task. The model leverages the knowledge gained from solving the first task to improve its performance on the second task. This allows for faster and better convergence than training the model from scratch. Our research aspires to develop a system capable of correctly detecting and classifying Covid-19 and pneumonia. Earlier disease diagnosis may lead to more effective treatments and longer survival. Using optimized and highly effective deep CNNs, we propose an ensemble architecture based on DL for covid-19 classification. The primary contributions of our work are as follows:

- Pre-processing: In the pre-processing step, the authors employed a data augmentation strategy to elude overfitting and achieve better results on small datasets. As a result, the effectiveness and robustness of the proposed method in detecting Covid-19 and pneumonia diseases utilizing a small dataset have enhanced.
- The authors developed a collaborative deep ensemble strategy to recognize Covid-19 and pneumonia diseases from chest X-ray images. The authors refine a variety of pre-trained deep learning algorithms by employing the proposed fully connected layer. The proposed deep ensemble strategy is created by fusing the weights of the three best-performing models.
- Experiments were conducted by utilizing chest X-ray images of patients infected with either COVID-19 or pneumonia. The purpose of these experiments was to evaluate and compare various algorithms for detecting and diagnosing these infections. The results of the experiments showed that the proposed deep ensemble strategy outperformed its competitors in several important performance metrics.

The remainder of the manuscript is organized as follows. Section II presents a summary of relevant prior work in the field. The proposed methodology is detailed in Section III. The experimental results are discussed in Section IV. Finally, in Section V, the paper concludes with a discussion of future directions for research.

II. LITERATURE REVIEW

The objective of this section of the research is to conduct a comprehensive review of the existing literature on the use of chest X-ray (CXR) images for diagnosing pneumonia and COVID-19, as well as to gather information on the application of machine learning (ML) and deep learning (DL) for image classification. The image classification process involves three crucial stages: pre-processing, feature extraction, and recognition. In recent literature, researchers have been using DL algorithms to analyze CXR images for Covid-19 identification. These methods involve preprocessing the images and then using CNNs to extract deep and high-quality features, which are then used by a classifier for image classification. DL methods in this context have shown promising results in accurately identifying COVID-19 in CXR images. Different researchers used DL algorithms for covid-19 classification. For instance, Loey et al. [18] introduced a new CNN model that utilizes Bayesian optimization for identifying COVID-19 in CXR images. The model is comprised of two primary steps: first, features are extracted using a CNN, and second, a Bayesian optimizer adjusts the CNN hyper-parameters based on an objective function. The researchers employed an extensive dataset of 10,848 images that included COVID-19, pneumonia, and normal classes. The proposed model achieved a high acc rate of 96% in classifying the images. In addition, Hussain et al. [19] suggested a DL-based method for the classification of COVID-19 using CXR images. They proposed their own classification model and compared its performance with two state-of-the-art DL models, VGG16 and AlexNet. The experimental results showed that the proposed CNN model achieved an accuracy of 95%, while VGG16 and AlexNet achieved 94% and 90%, respectively. Mousavi et al. [20] combined six different datasets and divided them into seven different scenarios, including COVID-19, Bacterial, Healthy, and Viral classes. They trained the CNN-LSTM model to classify all seven scenarios. Their experiments showed more than 90% accuracy for all scenarios. Kogilavani et al. [21] conducted a comparative study between six DL models: NASNet, VGG16, MobileNet, EfficientNet, Xception, and DeseNet121, for the classification of Covid-19. They finetuned all six models and trained them on a dataset of 3,873 CT images, which included both Covid-19 and normal cases. The results of their experiments indicated that VGG16 outperformed the other models, achieving an accuracy of 97.68%. Ravi et al. [22] proposed a DL-based metaclassifier method for the classification of Covid-19 using large-scale CXR and CT image datasets. They extracted features from images using EfficientNet-based pre-trained models and then reduced the dimensionality of the features using PCA. For prediction and classification, two stages are used; in the first stage, the extracted features are fed into the stacked meta classifiers, SVM, and Random forest for prediction and then passed to the second stage, where logistic regression is used for classification. Furthermore, Khan et al. [23] presented a transfer learning-based approach for distinguishing Covid-19 infections from other infections. To enhance their performance and efficiency, they employed and fine-tuned three DL models, namely MobileNetV2, EfficientNetB1, and NasNetMobile. Their method achieved a high accuracy of 96% in classifying COVID-19, lung opacity, pneumonia, and normal classes. Likewise, Luz et al. [24] presented an efficient screening method to classify Covid-19 using transfer learning. EfficientNet models were trained on a CXR images dataset containing four categories: non-Covid-19, healthy, Covid-19, and pneumonia. Results indicate that the highest accuracy of 93.9% was achieved. Guo et al. [49] approach for predicting images uses ensemble learning for ordinal regression, which involves applying different techniques like multi-binary, NSB, and SL to generate predictions. The final result is determined by selecting the median prediction, which yields lower error rates than relying on a single method. In addition, the ensemble approach achieves more precise results than a single model [39], [40], [41], [42], [45], [46], [47], [48]. Bagging is a popular method for creating ensemble-based algorithms. It is a straightforward and practical approach to enhancing performance. It consists of two main steps: first, the training model on the dataset, and then the best models are aggregated by combining the predictions of the various best models. Abdelhamid et al. [25] proposed a transfer learning-based multi-level diagnostic framework for detecting Covid-19 in X-ray images. The framework comprises three stages: pre-processing, feature extraction, and classification. During pre-processing, images are resized, and noise is removed. During feature extraction, features are extracted using a pre-trained Xception model, and the final step is classification. The framework was evaluated using a dataset of over 7,000 images from the Normal, Covid-19, and pneumonia classes and achieved the best performance. Agrawal and Choudhary [26] presented an AI-based method for the classification of Covid-19, while Aftab et al. [27] proposed a DL-based LSTM model for the classification of influenza and Covid-19 using CXR images. In [28], the authors suggested a technique named COVID-Net for identifying patients who were infected with COVID-19 and demonstrated 93.3% accuracy using their own COVIDx dataset. In order to produce a precise diagnosis supported by channel-based attention, a Vision Transformer (VIT)-based method named PneuNet is suggested [29]. This model focuses multi-head attention on channel patches instead of feature patches.

