INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

RESEARCH ARTICLE

Check for updates

OPEN ACCESS

Received: 13-12-2023

Accepted: 22-01-2024

Published: 14-02-2024

Deep Ensemble Learning Model for Diagnosis of Lung Diseases from Chest X -Ray Images

Mamta Patel[1]*, **Mehul Shah**[2]

1 Research Scholar, Instrumentation and Control Engineering, Gujarat Technological University, Gujarat, India

2 Associate Professor, Instrumentation and Control Engineering, Vishwakarma Government Engineering College, Gujarat, India

Citation: Patel M, Shah M (2024) Deep Ensemble Learning Model for Diagnosis of Lung Diseases from Chest X -Ray Images . Indian Journal of Science and Technology 17(8): 702-712. https://doi.org/10.17485/IJST/v17i8.3151

* **Corresponding author**.

mamtavp@vgecg.ac.in

Funding: None

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

Abstract

Objectives: This study aims to develop a robust medical recognition system using deep learning for the identification of various lung diseases, including COVID-19, pneumonia, lung opacity, and normal states, from chest X-ray images. The focus is on implementing ensemble fixed features learning methods to enhance diagnostic capabilities, contributing to the development of a cost-effective and reliable diagnostic tool for combating the global epidemic of lung disorders. **Methods:** The study utilizes a Kaggle dataset containing COVID-19 chest radiography images. Raw X-ray images undergo preprocessing for contrast enhancement and noise removal while addressing dataset imbalance through near-miss resampling. Ensemble learning techniques, including two and three-level methods, are employed to harness the strengths of individual base learners—VGG16, InceptionV3, and MobileNetV2. The model's performance is evaluated using metrics such as accuracy, recall, precision, and F1-score. For remote access, a user interface and a shared web link are developed using Python Gradio. **Findings:** In two-level ensembles, features from base learners are concatenated and classified using a support vector machine. Three-level ensembles use concatenated features classified by three machine learning classifiers, employing a majority voting system for the final prediction. The two-level method achieved 93% accuracy, precision, recall, and F1 score. The three-level ensemble model demonstrates superior performance, achieving 94% accuracy in detecting four lung diseases, namely COVID-19, pneumonia, lung opacity, and normal states. **Novelty:** This research contributes to the field by showcasing the efficacy of deep learning technology, particularly ensemble learning, in enhancing the detection of lung diseases from raw chest X-ray images. The model employs three modified and efficient pretrained networks for automatic feature extraction, eliminating the need for manual feature engineering. The developed model stands as a promising decision-support tool for healthcare professionals, particularly in low-resource environments.

Keywords: Convolutional Neural Network (CNN); Deep Learning (DL); Transfer Learning (TL); Ensemble learning (EL); Fixed feature extraction; Chest Xrays (CXR); Lung diseases

1 Introduction

Lung diseases include pneumonia, tuberculosis, lung opacity, and COVID-19 are a worldwide health issue. COVID-19 has increased the urgency of respiratory illnesses, according to the WHO in 2020 [1]. Traditional methods for identifying lung diseases include skin tests, blood tests, sputum sample analysis, chest X-rays, and computed tomography (CT) scans. Radiologists and doctors use X-ray and CT images to diagnose lung diseases. X-rays are popular in radiology because they are non-invasive, cost-effective, distant, and portable [2]. Due to interclass similarities, lung disease interpretation is difficult despite medical imaging advances, requiring more computer-aided systems (CAD).

Recent advances in GPU technology and deep learning, have greatly improved CAD system performance. Machine learning algorithms such as support vector machines (SVM), K-nearest neighbors (KNNs), and decision trees (DT) have contributed to disease prognosis, their performance heavily depends on feature extraction [3]. Deep learning techniques, especially, notably Convolutional Neural Network (CNN), have gained popularity in medical imaging to address these limitations [4,5]. However, the categorization of multiclass lung diseases remains a challenging task.

Several research articles have focused on binary classification of lung diseases using DL. Recent studies by various researchers have made significant strides in multiclass lung disorder detection using chest X-rays. Ozturk et al. [6] demonstrated the success of their 17-layer Darknet model in accurately identifying COVID-19 in both binary and multi-class classification tasks. The lightweight DCNN model designed by Sultana et al. [7] for the identification of lung diseases outperformed other pretrained CNN architectures. Hussain's work [8] introduced the CoroDet CNN model, emphasizing the importance of activation functions and various network layers in detecting lung diseases from X-ray and CT scan images. Furthermore, Ucar et al.'s [9] COVIDiagnosis-Net addressed class imbalance issues in classifying chest X-ray images into Covid, Pneumonia, and Normal categories; the researchers incorporated offline augmentation techniques to enhance the model's performance. ChestX-ray6 [10], despite its lightweight architecture, demonstrated impressive accuracy in detecting pneumonia, COVID-19, and other diseases. Goram et al. [11] proposed a model using VGG19 followed by CNN layers from scratch to classify six different diseases from chest X-rays. The study presented by AI, Sheikh [12], introduced a novel image enhancement algorithm using the k-symbol Lerch transcendent functions model in the pre-processing phase to enhance images based on pixel probability and classification, a customized CNN architecture and two pre-trained CNN models (AlexNet and VGG16Net) were employed. D3SENET [13], a hybrid feature extraction network combining multiple architectures and employing traditional machine learning methods for classification, including SVMs. Farhan et al. [14] proposed a hybrid network for lung diseases classification, in which 2D CNN network was designed to extract features from X-ray images, and the features were optimized using min-max scaling and classified using various ML algorithms.

