Leveraging DenseNet Features for Machine Learning based Lung Disease Diagnosis from X-rays

***Abstract*—Infectious lung diseases, including COVID-19, bacterial pneumonia, and viral pneumonia, are significant concerns for public health worldwide. Chest X-rays (CXR) are a common diagnostic tool, but their manual interpretation can be complicated due to the similar visual characteristics of these diseases. This paper presents an automated system that utilizes features from deep learning models (DenseNet-121, DenseNet-169, DenseNet-201) to classify lung diseases into four distinct categories: bacterial pneumonia, COVID-19, viral pneumonia, and normal. With a dataset of 4,202 X-ray images, DenseNet-201 achieved the highest accuracy of 94.10%, showing its potential to assist radiologists in clinical diagnosis. Additionally, integrating features from DenseNet models with machine learning classifiers such as SVM and Random Forest improved overall test accuracy, with DenseNet-201 combined with SVM achieving a near-perfect test accuracy of 97.67%.Feature extraction from the penultimate layers of DenseNet models played a critical role in enhancing the classification process, allowing traditional machine learning classifiers to achieve higher accuracy and reliability across various lung disease categories**

***Index Terms*—Lung Disease, COVID-19, Pneumonia, X-ray Classification, Deep Learning, DenseNet.**

I. Introduction

Lung diseases such as Bacterial Pneumonia, COVID-19, and Viral Pneumonia continue to pose significant challenges to global public health [1]. These illnesses affect millions of people globally and cause much morbidity and mortality particularly in special risk groups like children, the elderly and immune compromised patients [2]. Bacterial pneumonia is caused by bacterial infections that cause inflammation and the accumulation of fluids in the lungs; COVID 19, due to the SARS- CoV-2 virus, has significantly impacted the world [3]. Viral Pneumonia, which arises from various viruses, also contributes substantially to the burden of respiratory illnesses [4]. In almost all these diseases, accurate diagnosis is critical in the management and treatment.

One of the reasons chest X-rays are so widely used for diagnosing lung diseases is their effectiveness in highlighting important patterns in the lungs. [5]. However, traditional diagnostic methods relying on manual interpretation are often subject to variability and may struggle to differentiate between diseases that exhibit similar visual characteristics on X-ray images This highlights the need for more advanced and automated approaches to assist in diagnosis [6].

Deep learning has emerged as a dominant approach to solving medical image classification problem in recent years since it provides high accuracy for automated systems to detect complex patterns in the images. This advancement is owed to the Convolutional Neural Networks, or (CNNs), particularly architectures such as DenseNet-121, DenseNet-169, DenseNet-201, and other models like XceptionNet, VGG, and ResNet, have demonstrated impressive performance in medical image classification tasks [7]. These models leverage their deep architectures to learn hierarchical features from images, improving diagnostic accuracy and reducing the subjectivity associated with traditional methods [8].

To enhance diagnostic accuracy and efficiency, deep learning models have gained significant attention in medical image analysis. Convolutional neural networks (CNNs), particularly the models DenseNet-121, DenseNet-169, and DenseNet-201 have effectively extracted detailed features from X-ray images, leading to more accurate classifications of lung diseases. This study aims to group chest X-ray images into four categories, including Bacterial Pneumonia , COVID-19 , Viral Pneumonia, and Normal by leveraging feature extraction from these models and further refining the classification using machine learning techniques. This approach ensures better performance and practicality for clinical applications, ultimately improving diagnostic outcomes.

Phogat et al.'s study focused on leveraging Selective Kernel Networks (SkNets) for lung abnormality diagnosis using chest X-rays. The research demonstrated that SkNets significantly outperformed conventional CNN models such as ResNet and VGG in key performance metrics, including accuracy, precision, recall, and F1 score, with SkNet18 achieving 95% accuracy and a recall of 95.3%. The superior performance of SkNets was attributed to their dynamic kernel sizes, which enabled better adaptability to input data, particularly in capturing complex lung patterns like Lung Opacity[9].