III. METHODOLOGY

This section of the research aims to investigate the proposed framework to classify Covid-19 and Pneumonia employing CXR images. Our method involves a multi-stage approach that includes pre-processing, data augmentation, training, and evaluation. The flowchart of these stages is depicted in Figure 1. In our approach, DL models are adopted for transfer learning and fine-tuning, with hyper-parameters such as the learning rate, batch size, and activation function being optimized. The use of optimizers further helps in modifying the learning rates in neural networks. To achieve improved results, the final stage of our proposed method employs an ensemble of the top three deep learning algorithms. The deep

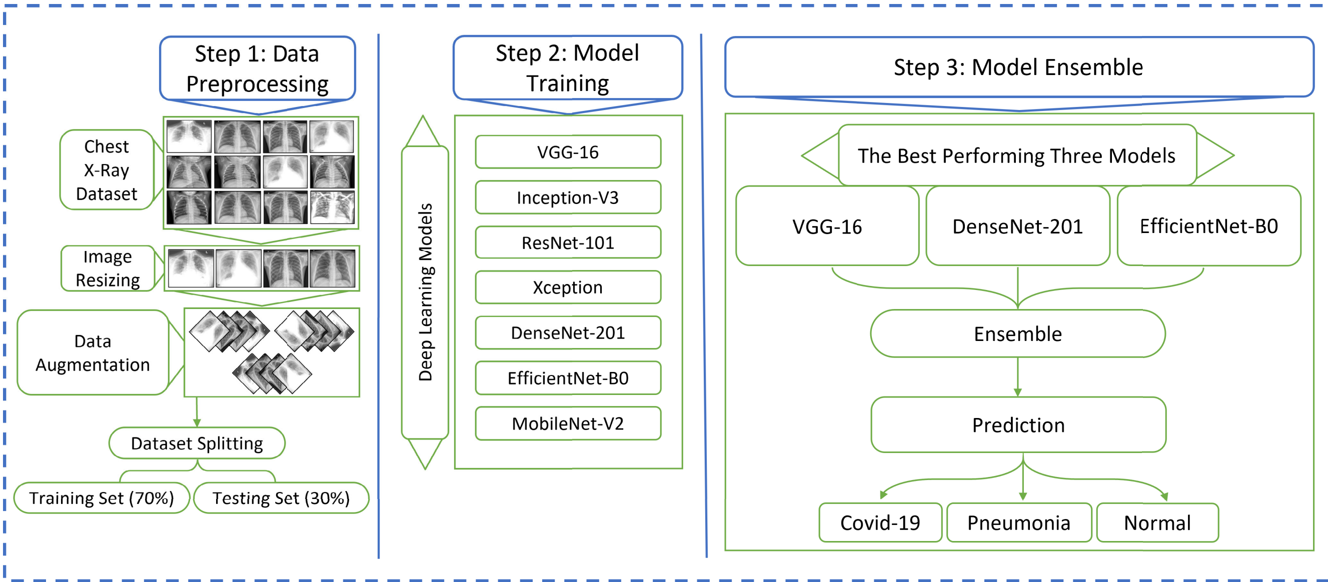

FIGURE 1. The proposed deep ensemble strategy consists of three main stages: i) pre-processing, ii) salient feature extraction, and iii) training and classification. The pre-processing step involves resizing the images to the target input shape. To increase the data samples and improve training accuracy, data augmentation methods were applied. The proposed strategy employs transfer-learning techniques with VGG-16, DenseNet-201, and Efficient-B0 models to extract deep features from the images. These salient features are then utilized by ensemble classifiers to predict the probability of the classes.

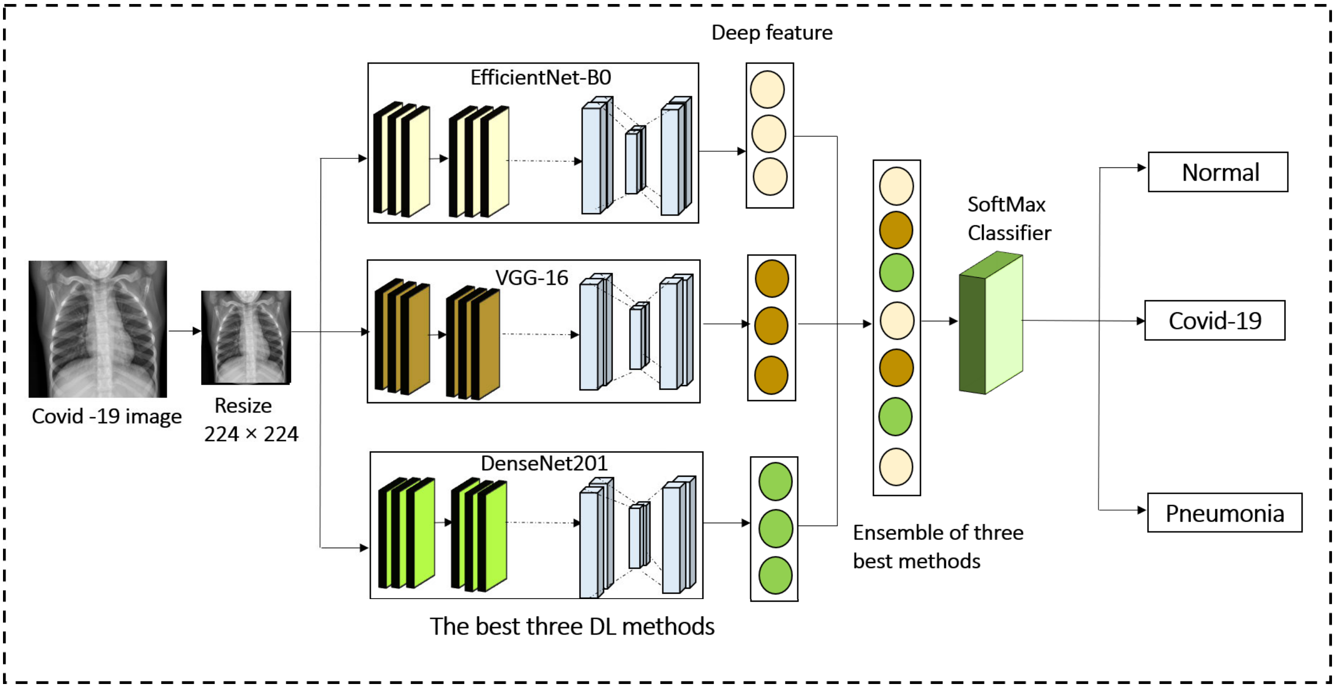

FIGURE 2. The pictorial representation of deep ensemble strategy with the top performing three fine-tuned models.

ensemble strategy combines the predictions of multiple models to generate more robust and accurate results than an individual model.