Despite the promise shown by CAD systems, multiclass lung disease categorization using chest X-ray images faces obstacles, particularly in improving image quality and addressing data balancing. Most studies in this domain have focused on individual pretrained architectures or CNN models developed from scratch, with a notable lack of exploration into combining these models to enhance detection capabilities. The existence of interclass similarities and the relatively underexplored nature of multiclass lung disease classification highlight the need for further advancement in this area.

We propose an effective deep ensemble learning-based multiclass classification method for COVID-19, pneumonia, lung opacity, and normal lung diseases to address these problems.

1.1 Contributions of the Research:

1. Development of an efficient DL model capable of accurately classifying various lung diseases using X-ray images.
2. Implementation of data preprocessing techniques to enhance image quality and reduce noise in raw images.
3. Utilization of resampling techniques to address the issue of an unbalanced dataset
4. Creation of a trained model through an ensemble of pretrained CNNs for feature extraction, with the incorporation of a majority voting system to generate the final classification score based on the outputs of different machine learning classifiers.
5. Enhancement of the accuracy of pretrained DL models through the incorporation of additional layers

2 Methodology

The proposed methodology for the multi-class classification of lung diseases using chest X-ray images is shown in Figure 1. It comprises several stages, including data acquisition, image pre-processing (involving image resizing, normalization, enhancement, and noise removal), data resampling, feature extraction, and classification. For feature extraction, we employed fine-tuned pre-trained models, such as VGG16, MobileNetV2, and InceptionV3. The resulting feature vectors were concatenated and then used in an ML classifier model (SVM, RFt, KNN, DT) to determine the final classification score through a majority voting system. Performance parameters of the trained model were measured.

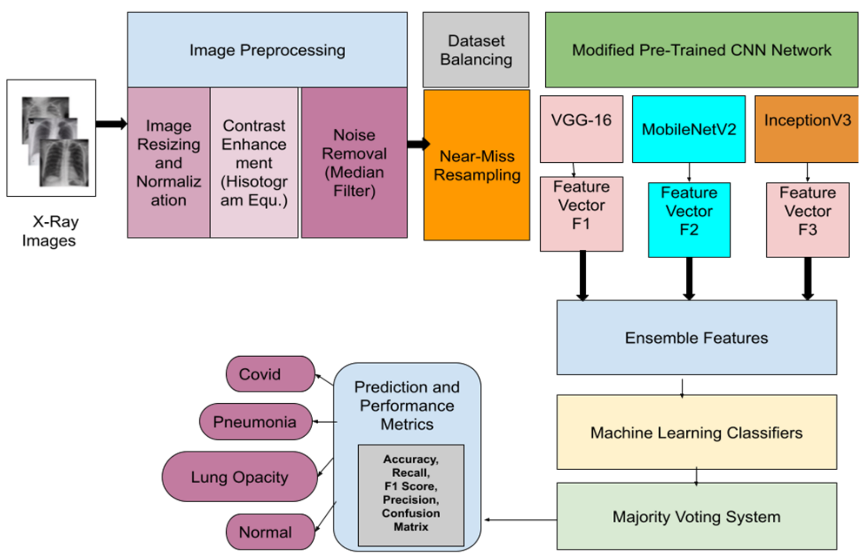


Fig 1. Proposed Methodology for lung diseases prediction using Chest X-rays

2.1 Dataset

The chest X-ray datasets utilized in this research were sourced from the COVID-19 Radiography Database, which received the COVID-19 Dataset Award from the Kaggle Community. These datasets are freely accessible on Kaggle and can be downloaded using the link[15]. The database is continually updated with contributions from researchers across different regions. The dataset comprises a total of 18,953 images distributed across four different classes: COVID-19, Lung Opacity, Normal, and Viral Pneumonia, with respective counts of 3616, 6012, 7980, and 1345. The distribution of these images is unbalanced, and they exhibit noise as well as a distinct difference in contrast.