Malik et al. introduced the Deep Convolutional Disease Diagnosis Network (DCDDNet), which integrates cough sound data with imaging data to address class imbalance and improve diagnostic accuracy. Their model surpassed others like InceptionResNet-V2 and EfficientNet-B0, achieving an accuracy of 96.67% [10]. Ko et al. studied the application of Vision Transformer (ViT) models, particularly FastViT and CrossViT, in classifying lung diseases based on chest X-rays. They found that Adam was the most effective optimizer for balanced datasets, with FastViT achieving an impressive accuracy of 97.63% [11].

Sanida and Dasygenis proposed a lightweight CNN model

tailored for embedded systems, securing an accuracy of 98.56% in the classification of lung diseases using images from chest X-rays. Their model, using focal loss to address class imbalances, demonstrates the feasibility of real-time diagnostics on resource-constrained devices [12].

Al-Sheikh et al. developed a multi-class deep learning architecture for classifying lung diseases from X-ray and CT images, incorporating advanced image enhancement techniques. Their approach achieved 98.60% accuracy with X-ray images and 98.80% with CT scans, showing significant improvements in diagnostic accuracy [13].

Hariri and Avşar examined CNN models for diagnosing COVID-19 and pneumonia from chest X-ray images. EfficientNet B2 performed competitively with 85.7% accuracy, while a novel lightweight CNN model achieved 89.89%, balancing performance and computational efficiency [14].

Maghdid et al. utilized deep learning and transfer learning algorithms to diagnose COVID-19 from X-ray and CT images. DenseNet121 and VGG16 achieved accuracies of approximately 94% and 92% respectively, showcasing the effectiveness of transfer learning in enhancing diagnostic performance [15].

Huy and Lin focused on tuberculosis detection through chest X-ray images, utilizing various CNN architectures. DenseNet121 and VGG16 showed strong performance, with CBAM-integrated models like CBAMWDNet achieving up to 98.80% accuracy, highlighting the potential of advanced deep learning techniques [16].

M. M et al. performed a comparative study on the effectiveness of EfficientNet and MobileNet models in classifying lung cancer through CT scan images. Their results indicated that the EfficientNetB3 model outperformed MobileNet significantly, achieving a remarkable accuracy of 97.78%. This research highlights the considerable promise of EfficientNet architectures in utilizing advanced deep learning models for medical image analysis.[17]

Shamrat et al. created LungNet22, a model that fine-tunes the VGG16 architecture for lung disease detection, to classify ten lung disease classes. With preprocessing techniques and hyperparameter tuning, LungNet22 achieved an accuracy of 98.89%, demonstrating high effectiveness in lung disease detection [18].The emergence of COVID-19 and different types of pneumonia highlights the urgent need for advanced algorithms that can clearly identify these illnesses.

II. METHODOLOGY

The workflow of this research is illustrated in Fig. 1, highlighting the initial step of data collection, followed by dataset preparation, and subsequent steps.

A. Data Collection

In our study ,dataset was obtained from the Kaggle repository [[https://www.kaggle.com/datasets/dionixius/lung-disease-5-class-dataset] and consists of 4202 chest X-ray images, divided into four categories: Bacterial Pneumonia (1026 images), COVID-19 (1054 images), Normal (1044 images), and Viral Pneumonia (1078 images). In this study, the dataset was separated into three segments: 80% designated for training, 10% for validation, and 10% for testing. This split facilitated effective model training while maintaining distinct datasets for validation and final performance testing. The dataset's balanced class distribution helped reduce potential bias and increase the effectiveness of the classification models.