A. DATA PREPROCESSING

Data preprocessing is a critical component in the application of DL methods. It involves preparing the data for use in DL problems and improving the quality of the input data. This step is crucial for various reasons, including enhancing the model's ability to generalize to new data and reducing the presence of noise and distortions, which can improve the network's performance. In our work, we employed data normalization as a first step, transforming all pixel values to a range of $[-1, 1]$ through multiplication by a factor of 1/255.

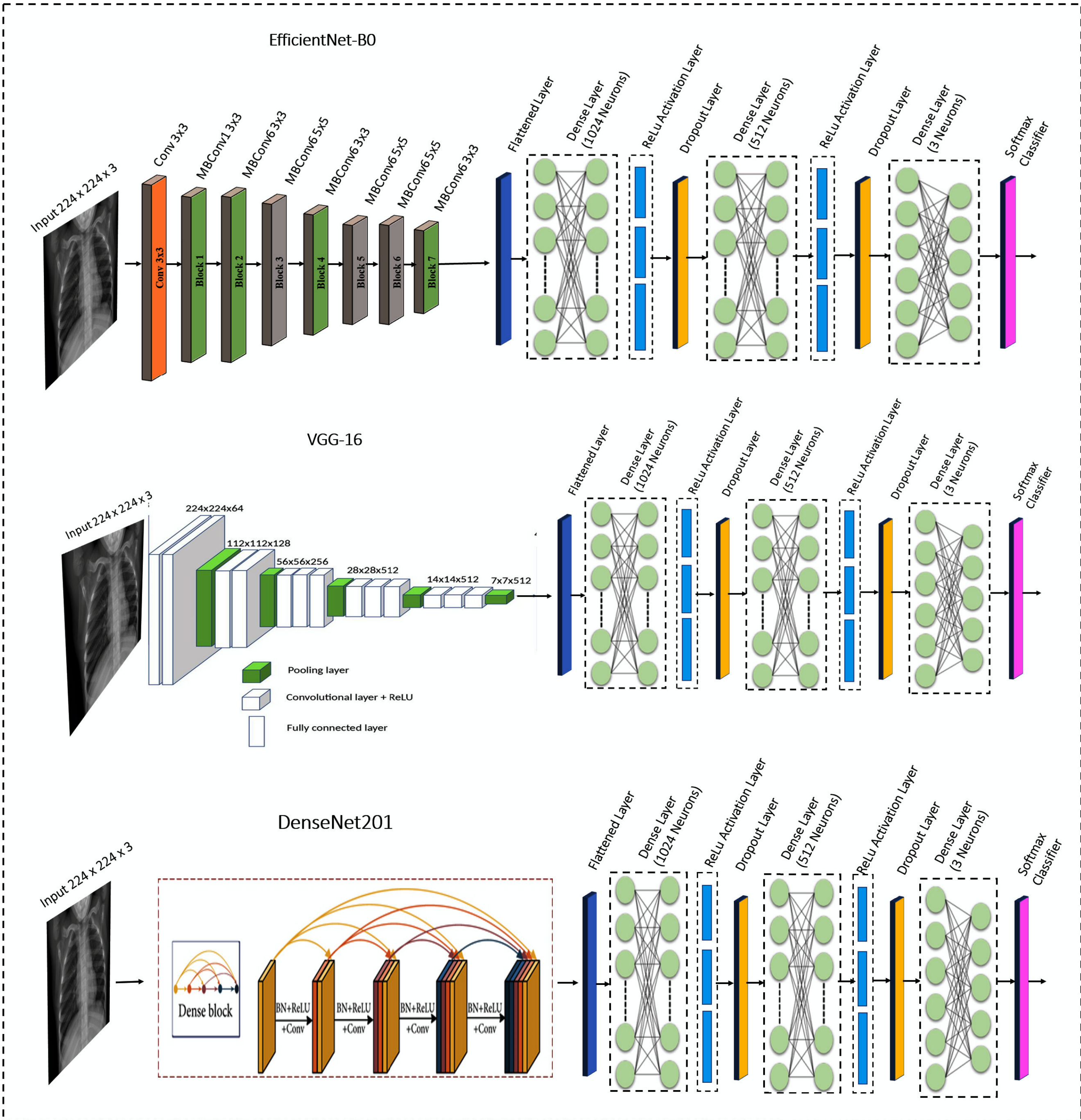

FIGURE 3. **Illustration of the CNN models with proposed layers.**

This is mathematically represented in Equation (1).

$$R_i = \frac{I - I_{min}}{I_{max} - I_{min}} \tag{1}$$

where I represents the original data, $Imax$ represents the maximum, $Imin$ represents the minimum value in the input, and Ri is the normalized data. Before starting the training, images were resized into $224 \times 224 \times 3$ size. Additionally, several data transformations were performed on the input images, including zooming with 0.2, setting the nearest full mode, flipping, and 15° rotation. We employ data augmentation to add variations in the dataset; it helps in the generalization capabilities of the proposed model by minimizing overfitting.

B. DEEP ENSEMBLE STRATEGY

In this research, we adopted a deep ensemble strategy to improve the classification accuracy rate for detecting and classifying Covid-19 and Pneumonia. Typically, the ensemble approach achieves more precise results than a single model. Bagging is a popular method for creating

