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Chest X-ray Based Pneumonia Diagnosis Using Deep Learning Technique

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***Abstract*—Pneumonia is a common respiratory illness. This study utilizes deep learning techniques to analyze chest X-ray images for pneumonia diagnosis, integrating four pre-trained feature extractors—DenseNet169, DenseNet201, MobileNet, and InceptionResNetV2—with classifiers like Random Forest, Support Vector Machine (SVM), and XGBoost. We employ various libraries for image processing, machine learning, deep learning (TensorFlow/Keras), and explainability methods like CLAHE and Laplacian filters to enhance images before model input. Our evaluation focuses on key metrics, including accuracy, precision, recall, F1-score, and AUC. The combination of DenseNet201 and Custom Classification has shown the highest accuracy in detecting pneumonia, highlighting its potential to improve diagnostic practices and healthcare outcomes. Overall, chest X-rays are highly effective for diagnosing pneumonia.**

***Index Terms*—Pneumonia,Chest X-ray, Deep Learning, Machine Learning, Feature Extractor, Classifier,**

I. Introduction

Pneumonia constitutes a significant pulmonary infection, influenced by a multitude of geographical, seasonal, and demographic factors. Timely and accurate detection of this condition is imperative for mitigating its prevalence and enhancing patient outcomes. Common clinical manifestations include a productive or dry cough, chest pain, fever, and dyspnea.

On a global scale, pneumonia affects more than 1,400 cases per 100,000 children, which corresponds to approximately 1 case for every 71 children annually. It stands as the foremost cause of mortality associated with infectious diseases worldwide, resulting in approximately 2.5 million fatalities recorded in the year 2019. In pediatric populations, pneumonia is the primary infectious cause of death, leading to the untimely loss of over 700,000 lives among children under the age of five each year. Preventive strategies may be effectively implemented through early diagnosis via chest X-rays. Certain demographics are at increased risk for pneumonia, including:Young children,Adults aged 65 years and older,Individuals with compromised immune systems,Patients undergoing treatment with specific pharmacological. The paper addresses the complexities associated with pneumonia and investigates the application of deep learning methodologies for the analysis of X-ray imagery. Deep learning techniques represent a sophisticated category of machine learning algorithms that utilize multiple layers within ANN to extract pattern from data, mimicking process of Human brain. This methodology emulates the cognitive processes of the human brain, facilitating computational excellence in tasks such as image recognition. Medical imaging constitutes an indispensable tool in disease diagnosis and treatment planning and monitoring of various medical conditions. Among the array of imaging modalities, chest X-rays are routinely employed to diagnose respiratory and cardiovascular disorders. However, the manual analysis of X-ray images is labor-intensive and may be susceptible to variability among different observers. The emergence of deep learning and machine learning technologies has profoundly transformed the landscape of medical image analysis, enabling precise and automated classification of medical imagery. Pre-trained CNNs such as DenseNet169, DenseNet201, InceptionResNetV2, and MobileNet have effectively extracted hierarchical and meaningful features from imaging data. Nonetheless, challenges such as imbalanced datasets and the high dimensionality of image features may significantly impede the performance of these models. In this study, we propose a hybrid framework that integrates transfer learning with classifiers including SVM, Random Forest, and XGBoost, a robust gradient-boosting algorithm. This integration aims to systematically address existing challenges and achieve reliable classification of chest X-ray images. Our methodology encompasses feature extraction alongside the fine-tuning of selected layers to tailor the model to specific diagnostic tasks. Moreover, we incorporate CLAHE and Laplacian filtering, to enhance image quality and improve the efficacy of feature extraction. The resultant deep features are subsequently processed through classifier. In conclusion, The proposed framework utilizing a comprehensive array of metrics, including accuracy, precision, recall, F1-score, and area under the curve (AUC), in addition to class-wise performance metrics and visualizations, such as ROC curves and Precision-Recall curves. The findings of this investigation suggest that our approach effectively amalgamates the strengths of deep feature extraction with gradient boosting, providing an accurate and interpretable solution for medical image classification. This research contributes to the ongoing efforts aimed at developing automated diagnostic systems capable of assisting healthcare professionals in making informed, data-driven decisions, particularly in resource-constrained environments where access to specialist radiologists may be limited.

II. Related Work

Several researchers have explored the application of deep learning and machine learning techniques for pneumonia detection using chest X-ray images.

Sharma *et al.* [1] employed VGG-16 and neural networks for pneumonia detection. Their model achieved an accuracy of 95.4%, with recall, precision, and F1-score values of 0.954 each.

Goyal *et al.* [2] investigated machine and deep learning techniques for pneumonia detection. They utilized ANN, Support Vector Machines (SVM), and KNN, as well as deep learning models such as RNN and Long Short-Term Memory (LSTM). Their approach achieved an accuracy of 95%.