2.2 Image Quality Enhancement

The proposed model undergoes preprocessing on input chest X-ray images, including image resizing, histogram equalization, and median filtering. To standardize image sizes due to variations, resizing is performed to achieve dimensions of 224x224x3, consistent with the input requirements of pretrained networks. Histogram equalization is employed to enhance image intensity. Noise is introduced during the X-ray scanning process when adjusting image intensity. As indicated in a study[16], median filtering exhibits superior efficiency in enhancing X-ray datasets compared to techniques like adaptive bilateral filtering, average filtering, and Wiener filtering. In this model, a 2D median filtering technique is utilized, processing pixels individually. This technique entails substituting each pixel's value with the median value of its neighboring pixels, determined by a specified window size. In this design, a window size representing a 5 x 5 neighborhood is employed. The resulting output after median filtering is defined by the following equation:

$$I2(i,\ j)\ =\ median\, I1(i,\ j)(i,\ j)\, w$$

Where I2 is the output of the median filtering, and w is the window size. Figure 2 illustrates the effect of image quality enhancement after applying histogram equalization and median filtering techniques.

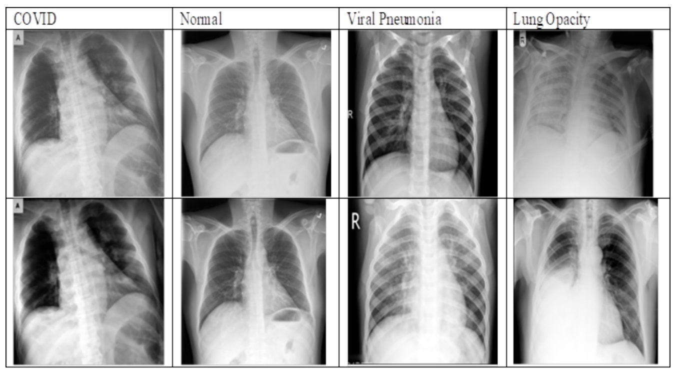


Fig 2. Original images and pre-processed images of various class

The issue of class imbalance in medical image classification poses a challenge, leading to bias that favors the majority class and compromises classifier accuracy. To tackle this problem, the Near-Miss under-sampling technique is utilized, selectively eliminating samples from the majority class while retaining essential learning-related data. This approach alleviates bias by identifying samples based on their shortest average distance to their K nearest neighbors.

2.3 Feature extraction for classification

The key step in developing any classification application is identifying the optimal deep learning (DL) architecture for the dataset. In this study, the potency of DNN is harnessed to derive feature vectors for the classification of diseases from CXR images. The principal aim of this investigation is to acquire features from CXR images through the application of transfer learning. Subsequently, these features are employed in the classification process using traditional machine learning classifiers.

Transfer learning, essentially, leverages the capabilities of a neural network previously trained on extensive and diverse datasets to extract meaningful information for application in other tasks. There are three fundamental strategies of transfer learning:

1. Transfer learning
2. TL with tuning
3. Fixed feature extraction

Transfer learning strategies are shown in Figure 3.

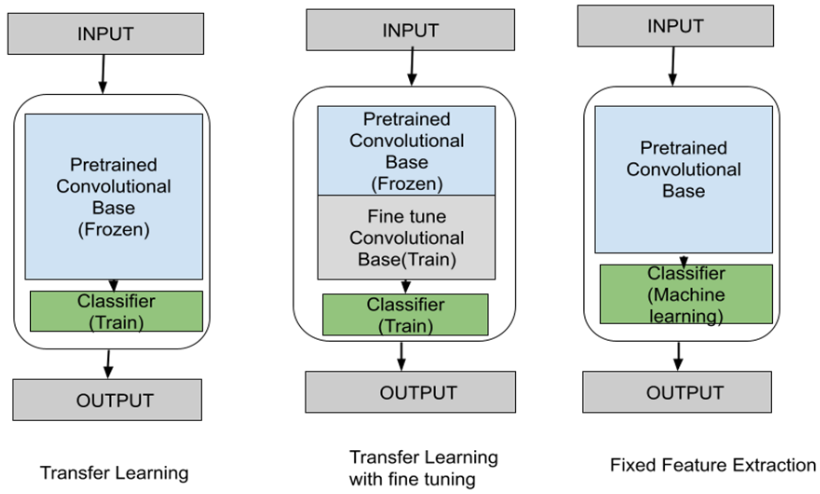


Fig 3. Transfer learning strategies

Below is a brief explanation of the TL, TL with fine-tuning, and fixed feature extraction techniques.

2.3.1 Transfer Learning

It enables an existing neural network to adjust to new datasets or domains. This entails retraining solely the fully connected (classification) layer, preserving the pre-trained model's convolutional base. The architecture is then configured to accommodate the specific application's class requirements, offering efficiency in adapting to novel datasets.

2.3.2 Transfer learning with a fine-tuning

In deep learning models, higher-level layers capture problem-specific features, while lower-level layers encode more general features. To enhance the performance of pre-trained networks on new datasets, the process involves unfreezing the entire pre-trained model or part of it and retraining.

2.3.3 Fixed feature extraction

This approach begins with a model pre-trained on a standard dataset, like ImageNet. The classification part of the model is discarded, leaving only the feature extraction layers. These layers function as a feature extractor, and machine learning classifiers are employed for subsequent classification tasks.