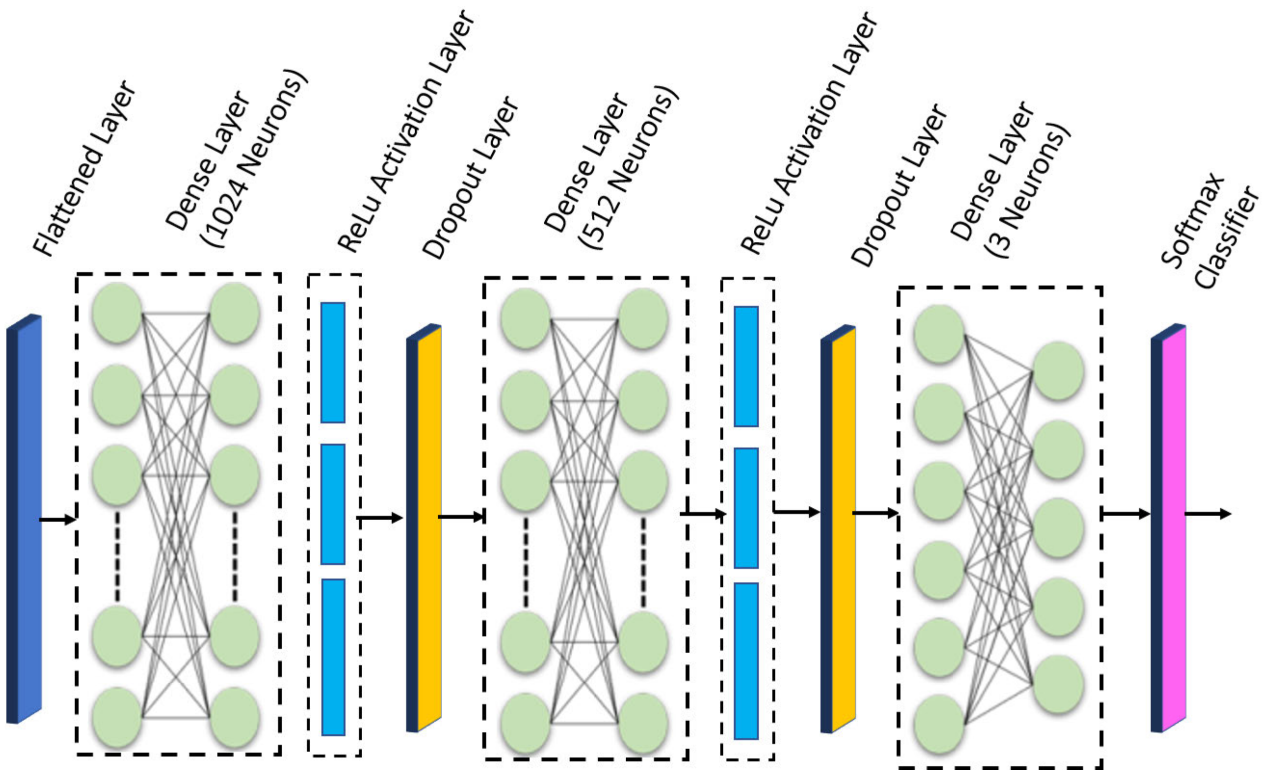

FIGURE 4. Proposed schematic diagram of the fully connected layers.

TABLE 1. Hyper-parameters of the proposed models.

Performance Measures	EfficientNet-B0	VGG-16	DensNet201	Xception	Inception-V3	ResNet101	MobileNet-V2
Image Dimension	$224 \times 224 \times 3$	$224 \times 224 \times 3$	$224 \times 224 \times 3$	$224 \times 224 \times 3$	$224 \times 224 \times 3$	$224 \times 224 \times 3$	$224 \times 224 \times 3$
Optimizer	SGD	SGD	SGD	SGD	SGD	SGD	SGD
Batch Size	32	32	32	32	32	32	32
Loss	CC	CC	CC	CC	CC	CC	CC
Activation Function	Softmax	Softmax	Softmax	Softmax	Softmax	Softmax	Softmax

ensemble-based algorithms. It is a straightforward and practical approach to enhancing performance. It consists of two main steps: first, the training model on the dataset, and then the best models are aggregated by combining the predictions of the various best models. Figure 2 illustrates the ensemble method architecture, combining the EfficientNet-B0, VGG-16, and DenseNet201, the three best DL models considered in this study. The mathematical expression for deep ensemble learning is presented in Eq (2).

$$\mathrm{f(Y)} = \sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{W_k f_i(Y)} \tag{2}$$

where $f(Y)$ is the combined output of all models, Y is the input vector, W_k is the weight assigned to the i^{th} model, n is the total number of algorithms, and $f_i(X)$ is the output of the i^{th} model. The confidence in the model's predictions is determined by standard error predictions, which are expressed as follows:

$$\sigma_e = \left\{ \frac{1}{n-1} \sum_{b=1}^{n} \left[y\left(x_j; W^b\right) - y\left(x_j; \cdot\right) \right]^2 \right\}^{1/2} \tag{3}$$

where $y\left(x_j; .\right) = \sum_{b=1}^{n} y\left(x_j; W^b\right)/n$ is the predicted output for input xj, n is the number of neural networks used, $y(x_j; W^b)$ is the predicted output for input x_j using the b-th neural network, and a smaller σ_e indicates a more reliable model prediction. We improve the performance of our DL models by using transfer learning and freezing certain layers during the fine-tuning process. Images are scaled and enhanced to a resolution of $224 \times 224 \times 3$, which are then used for feature extraction. We used VGG-16 [30],