M. Alshmrani *et al.* [3]proposed a deep learning-based approach using CNN and VGG-19 for lung disease detection. Their model achieved an accuracy of 96.48%, with recall, precision, and F1-score values of 93.75%, 97.56%, and 95.62%, respectively.

Kumar *et al.* [4] introduced the CLACHE and COVID-DeepNet models to detect pneumonia caused by COVID-19. Their method attained an accuracy of 99.93%, sensitivity of 99.90%, specificity of 100%, precision of 100%, and an F1-score of 99.93%.

Hashmi *et al.*[5] employed CNN and ANN for pneumonia detection, achieving an Area Under the Curve (AUC) of 0.9582.

III. Methodologies

In this section, the methodology adopted in this study is explained. In Fig. 1, the methodology is demonstrated with a concise diagram.

A. *Data Preparation*

The dataset utilized in this study consists of chest X-ray images categorized into two classes: normal and diseased. The dataset is systematically organized into separate directories for each class. class normal contains total of 1587 healthy images of chest and class disease contains 4273 effected images. Sample data is provided in Fig. 2.

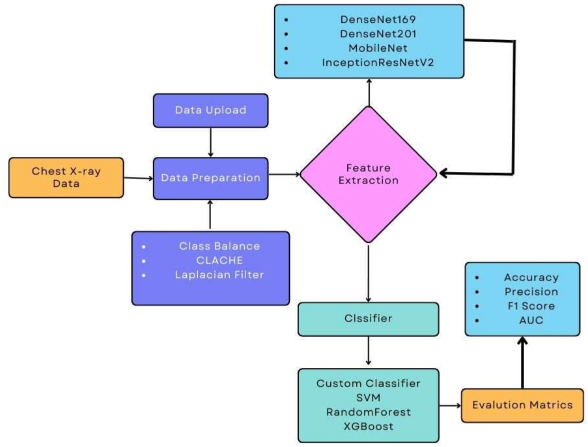

Fig. 1. Methodology

CLASS	Data
normal	1587
disease	4273

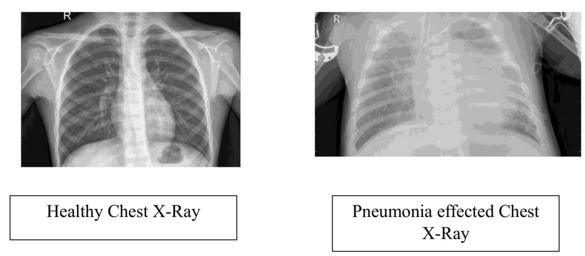

Fig. 2. Sample Data

- **Data Upload**: Images were imported from the designated directory and appropriately labeled according to their respective classes..
- **Class Balancing:** To address the issue of class imbalance SMOTE was employed to generate synthetic samples for the minority class, thereby ensuring a balanced dataset.

B. *Image Processing*

- **CLAHE:** It was applied to improve the contrast of the X-ray images, thereby making key features more prominent.
- **Laplacian Filtering:** This technique was utilized to sharpen the images and emphasize edge details.

C. *Feature Extraction*

- **Feature Extractor:**The DenseNet169, DenseNet201, MobileNet, Inception model, which has been pre-trained

TABLE I: PERFORMANCE METRICS OF FEATURE EXTRACTORS AND CLASSIFIERS

Feature Extractor	Classifier	Accuracy	Precision				Recall				F1 Score				AUC
			Class 0	Class 1	Mac. AVG	Wtd AVG	Class 1	Class 2	Mac. AVG	Wtd AVG	Class 1	Class 2	Mac. AVG	Wtd AVG	
DenseNet169	CustomClassifier	0.9784	0.9824	0.9824	0.9824	0.9824	0.9824	0.9824	0.9824	0.9824	0.9824	0.9824	0.9824	0.9824	0.99
	SVM	0.9789	0.9789	0.9811	0.98	0.98	0.9789	0.9811	0.98	0.98	.09789	0.9811	0.98	0.98	0.9975
	RF	0.9591	0.9612	0.9569	0.9591	0.9591	0.9567	0.9614	0.9591	0.9591	0.9589	0.9589	0.9591	0.9591	0.9922
	XGB	0.9618	0.9694	0.9562	0.9628	0.9628	0.9678	0.9645	0.9661	0.9661	0.9591	0.9579	0.9585	0.9585	0.9954
DenseNet201	CustomClassifier	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	SVM	0.9989	0.9978	1.000	0.9989	0.9989	1	0.9978	0.9989	0.9989	0.9989	0.9989	0.9989	0.9989	1.000
	RF	0.9602	0.9635	0.9570	0.9603	0.9603	0.9567	0.9637	0.9602	0.9602	0.9601	0.9604	0.9602	0.9602	0.9931
	XGB	0.9732	0.9597	0.9887	0.9742	0.9742	0.9738	0.9432	0.9585	0.9585	0.9742	0.9734	0.9738	0.9738	0.9985
MobileNet	CustomClassifier	0.97427	0.9710	0.9776	0.9743	0.9743	0.9778	0.9708	0.9743	0.9743	0.9744	0.9742	0.9743	0.9743	0.9977
	SVM	0.9719	0.98	0.97	0.97	0.98	0.97	0.98	0.97	0.97	0.97	0.97	0.97	0.97	0.9964
	RF	0.9620	0.9748	0.9498	0.9623	0.9632	0.9485	0.9754	0.9619	0.9619	0.9615	0.9625	0.9619	0.9619	0.9915
	XGB	0.9678	0.9728	0.9630	0.9679	0.9679	0.9626	0.9731	0.9678	0.9678	0.9677	0.9680	0.9678	0.9678	0.9946
InceptionResNetV2	CustomClassifier	0.9719	0.9622	0.9821	0.9721	0.9721	0.9825	0.9614	0.9719	0.9719	0.9722	0.9716	0.9719	0.9719	0.9952
	SVM	0.9588	0.9566	0.9755	0.9660	0.9660	0.9725	0.9508	0.9616	0.9616	0.9581	0.9581	0.9581	0.9581	0.9928
	RF	0.9421	0.9416	0.9426	0.9421	0.9421	0.9427	0.9421	0.9421	0.9421	0.9421	0.9421	0.9421	0.9421	0.9853
	XGB	0.9585	0.9449	0.9730	0.9589	0.9589	0.9598	0.9432	0.9515	0.9515	0.9591	0.9579	0.9585	0.9585	0.9901