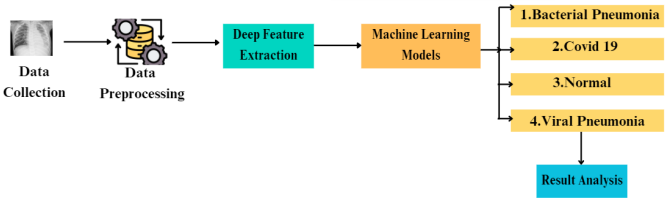

Fig. 1. Workflow Diagram

Here are some sample images from each class, showcasing the variations in lung disease appearance across different categories as shown in Fig.2. Each X-ray category showed distinct features, bacterial pneumonia had patchy, irregular opacities in one or more lobes, indicating fluid accumulation. COVID-19 displayed diffuse, ground-glass opacities across both lungs. Normal X-rays showed clear lung fields with well-defined heart and diaphragm outlines. Viral pneumonia presented bilateral, interstitial opacities, distinguishing it from bacterial.

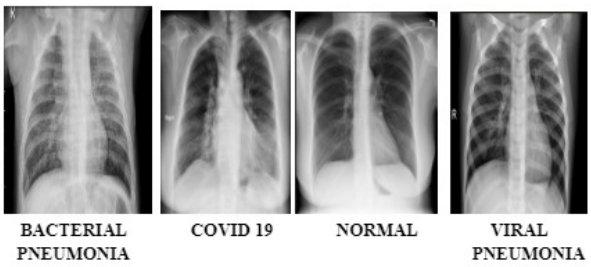

Fig. 2. Sample Images from dataset

B. Data Preprocessing

For increasing the models accuracy, precision and recall ,we perform some essential preprocessing steps to retrieve relevant information and to remove the redundant information.The collected images were of varying size ,which leads to difficulty in training stage.To overcome this the images were resized to (224,224). The class mode was kept categorical, transforms class labels into one-hot encoded vectors, enabling the model to output probabilities for each class. This approach is crucial for training models to differentiate between multiple categories. Normalization adjusts data to a common scale, usually between 0 and 1, which helps the model train more effectively by ensuring features contribute equally.

C. Deep Feature Extraction

We found that deep learning models like DenseNet-121, DenseNet-169, and DenseNet-201 are particularly effective at detecting abnormalities in chest X-rays.[19] Their architecture, which enables efficient information flow between layers, proved to be well-suited for classifying medical images. The models ability to capture intricate patterns in the data played a crucial role in distinguishing the four categories of lung diseases.

This process adapts the model to specific tasks for which it wasn't originally trained. It allows the model to leverage existing knowledge, improving performance on new tasks. The fine-tuning parameters done in this project are as mentioned below in Table I.

TABLE I
MODEL PARAMETERS

Parameter	Value
Batch Size	32
Steps per Epoch	32
Epoch	50
Optimizer	RMSProp
Learning Rate	1e-4
Loss Function	Categorical Crossentropy
Activation Function	ReLU