The most widely employed pre-trained CNN architectures in the field include ResNet, VGG, Inception, AlexNet, and, MobileNet, among others. In our experiment, three prominent architectures were utilized: VGG-16, InceptionV3, and MobileNetV2.

VGG: VGGNet, notably VGG-16 and VGG-19, outperforms AlexNet by using cascaded 3x3 kernel-sized filters for improved performance.

MobileNet: MobileNet, available in versions like MobileNetV1, V2, and V3, is optimized for mobile devices. Introduced by Szegedy et al. (2014), its lightweight architecture, featuring depth-separable convolutional layers and bottleneck modules, provides an efficient solution for deploying deep learning models on smart devices.

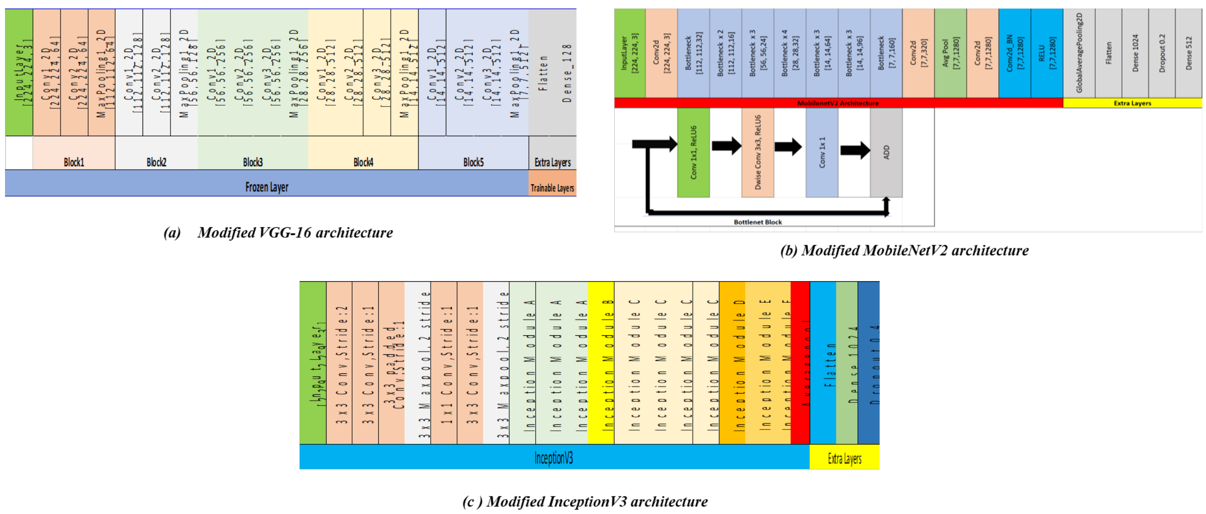
Inception: The Inception family encompasses various iterations such as InceptionV1 (GoogLeNet), InceptionV2, InceptionV3, InceptionV4, and InceptionResNet. The key feature of the inception block is its unique approach, applying multiple filter sizes simultaneously to the input image instead of merely increasing the depth with additional layers. Outputs from each inception block are concatenated and passed to the next, facilitating parallel processing of diverse receptive field sizes within a single layer. This design significantly boosts the network's ability to capture a wide range of features.

2.4 Ensemble of Learning

It is a technique that involves combining multiple models to create a more robust and accurate predictive model. This approach often achieves better performance than any individual model [17]. In our experiments, we employed two different ensemble learning approaches.

2.4.1 First Approach - Two-Level Ensemble Method

Pretrained CNN networks, namely VGG-16, InceptionV3, and MobileNetV2, exhibited superior performance on the COVID-19 classification dataset in terms of accuracy [18]. To customize them for the specific task, modifications are introduced to the architectures. Figure 4 illustrates the proposed adjustments to VGG-16, Inception-V3, and MobileNetV2, incorporating additional layers and removing the classification layer. These modifications were implemented to enhance the models' performance in the targeted lung disease classification task.



(a) Modified VGG-16 architecture

(b) Modified MobileNetV2 architecture

(c) Modified InceptionV3 architecture

Fig 4. Modified VGG-16, MobileNetV2 and InceptionV3 architecture

The proposed modified architectures are employed to extract features from the processed chest X-ray image dataset, with all layers frozen using ImageNet weights. Each model produces feature vectors: F1, F2, and F3, respectively. These feature vectors are subsequently combined and inputted into the ML classifier for the assessment of the classification scoreIn this study, the selected machine learning classifier is SVM. It is chosen for its effectiveness, especially with relatively small to moderately-sized datasets, and its capability to handle both linear and non-linear separations. The two-level ensemble method is depicted in Figure 5.