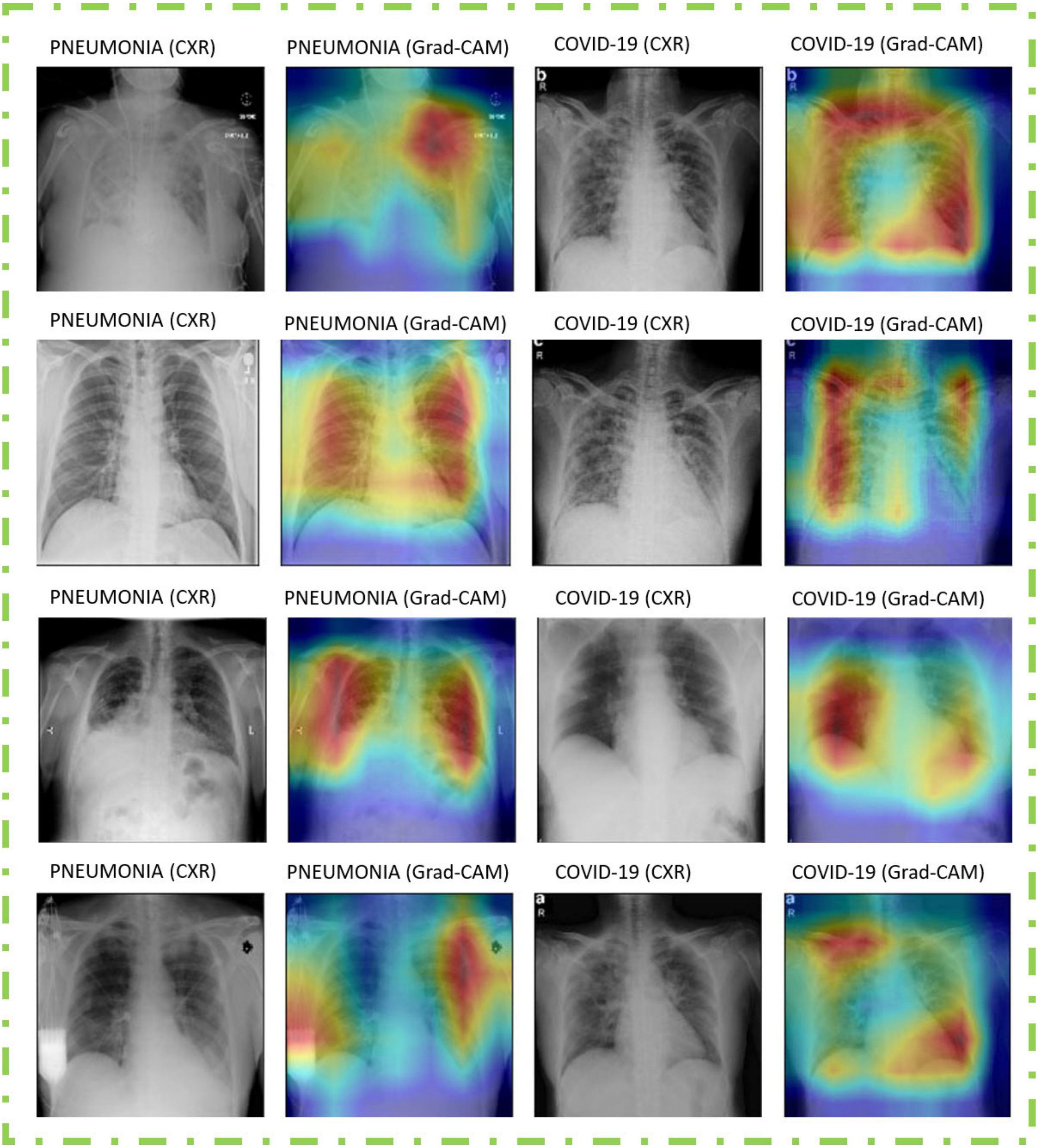

FIGURE 5. Grad-CAM of all three classes.

ResNet101 [31], InceptionV3 [32], MobileNetV2 [33], Xception [34], EfficientNet-B0 [35], and DenseNet201 [36] for our recommended layer. All of these models are fine-tuned, and their final layers are changed. The final layer consists of a flattening layer, three fully connected layers, two dropout layers, and finally, an output layer with a softmax classifier. After passing through the flattened layer, the features are converted into a $1D$ vector and then fed into a dense layer with 1024 and 512 hidden units. Figure 4 illustrated our proposed layers. The activation function used in this layer is ReLu, which is given by:

$$f(x) = max(0, x) \tag{4}$$

Before making a prediction, the dense layer is activated, which maps the output of each neuron to a label using a ReLu function. This approach employs a linear strategy to generate the probability by multiplying weights and biases with each activation map. To avoid overfitting in the hidden layer that contains 1024 neurons, a dropout layer with a 30% dropout rate was used. We employ the softmax classifier as our final classifier [37], which is given by:

$$\sigma(\vec{Z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_i}} \tag{5}$$

The components of the input vector are denoted by $\vec{Z}_i$, the number of classes is denoted by K, and the input vector itself is represented by z_i.

Additionally, DenseNet-201 is a CNN model that consists of 201 layers. All layers in a dense-net architecture are directly connected to one another in a feed-forward manner. Each layer receives data from previous layers and provides feature maps to successive layers. DenseNet has several significant advantages, including enhancing feature propagation, significantly reducing the number of parameters, encouraging feature reuse, and limiting the vanishing gradient problem. Subsequently, EfficientNet-B0 is a series of CNN-family models that are generated by using a composite scaling technique. This series of models has been shown to outperform other DNNs, including Inception-V3, ResNet-152, DenseNet201, and VGG-16, in terms of both speed and size. Specifically, this model is significantly smaller and faster, approximately eight times smaller and six times faster, than the compared models. The resolution of the input image is determined by its width and height, and the depth of a network is determined by the number of convolutional layers. The VGG-16 model is regarded as one of the leading models in computer vision, as noted in [30]. This model has made great progress compared to previous models by incorporating a deep architecture that uses a (3×3) convolutional filter. Figure 3 illustrated the CNN models with proposed layers.

C. FINE TUNING AND TRANSFER LEARNING

This section describes the process of training and fine-tuning our models. Initially, we utilize pre-trained weights from the ImageNet dataset, which includes 14 million images classified into 1000 categories. The Keras library can be utilized to import these weights. Utilizing pre-trained weights from the ImageNet dataset allows for quick utilization of already learned features and improved image recognition capabilities. The ImageNet weights, acquired through training, contain features specific to image classification. The transfer learning method, which utilizes these pre-trained weights, requires less effort and speeds up the process compared to using randomly initialized weights [38]. After that, to fine-tune the model, we froze all the layers of the base model except the end layers and trained them using the Covid-19 images as training data. This approach prevents the initial layers from changing the weights from the Covid-19 dataset during the initial training. This allows to maintain the pre-trained ImageNet weights in the initial layers and improves the training.

TABLE 2. Evaluation of the proposed deep ensemble strategy with contemporary fine-tuned methods.

Models	Precision	Recall	F1-Score
EfficientNet-B0 [35]	96%	95%	96%
VGG-16 [30]	94%	95%	95%
DensNet-201 [36]	95%	95%	95%
Inception-V3 [32]	90%	92%	92%
Xception [34]	89%	90%	90%
MobileNet-V2 [33]	46%	33%	37%
ResNet-101 [31]	35%	33%	34%
Proposed Ensemble Model	**96%**	**95%**	**97%**

Once the final layers have been trained on the Covid-19 dataset, the overall network is unfrozen, and the proposed layers and classifier are combined. Thereafter, the proposed model incorporates weights from both Covid-19 images and the ImageNet dataset, and its accuracy is assessed using test data.

IV. RESULTS AND DISCUSSION

A. DATASET

We acquired our experimental results by employing a large CXR (Chest X-ray) image dataset. We carefully selected a random and balanced collection of images for our study's dataset to ensure accurate outcomes. This CXR image dataset contains a total of 3,777 samples, including 1,259 COVID-19 chest X-ray samples taken from the COVID19 database [43], as well as 1,259 normal and Pneumonia chest X-ray samples obtained from the Pneumonia database [44]. Joseph et al. [43] meticulously selected the COVID19 dataset, using insights from existing research and GitHub resources. The images in this dataset were rigorously evaluated by highly qualified radiologists, with diagnostic conclusions independently validated through a comprehensive assessment that includes clinical history, symptomatology, and laboratory testing. Chest X-rays acquired from children patients aged one to five years at the Guangzhou Women and Children's Healthcare Center comprise the Pneumonia collection. This dataset is published on Kaggle. Each chest X-ray was subjected to a first quality control assessment to exclude illegible or not satisfactory images. Two competent physicians evaluated the chest X-rays for diagnostic purposes. The size of the images varied due to differences in X-ray equipment and image source materials. The dataset producers meticulously assessed the chest X-ray scans and applied appropriate revisions to ensure uniformity and reliability. Figure 6 depicts sample images from this dataset. The dataset is divided into training and testing sets, with 70% allocated for training and 30% for testing, as shown in Table 6.