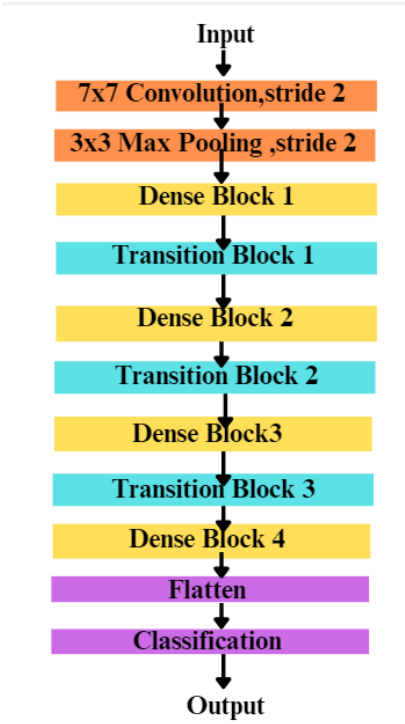

Fig. 3. Densenet architecture

DenseNet

DenseNet is a deep learning model that stands out due to its distinctive structure where each layer is connected to every other layer that comes after it. This direct connection ensures efficient reuse of features and helps avoid problems like vanishing gradients, which can occur in deep networks [20].The architecture begins with a 7x7 convolutional layer (stride of 2) to extract basic features from the input, followed by a 3x3 max-pooling layer that reduces the size of the feature maps. The core of DenseNet consists of dense blocks, where each layer is batch normalized, activated with ReLU, and processed through 3x3 convolutions, with all outputs concatenated. Transition blocks are placed between these dense blocks to downsample the data using 1x1 convolutions and 2x2 average pooling, effectively managing the model's complexity. The network concludes with a global average pooling layer and a fully connected classifier, striking a balance between parameter efficiency and robust feature learning.As illustrated in Fig.3.

The primary difference between DenseNet-121, DenseNet-169, and DenseNet-201 lies in the number of layers within their dense blocks. DenseNet-121 consists of four dense blocks containing 6, 12, 24, and 16 layers, respectively. DenseNet-169 builds on this by expanding the third and fourth blocks to 32 layers each, resulting in dense block configurations of 6, 12, 32, and 32 layers. DenseNet-201 takes it a step further, incorporating 6, 12, 48, and 32 layers across its dense blocks. These deeper variants are better suited for tasks involving large or complex datasets, as they can learn more intricate features and patterns [21].

D. Machine Learning Classifier

After completing the training, validation, and testing phases for the three DenseNet models, we analyzed their respective accuracies using metrics such as accuracy, precision, recall, F1-score, and loss for training testing and validation datasets. To enhance classification performance and overall efficiency, we introduced a novel approach that involved extracting features from the penultimate layer of each model. These features capture essential high-level information from the images and were subsequently used as inputs for various machine learning classifiers, including Support Vector Machine (SVM), Random Forest, Gradient Boosting, K-Nearest Neighbors (KNN), Naïve Bayes, and Decision Tree.

The effectiveness of traditional machine learning models is significantly influenced by the quality of the input features. By leveraging the meaningful features extracted from the deep learning models, we aimed to improve the classification performance of these conventional classifiers. This method preserved the strong feature extraction capabilities in deep learning architectures while taking advantage of the computational efficiency and simplicity offered by machine learning classifiers. Integrating deep feature extraction with traditional models establishes a powerful framework capable of achieving remarkable results in the classification of lung diseases from chest X-ray images.

III. Results and Discussions

The deployed model runs on an Intel Core i5 8th Gen processor with a 1TB hard drive. For handling computationally demanding tasks like model training and evaluation, the system utilized a GPU provided by Kaggle. The model development was carried out using Python 3.9.12 and TensorFlow 2.9.1, ensuring efficient execution of deep learning operations.