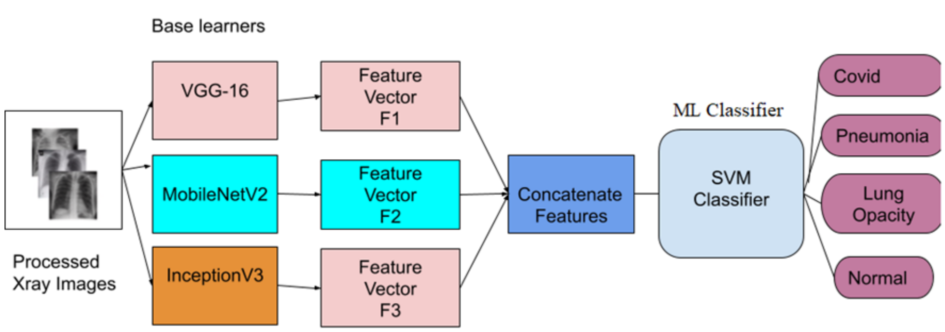


Fig 5. Two Level Ensemble Method

2.4.2 Second Approach - Three-Level Ensemble Method

In contrast to the first approach, which trained three base learners and concatenated their extracted features into a single vector, the second method employs four distinct classifiers: SVM DT, RF, and KNN. Instead of relying on a single classifier, a maximum voting system is employed to make predictions for the classification category, minimizing misclassification rates. The figure illustrates the majority voting system integrated into the ensemble machine classifier model for predicting lung diseases. This approach leverages the collective decisions of multiple classifiers to enhance the accuracy and reliability of the classification results. The three-level ensemble method is depicted in Figure 6.

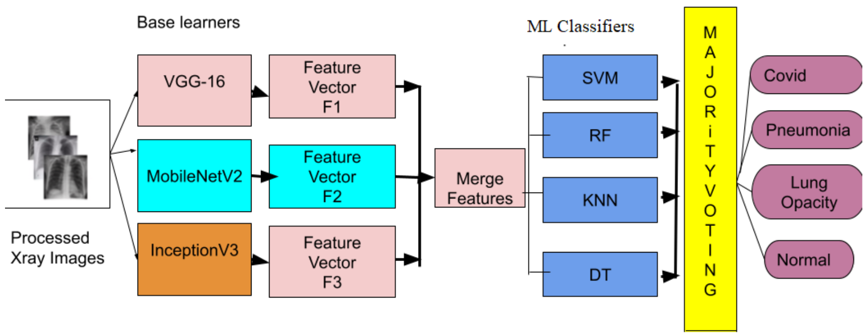


Fig 6. Three level Ensemble Method

2.5 Measurement of Performance Metrics

The model's performance is evaluated through the generation of a confusion matrix. A confusion matrix is a tabular representation summarizing the classifier's performance, involving four fundamental terms: False Positives (FP), False Negatives (FN), True Positives (TP), and True Negatives (TN). By utilizing this confusion matrix, various performance metrics such as accuracy, precision, recall (sensitivity), the F1 score, and others are calculated to comprehensively evaluate the classifier model.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$$
$$Precision = \frac{TP}{TP+FP}$$
$$Recall = \frac{TP}{TP+FN}$$
$$F1\ Score = 2 * \frac{Precision*Recall}{Precision+Recall}$$

2.6 User Interface

The proposed model features a user interface built with Python Gradio. This interface enables users to interact with the machine learning model through a web browser, enhancing accessibility and shareability. As a result, users can conveniently access the model remotely to conduct lung disease classification from chest X-ray images.

3 Results and Discussion

As mentioned earlier, the chest X-ray dataset comprising four classes was obtained from Kaggle. The experiments were conducted on a machine equipped with a 2.70GHz Intel(R) Core(TM) i7-6820HQ CPU, utilizing the TensorFlow/Keras Python framework. Many contemporary techniques apply deep learning models directly without addressing image quality enhancement, leading to inaccurate outcomes. Table 1 presents the training and validation accuracy of CNN models, such as CNN from scratch, ResNet50, VGG16, InceptionV3, and MobileNetV2, on our dataset without any image quality enhancement or data balancing. The results reveal a noteworthy gap between training and validation accuracy, highlighting the challenges these networks face when dealing with low-quality input data. Table 1 provides training and validation accuracy for various pretrained networks without any preprocessing.

Data preparation is a crucial step in DL, involving preprocessing the dataset to eliminate noise, adjust contrast, and resize images. To address the challenge of class imbalance and mitigate bias during model training, data resampling was performed. The dataset was then divided into two subsets with a 70:30 ratio, forming a training set and a validation set. Various strategies were employed to evaluate the DL model's performance.

Table 1. Training accuracy and validation accuracy of various pretrained network without any processing

Network Architecture	Training Accuracy	Validation Accuracy
CNN from scratch (6 Layers)	0.42	042
ResNet50	0.60	0.32
MobileNetV2	0.81	0.78
InceptionV3	0.82	0.77
VGG-16	0.87	0.76

As indicated in Table 1, VGG-16, MobileNetV2, and InceptionV3 architectures demonstrated better performance compared to other pretrained models on the dataset. These models operated independently as feature extractors, and the extracted features were subsequently classified using a single ML classifier. In this proposed method, the performance of SVM and RF classifiers was compared, utilizing 42 decision trees and a random state value of 32 of RF. Table 2 represent the performance matrix of various pretrained architecture.