B. EVALUATION PARAMETERS

In general, various metrics are employed to assess the efficacy of classification models. These metrics encompass recall (rec), precision (pre), F1-score, and classification accuracy (acc). All of these metrics are derived from the four basic outcomes, namely True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

TABLE 3. Comparison of the proposed method with existing methods in terms of computational complexity.

Methods	Parameter Count (in million)	Model Size (MB)	Latency (sec)
EfficientNet-B0 [35]	5.3	29	84
VGG-16 [30]	138.4	528	93
DensNet-201 [36]	20.2	80	92
Inception-V3 [32]	23.9	92	67
Xception [34]	22.9	88	90
MobileNet-V2 [33]	3.5	14	87
ResNet-101 [31]	44.7	171	90
Proposed Ensemble Model	**-**	**175**	**79**

TABLE 4. Comparison of the proposed ensemble method with contemporary techniques in terms of accuracy.

Reference	Dataset	Ensemble Models	Accuracy %
Aversano et al. [39]	CT images	VGG, Xception, and ResNet	95
Chowdhury et al. [40]	X-Ray Images	EfficientNet family	96
Majid et al. [41]	CT Images	ResNet50 and DarkNet53	95.6
Xue et al. [42]	X-Ray Images	VGG-16, ResNet, and DenseNet	95
Tang et al. [45]	X-Ray Images	COVID-NET-M1 to M6	95
Iqball et al. [46]	X-Ray Images	ResNet101, Inception, MobileNetV2, NasNet and Xception	94.6
Mouhafid et al. [47]	COVID-CT dataset	VGG19, ResNet50, and DenseNet201	95
Das et al. [48]	X-Ray Images	DenseNet201, Resnet50V2 and Inceptionv3	91.6
Proposed Ensemble Model	**X-Ray Images**	**DensNet-201, EfficientNet-B0, and VGG-16**	**97**

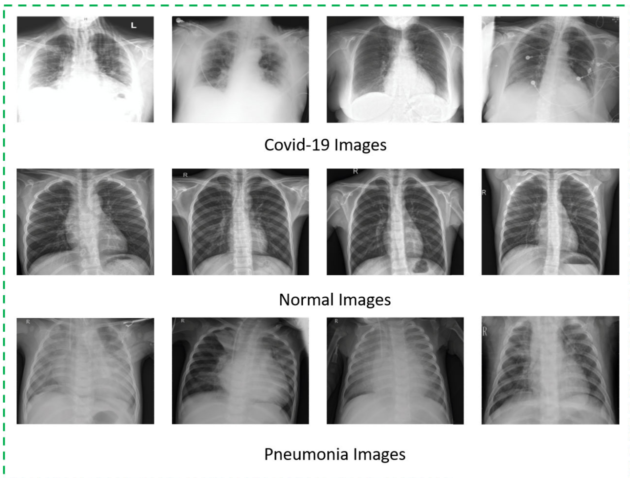

FIGURE 6. Illustration of sample images of the Dataset.

TABLE 5. Comparison of the proposed paradigm with contemporary fine-tuned techniques in terms of accuracy.

Models	Accuracy
EfficientNet-B0 [35]	96%
VGG-16 [30]	95%
DensNet-201 [36]	95%
Inception-V3 [32]	92%
Xception [34]	91%
MobileNet-V2 [33]	38%
ResNet-101 [31]	34%
Proposed Ensemble Model	**97%**

These outcomes provide the basis for computing a range of evaluation parameters. For example, acc represents the ratio of correctly classified data instances to the total number of data instances, rec measures the proportion of positive cases that are correctly predicted, and pre quantifies the acc of positive predictions among all positive patterns. Finally, the F1-score is the harmonic mean of pre and rec. The mathematical formulations for these metrics are presented below:

TABLE 6. The statistical details of the CXR images dataset [43], [50].

Class	No. of Images	Training set	Testing set
Covid-19	1,259	882	377
Pneumonia	1,259	882	377
Normal	1,259	882	377
Total Images	3,777	2,646	1,131

$$\text{pre} = \frac{TP}{TP+FP} \tag{6}$$

$$\text{rec} = \frac{TP}{TP+FN} \tag{7}$$

$$\text{F1-Score} = 2 \times \left(\frac{\text{pre} \times \text{rec}}{\text{pre} + \text{rec}} \right) \tag{8}$$

$$\text{acc} = \frac{TP+TN}{TP+TN+FP+FN} \tag{9}$$

C. SETTING OF HYPER-PARAMETERS AND FINE-TUNING

The different hyper-parameters are used to fine-tune all DL models, shown in Table 1, where $224 \times 224 \times 3$ size images are used with 32 batch size, SGD optimizer, Categorical Crossentropy (CC) as loss function, and finally softmax as an activation function.

D. EXPERIMENTAL SETUP

Experiments are performed by using the 64-bit Windows-10 OS, Python 3.8, with the Keras and TensorFlow frameworks. Implementation is done on a computer with 2.80GHz (dual processors), NVIDIA GeForce GTX 1080 Graphics card GPU, and 24 GB RAM. Table 7 describes the software and hardware specifications used for experiments.