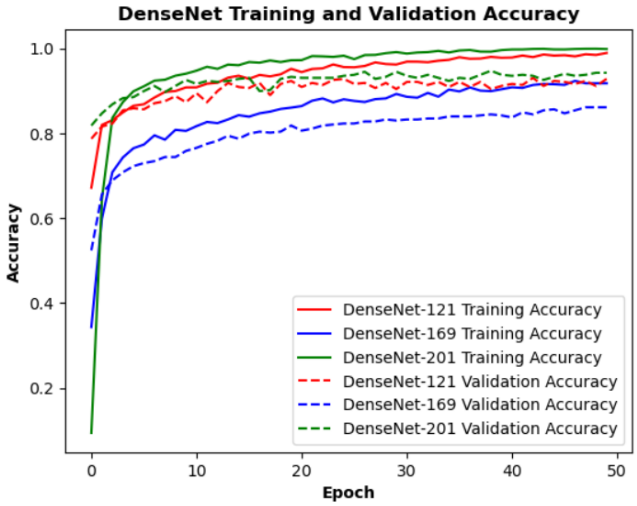

Fig. 4. Training and Validation Accuracy of deep models

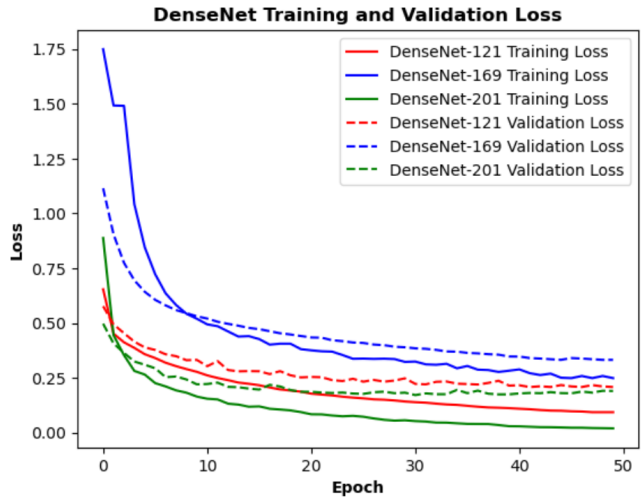

Fig. 5. Training and Validation Loss of deep models

The performance of DenseNet models across various accuracy metrics demonstrates their ability to generalize and capture important features. DenseNet-121 stood out with a training accuracy of 98.93%, validation accuracy of 92.82%, and a test accuracy of 91.51%. DenseNet-201 slightly outperformed it in terms of validation and test accuracy, achieving 93.78% and 94.10%, respectively. On the other hand, DenseNet-169 showed solid but relatively lower performance, with training, validation, and test accuracies of 89.39%, 86.12%, and 91.78%.The training and loss curves for these models, which highlight the differences in training and validation accuracy and loss over time, are plotted in Fig .4. and 5 to visually represent the performance trends.

The classification report for all three models revealed high precision and recall, particularly with DenseNet-121 achieving an F1-score of 1.00 across all classes, both during validation and testing. DenseNet-201 also delivered strong classification performance, with an F1-score of 0.96 for the Bacterial Pneumonia class. DenseNet-169, however, exhibited a slightly lower recall, particularly in the Normal class, which had a recall of 93%. These performance metrics are outlined in detail in Table II .

In terms of classifier results, DenseNet-201 showed strong performance, particularly when integrated with the SVM classifier. It achieved solid metrics across all classes with a near-perfect balance of precision, recall, and F1-scores during both testing and validation. Specifically, the model achieved a validation accuracy of 96.48%, with notable precision for COVID-19 and Normal cases. The test accuracy was 90.70%, indicating the robustness of DenseNet-201 in practical scenarios as demonstrated in Table III.

TABLE II
Testing and Validation performance of DenseNet models across different classes.

Model	Classes	Dataset	Precision	Recall	F1-Score
DenseNet-121	Bacterial Pneumonia	Testing	1.00	1.00	1.00
		Validation	1.00	1.00	1.00
	Covid 19	Testing	0.99	1.00	1.00
		Validation	0.98	1.00	0.99
	Normal	Testing	1.00	0.95	0.98
		Validation	1.00	0.95	0.98
	Viral Pneumonia	Testing	0.96	1.00	0.98
		Validation	0.97	1.00	0.99
DenseNet-169	Bacterial Pneumonia	Testing	0.88	0.87	0.87
		Validation	0.91	0.88	0.90
	Covid 19	Testing	0.94	0.86	0.90
		Validation	0.89	0.81	0.85
	Normal	Testing	0.87	0.93	0.90
		Validation	0.81	0.88	0.84
	Viral Pneumonia	Testing	0.87	0.89	0.88
		Validation	0.87	0.91	0.89
DenseNet-201	Bacterial Pneumonia	Testing	0.95	0.96	0.96
		Validation	0.96	0.95	0.96
	Covid 19	Testing	0.94	0.96	0.95
		Validation	0.95	0.90	0.92
	Normal	Testing	0.92	0.93	0.93
		Validation	0.91	0.94	0.92
	Viral Pneumonia	Testing	0.94	0.91	0.93
		Validation	0.94	0.96	0.95

Fig.6. compares the accuracy of DenseNet models integrated with different classifiers, where DenseNet-201 with SVM stands out for its balanced performance. The confusion matrix for the test set is provided in Fig.7., further validating the

TABLE III
TESTING AND VALIDATION PERFORMANCE OF THE SVM CLASSIFIER ACROSS DIFFERENT CLASSES.