Table 2. Comparison of performance metrics of modified pretrained Network + ML Classifier

Modified pretrained Network	ML Classifier	Accuracy	Precision	Recall	F1 Score	Feature extraction Time (In minutes)
VGG-16	RF	0.78	0.78	0.78	0.78	13.18
VGG-16	SVM	0.87	0.93	0.93	0.93	
InceptionV3	RF	0.75	0.76	0.75	0.76	17.63
InceptionV3	SVM	0.86	0.86	0.86	0.86	
MobileNetV2	RF	0.85	0.85	0.85	0.85	1.96
MobileNetV2	SVM	0.92	0.92	0.92	0.92	

As presented in Table 2, the SVM classifier consistently outperforms the RF classifier across all pretrained architectures. Moreover, MobileNetV2 demonstrates faster feature extraction times compared to VGG-16 and InceptionV3, likely owing to its lighter architecture. Notably, the combined use of the modified MobileNetV2 pretrained architecture with the SVM classifier achieves the best performance among the evaluated architectures for the dataset.

In the first approach, an ensemble is created by merging feature vectors extracted from pretrained VGG-16, InceptionV3, and MobileNetV2 models. These concatenated features were employed with an SVM classifier for prediction, yielding noteworthy performance measures. The accuracy score, precision, recall, and F1 score all achieved 0.93. In classification problems, accuracy is a crucial metric, reflecting the alignment of estimated values with the original values in the classification process. The outcomes indicate that the 2-level ensemble approach enhances accuracy from 0.92 to 0.93, underscoring its effectiveness.

In the second approach, feature vectors were generated by combining pretrained networks VGG-16, InceptionV3, and MobileNetV2. Prediction was carried out using various machine learning classifiers such as SVM, RF, DT, and KNN, followed by majority voting for the final prediction. Table 3 presents the performance measures for the two- and three-level ensemble approach.

Table 3. Performance measures of two and three level ensemble method

Approach	Base Learner	ML Classifier(s)	Accuracy	Precision	Recall	F1 Score
First approach (2 Level ensemble)	VGG16+InceptionV3+MobileNetV2	SVM	0.93	0.93	0.93	0.93
Second Approach (3 Level Ensemble)	VGG16+InceptionV3+ MobileNetV2	SVM+RF+DT+KNN(Majority Voting System)	0.94	0.94	0.94	0.94

Three level ensemble approaches the performance measures improved from 0.93 to 0.94. The confusion matrices for two approaches are presented in Figure 7.

To enable remote access to the model for classification, a shared web link and user interface was developed using Python Gradio. Figure 8 showcases the predicted result within the user interface. This user-friendly interface allows users to interact with the model through a web browser, making it accessible and convenient for remote classification of lung diseases from chest

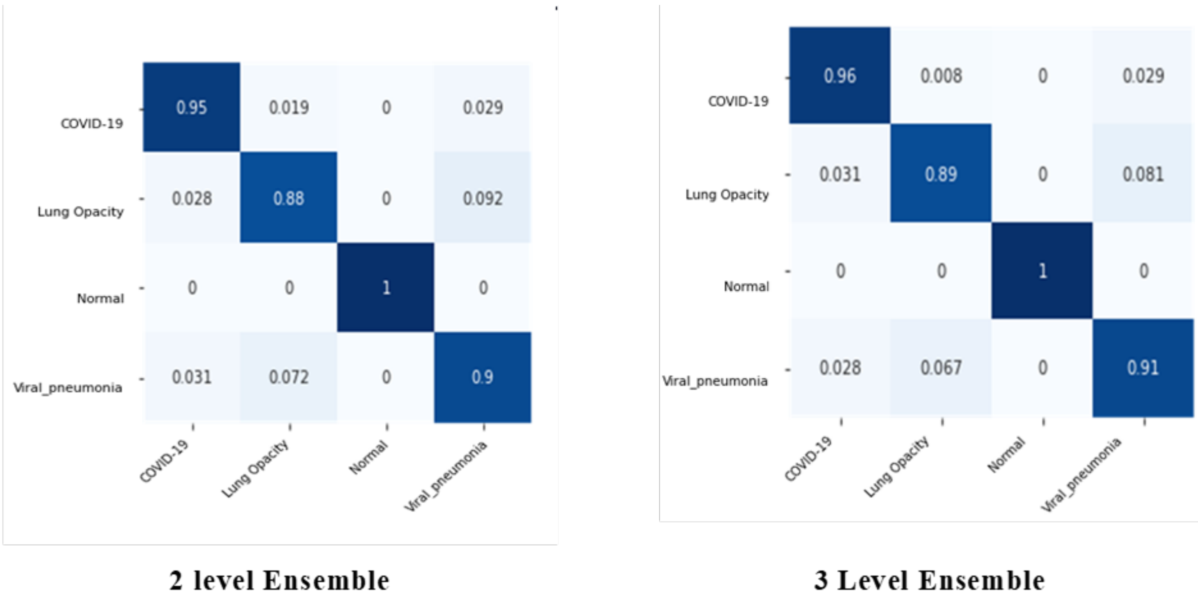


Fig 7. Confusion Matrix for 2 level and 3 level ensemble method

X-ray images.