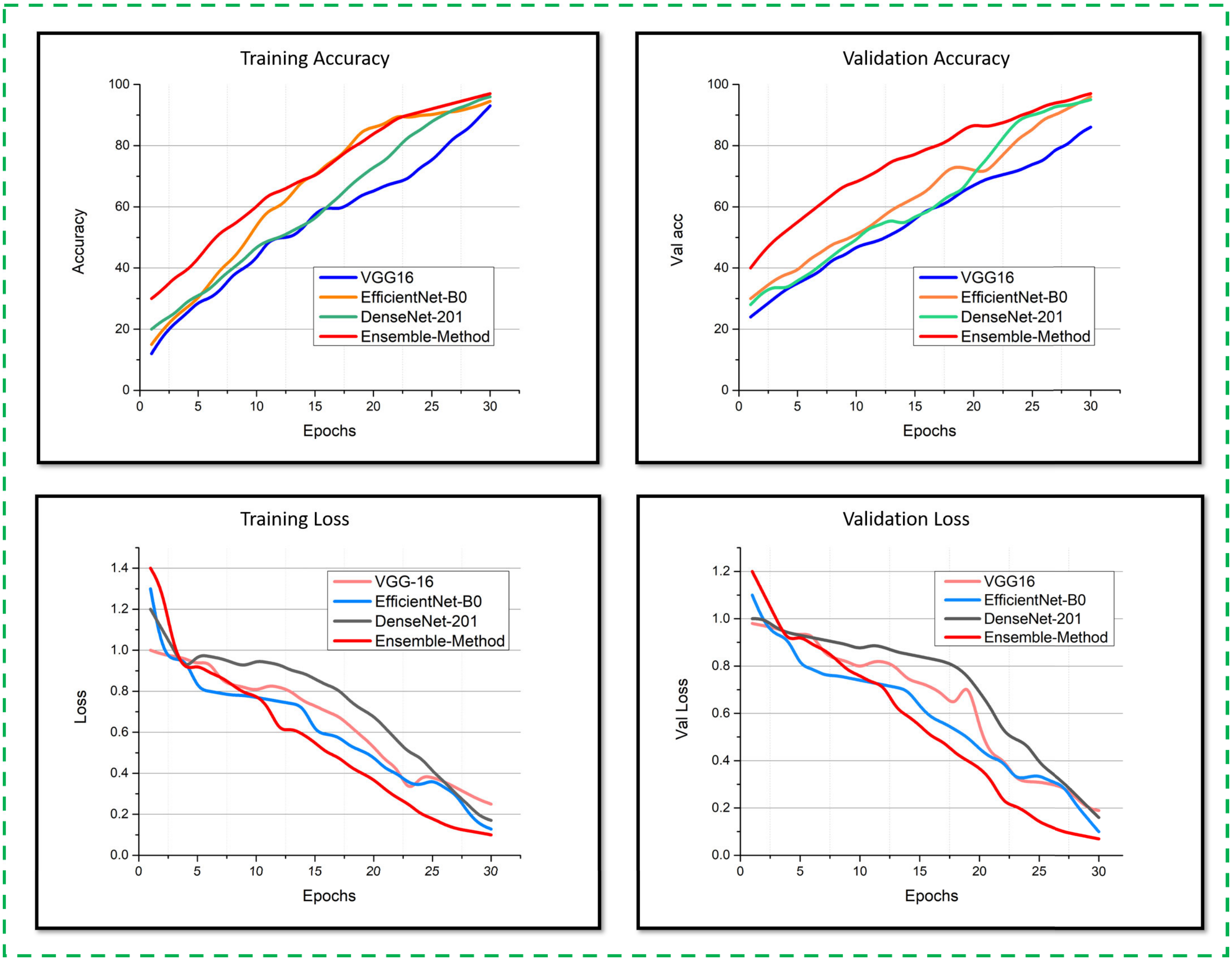

FIGURE 7. A pictorial representation of the ups and downs, depicting the Loss and Accuracy graphs of the proposed deep ensemble strategy and its high-achieving peers, spanning a total of 50 epochs, utilizing the CXR images dataset.

TABLE 7. Hardware & software specification used in the proposed system.

Name	Description
Processor:	2.80GHz (dual processors) and GeForce GTX 1080 NVIDIA card
Development Tool	Windows 10, 64 bit, Python 3.8
Libraries	Keras, TensorFlow, Opencv, NumPy, sklearn, matplotlib, os.
Memory:	24GB

E. EXPERIMENTAL RESULTS

We evaluate the efficiency of the presented technique by using a publicly available dataset. We use the Covid-19 CXR dataset, dividaed into three categories: Covid-19, Pneumonia, and Normal, further divided into 70% and 30% for training and testing, respectively. For model development, we used VGG-16, ResNet101, InceptionV3, EfficientNet-B0, MobileNetV2, Xception, and DenseNet201 with data augmentation and pre-processing techniques. We used SGD as an optimizer with a 0.0001 initial learning rate, which has been widely used in earlier research. This study uses a categorical-cross-entropy loss function for the other hyper-parameter and a mini-batch of size 32 for the other hyper-parameters. To design fine-tuned baseline architectures, we used Keras and TensorFlow APIs simultaneously. The hyper-parameters used in this suggested design show that increasing the number of epochs significantly increases the models' acc. All the models are trained for 30 epochs. Figure 7 illustrates the loss and acc graphs for training and validating the three best DL models used in the proposed system. The graph shows that DensNet201, EfficientNet-B0, and VGG-16 models perform well, surpassing an acc of 90%. The validation acc graph also shows that EfficientNet-B0 has the highest validation acc of 96% and the lowest loss. VGG-16 and DensNet201 also achieved 95% validation acc. These results suggest that EfficientNet-B0, VGG-16, and DensNet201 are the best models for identifying Covid-19 in CXR images. Finally, the proposed research ensemble the DensNet-201,

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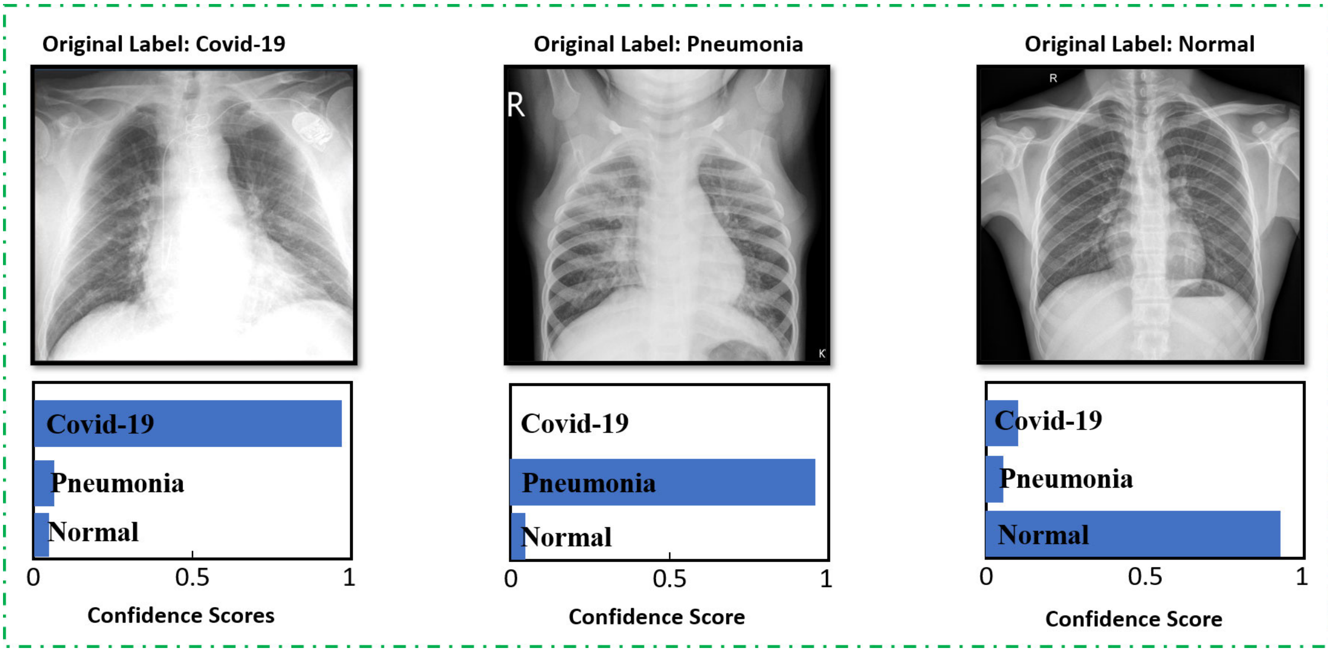