Classes	Dataset	Precision	Recall	F1-Score	Support
Bacterial Pneumonia	Testing	0.90	0.88	0.88	12
	Validation	0.96	0.94	0.94	17
Covid 19	Testing	0.93	0.99	0.96	11
	Validation	0.92	0.97	0.96	6
Normal	Testing	0.99	0.88	0.93	8
	Validation	0.98	0.90	0.91	10
Viral Pneumonia	Testing	0.91	0.89	0.88	12
	Validation	0.89	0.88	0.87	9

model's effectiveness.

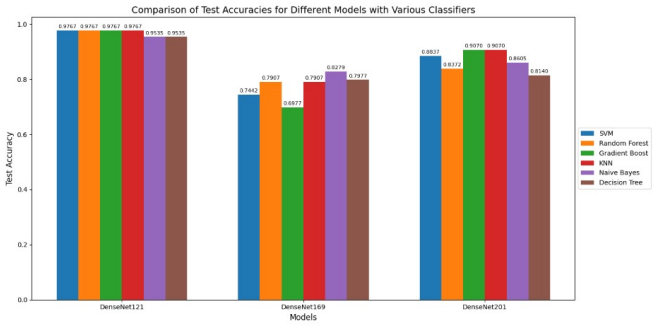

Fig. 6. Test accuracies obtained with ML Classifiers

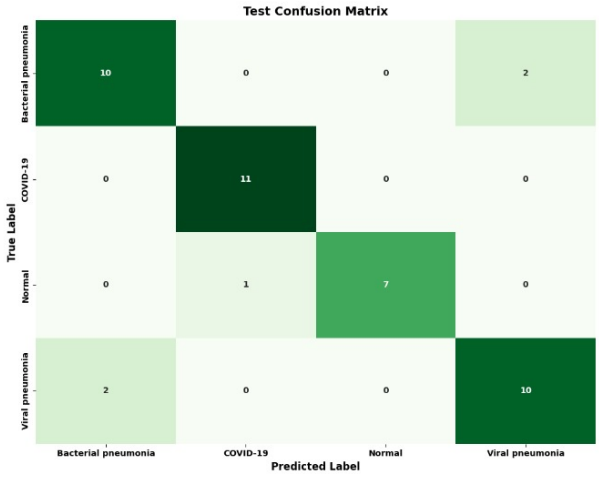

Fig. 7. Test Confusion Matrix of SVM with DenseNet-201 features

IV. CONCLUSION

In this research, we explored the effectiveness of DenseNet architectures (DenseNet-121, DenseNet-169, and DenseNet-201) to classification of lung diseases using chest X-ray images. The study highlighted that DenseNet-201 achieved the best performance, with superior test accuracy and low test loss, demonstrating its ability to generalize effectively across different lung conditions. DenseNet-121 also offered a compelling balance between accuracy and computational efficiency, making it an attractive option for resource-constrained environments. DenseNet-169, while competent, exhibited a tendency toward overfitting, emphasizing the importance of model selection and tuning.

By extracting features from the penultimate layer of the DenseNet models and using them in traditional machine learning classifiers like SVM, Random Forest, and Gradient Boosting, we further enhanced the diagnostic accuracy. This hybrid approach of combining deep learning with classical machine learning resulted in significant improvements in performance while maintaining computational efficiency. The results suggest that leveraging deep features from advanced neural networks, alongside more traditional classification algorithms, offers a robust method for diagnosing lung diseases from X-ray images. Future work should investigate additional deep learning architectures and hybrid models, potentially improving diagnostic accuracy and addressing challenges posed by diverse real-world medical datasets.

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