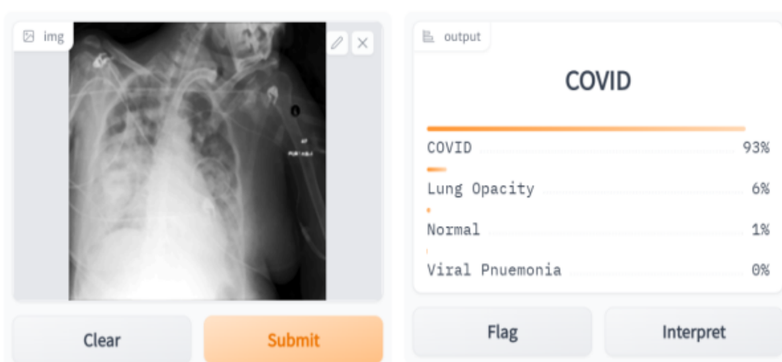


Fig 8. User Interface for Lung Diseases Classification

3.1 Comparison with State-of-the-Art Methods

We conducted a performance comparison of the proposed ensemble method against existing methods. In summary, Table 4 presents a compilation of studies utilizing CNN models, showcasing encouraging outcomes. However, these investigations employ a variety of CNN architectures, training datasets, the number of classes, and design parameters. Consequently, a direct comparison between these studies would be unjust. It is widely recognized that models trained with limited training data often yield subpar approximations, whereas models trained with fewer classification categories tend to perform better.

Table 4. Comparison of proposed work with other related research work

Continued on next page

Table 4 continued

References	No of Classes	Architecture	Accuracy
(19)	4 (Covid-19, Viral Pneumonia, Bacterial Pneumonia, Normal)	Xcepion	89 %
(20)	3 (Normal, Covid-19, SARS)	DeTraC	93 %
(21)	4 (normal, pneumonia, and pneumothorax, normal, pneumonia, and pneumothorax)	EfficientnetV2	82 %
(22)	3 (Covid-19, Viral and Bacterial Pneumonia)	MobileNetv2 fine tuned	92 %
(23)	4, (normal, viral, bacterial pneumonia and COVID-19)	Ensemble of ResNet50 with MobileNet_V2 with InceptionResNet_V2	94 %
Proposed	4, normal, viral pneumonia, lung opacity and COVID-19	Ensemble of VGG16, Inceptinv3 and MobilenetV2 with fixed feature extraction and ML Classifiers	94 %

4 Conclusion

The proposed convolutional deep learning-based technique utilizes an ensemble fixed feature extraction approach for classifying various lung disorders from chest X-ray images. This fully automated and end-to-end model eliminates the need for manual feature extraction. In the multiclass classification of COVID, viral pneumonia, normal, and lung opacity, the ensemble model achieves a classification accuracy of 94%. The user-friendly interface further enhances convenience for remote classification. In the future, this study may involve expanding the database to include more classes for classifying other lung disorders. Additionally, we may incorporate X-ray images with additional metadata, such as age, gender, region, smoking habits, and other physical symptoms, for training. Furthermore, testing the proposed models in clinical practice and consulting with medical professionals would validate their practical use in diagnosing lung diseases.

5 Acknowledgement

The authors would like to acknowledge the COVID-19 radiography database, which is freely available on Kaggle, for making this research possible.