FIGURE 8. Illustration of Visual Results of the presented deep ensemble strategy.

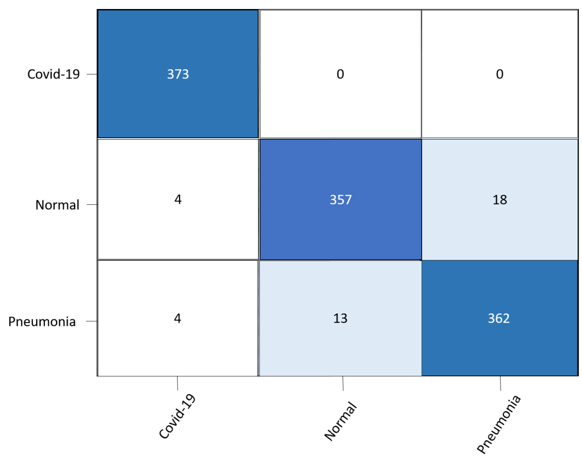

FIGURE 9. Illustrates the confusion matrix of the proposed deep ensemble strategy.

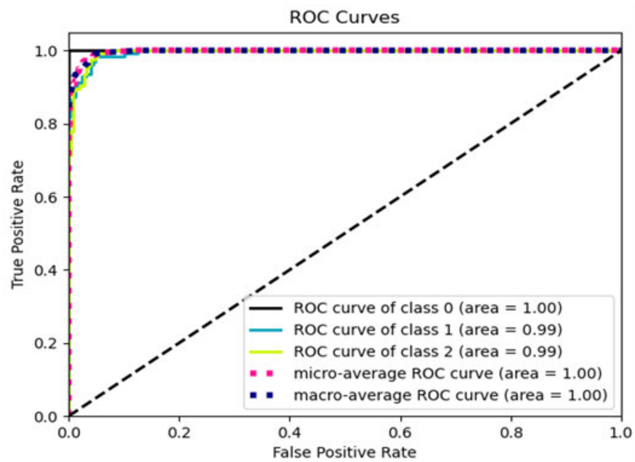

FIGURE 10. ROC-AUC curve of the ensemble model.

EfficientNet-B0, and VGG-16 models. The ensemble method combines the predictions of multiple models to achieve better results than any individual model alone. The results indicate that the ensemble model reached the highest validation acc of 97% with a minimum loss. Table 3 illustrates the comparison of the proposed method with existing methods in terms of computational complexity.

Additionally, We use the confusion matrix technique to evaluate the performance of the proposed ensemble model. Moreover, the suggested ensemble model outperformed all other models, with 97% acc, 96% pre, 95% recall, and 97% F1-score as illustrated in Table 2 and Table 5. The EfficientNet-B0 model also performed well, with an acc of 96%, while 96%, 95%, and 96%, pre, rec, and F1-score, respectively. VGG-16 follows, achieving 95% of acc, while 94%, 95%, and 95%, pre, rec, and F1-score respectively. Next, DensNet-101 achieved 95% acc, 95% pre, 95% rec, and 95% F1-score. The Inception-V3 obtained 92% of acc, while 90%, 92%, and 92% pre, rec, and F1-score respectively. The ResNet-101 and MobileNet-V2 models performed poorly, achieving the lowest performance among all the models. The ResNet-101 model achieved an acc of 34%, while 35%, 33%, and 34% pre, rec, and F1-score, respectively. The MobileNet-V2 model achieved an acc of 38%, while 46%, 33%, and 37%, pre, rec, and F1-score, respectively. These results suggest that these models are less effective in identifying Covid-19 in chest X-ray images than the proposed ensemble model. Table 4 compares the proposed method with contemporary ensemble methods to show its efficiency. Figure 10 and Figure 9 present the confusion matrix and the ROC-AUC curve of the proposed ensemble architecture, respectively. These figures further demonstrate the ensemble model's high performance in diagnosing Covid-19 in chest X-ray images.

The visual result of the suggested ensemble method is illustrated in Figure 8, where images of all three classes are used for prediction. The actual and predicted labels are shown at the top and bottom of each image, respectively, along with the model confidence scores for each class.

V. CONCLUSION AND FUTURE DIRECTION

Due to Covid-19, all humans are currently facing new challenges in their daily lives. This virus continues to infect a large number of people rapidly. This work presents an efficient and effective architecture based on an ensemble technique for classifying Covid-19 and pneumonia employing CXR images. The ensemble model is based on DenseNet-201, EfficientNet-B0, and VGG16 models, achieving the highest validation acc of 97%. This study employs seven transfer learning models and architectures to detect Covid-19 and Pneumonia disease. Although our method produces state-of-the-art results, this study only partially solves the problem statement. In the future, we intend to create highly sophisticated CNN algorithms for detecting Covid-19 and Pneumonia diseases, including improving segmentation [51] and expanding the dataset images. This CNN will be applied to multiple X-ray images for Covid-19 identification, Pneumonia detection, and Normal class detection, providing the foundation for future research. The final goal is to develop a procedure that correctly detects and classifies Covid-19 and Pneumonia, leading to more effective treatments and prolonged survival.

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