References

1) Coronavirus overview, prevention and symptoms. 2020. Available from: https://www.who.int/emergencies/diseases/novel-coronavirus-2019.
2) Rehman A, Saba T, Tariq U, Ayesha N. Deep Learning-Based COVID-19 Detection Using CT and X-Ray Images: Current Analytics and Comparisons. *IT Professional*. 2021;23(3):63–68. Available from: https://doi.org/10.1109/MITP.2020.3036820.
3) Zak M, zak AK. Classification of Lung Diseases Using Deep Learning Models. In: International Conference on Computational Science- ICCS 2020;vol. 12139 of Lecture Notes in Computer Science. Springer, Cham. 2020;p. 621–634. Available from: https://doi.org/10.1007/978-3-030-50420-5_47.
4) Alzubaidi L, Zhang J, Humaidi AJ, Al-Dujaili A, Duan Y, Al-Shamma O, et al. Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. *Journal of Big Data*. 2021;8(1):1–74. Available from: https://doi.org/10.1186/s40537-021-00444-8.
5) Goyal S, Singh R. Detection and classification of lung diseases for pneumonia and Covid-19 using machine and deep learning techniques. *Journal of Ambient Intelligence and Humanized Computing*. 2023;14(4):3239–3259. Available from: https://doi.org/10.1007/s12652-021-03464-7.
6) Ozturk T, Talo M, Yildirim EA, Baloglu UB, Yildirim OA, Acharya UR. Automated detection of COVID-19 cases using deep neural networks with X-ray images. *Computers in Biology and Medicine*. 2020;121:1–11. Available from: https://doi.org/10.1016/j.compbiomed.2020.103792.
7) Sultana S, Pramanik A, Rahman MS. Lung Disease Classification Using Deep Learning Models from Chest X-ray Images. In: 2023 3rd International Conference on Intelligent Communication and Computational Techniques (ICCT). IEEE. 2023;p. 1–7. Available from: https://doi.org/10.1109/ICCT56969.2023.10075968.
8) Hussain E, Hasan M, Rahman MA, Lee I, Tamanna T, Parvez MZ. CoroDet: A deep learning based classification for COVID-19 detection using chest X-ray images. *Chaos, Solitons & Fractals*. 2021;142:1–12. Available from: https://doi.org/10.1016/j.chaos.2020.110495.
9) Ucar F, Korkmaz D. COVIDiagnosis-Net: Deep Bayes-SqueezeNet based diagnosis of the coronavirus disease 2019 (COVID-19) from X-ray images. *Medical Hypotheses*. 2020;140:1–12. Available from: https://doi.org/10.1016/j.mehy.2020.109761.
10) Nahiduzzaman M, Islam MR, Hassan R. ChestX-Ray6: Prediction of multiple diseases including COVID-19 from chest X-ray images using convolutional neural network. *Expert Systems with Applications*. 2023;211:1–14. Available from: https://doi.org/10.1016/j.eswa.2022.118576.
11) Alshmrani GMM, Ni Q, Jiang R, Pervaiz H, Elshennawy NM. A deep learning architecture for multi-class lung diseases classification using chest X-ray (CXR) images. *Alexandria Engineering Journal*. 2023;64:923–935. Available from: https://doi.org/10.1016/j.aej.2022.10.053.
12) Al-Sheikh MH, Dandan OA, Al-Shamayleh AS, Jalab HA, Ibrahim RW. Multi-class deep learning architecture for classifying lung diseases from chest X-Ray and CT images. *Scientific Reports*. 2023;13(1):1–14. Available from: https://doi.org/10.1038/s41598-023-46147-3.
13) Kaya M, Eris M. D3SENet: A hybrid deep feature extraction network for Covid-19 classification using chest X-ray images. *Biomedical Signal Processing and Control*. 2023;82:1–10. Available from: https://doi.org/10.1016/j.bspc.2022.104559.

14) Farhan AMQ, Yang S. Automatic lung disease classification from the chest X-ray images using hybrid deep learning algorithm. *Multimedia Tools and Applications*. 2023;82(25):38561–38587. Available from: https://doi.org/10.1007/s11042-023-15047-z.
15) COVID-19 Radiography Database. . Available from: https://www.kaggle.com/datasets/tawsifurrahman/covid19-radiography-database.
16) Asuntha A, Srinivasan A. Deep learning for lung Cancer detection and classification. *Multimedia Tools and Applications*. 2020;79:7731–7762. Available from: https://doi.org/10.1007/s11042-019-08394-3.
17) Bokade AN, Shah A. Classification of Mammography Images Using Deep-CNN based Feature Ensemble Approach and its Implementation on a Low-Cost Raspberry Pi. *International Journal of Computing and Digital Systems*. 2023;13(1):1451–1463. Available from: http://dx.doi.org/10.12785/ijcds/1301117.
18) Patel M, Shah M. Transfer learning with fine-tuned deep CNN model for COVID-19 diagnosis from chest X-ray images. *International Journal of Advanced Technology and Engineering Exploration*. 2023;10(103):720–740. Available from: https://doi.org/10.19101/IJATEE.2022.10100044.
19) Khan AI, Shah JL, Bhat MM. CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images. *Computer Methods and Programs in Biomedicine*. 2020;196:1–9. Available from: https://doi.org/10.1016/j.cmpb.2020.105581.
20) Abbas A, Abdelsamea MM, Gaber MM. Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network. *Applied Intelligence*. 2021;51(2):854–864. Available from: https://doi.org/10.1007/s10489-020-01829-7.
21) Kim S, Rim B, Choi S, Lee A, Min S, Hong M. Deep Learning in Multi-Class Lung Diseases' Classification on Chest X-ray Images. *Diagnostics*. 2022;12(4). Available from: https://doi.org/10.3390/diagnostics12040915.
22) Velu S. An efficient, lightweight MobileNetV2-based fine-tuned model for COVID-19 detection using chest X-ray images. *Mathematical Biosciences and Engineering*. 2023;20(5):8400–8427. Available from: https://doi.org/10.3934/mbe.2023368.
23) Asnaoui KE. Design ensemble deep learning model for pneumonia disease classification. *International Journal of Multimedia Information Retrieval*. 2021;10(1):55–68. Available from: https://doi.org/10.1007/s13735-021-00204-7.