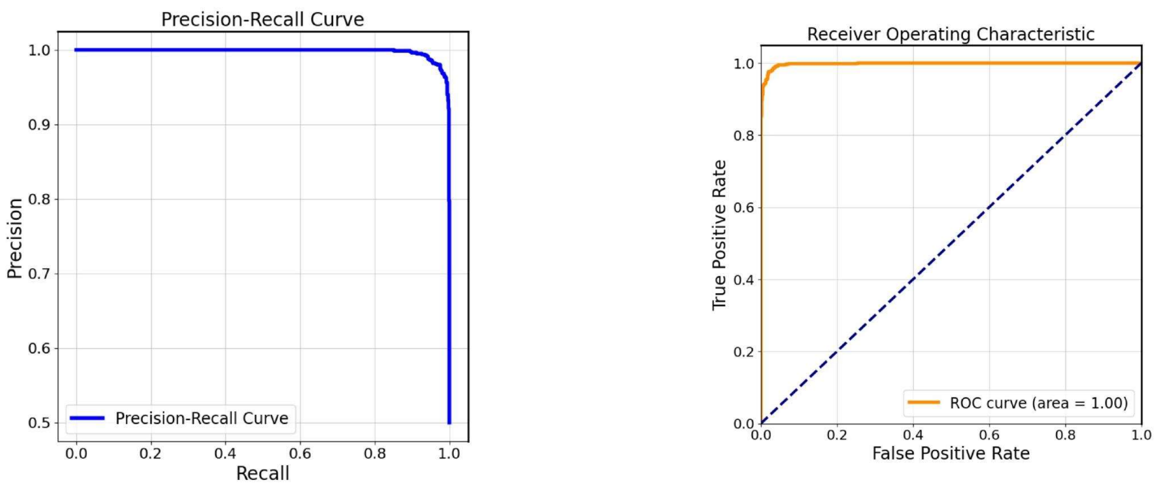

Fig. 3. ROC, Precision-Recall Curve (DenseNet201)

on the ImageNet dataset, was utilized as a feature extractor.

- **Fine-Tuning:** Selected layers were fine-tuned to adapt the model to the specific characteristics inherent in chest X-ray images.

D. Classification

- **Classifier:**The The extracted features were utilized as input for the SVM,RandomForest, XGBoost classifier, a gradient-boosting algorithm known for its robustness and efficiency
- **Model Initialization:** The classifier was configured with optimal hyper-parameters(density=512, epoch=6, layer drop-out=0.25), including the number of estimators, learning rate(1e-4), and maximum tree depth.
- **Training:** The classifier was trained using the extracted features from the training dataset.
- **Prediction:** The model was evaluated in the test data set to generate predictions and class probabilities.

E. Evaluation Metrics

- **Overall Metrics:**Indicators such as accuracy, precision, recall, F1-score, and Area Under the Curve (AUC) were calculated.
- **Class-Wise Metrics:** Metrics were computed independently for each class, providing information on the performance of the model for normal and diseased images.
- **Visualizations:** Confusion matrices, ROC curves, and Precision-Recall curves were generated to present a comprehensive overview of the model's performance.

IV. EXPERIMENTAL RESULT AND ANALYSIS

We have combined a feature extractor with a classifier to get the best result. The best result we get is from the combination of feature extractor DenseNet201 and custom classification. We have achieved accuracy of 1.000, prescision, recall and f1 score are for both classes is 1.000 and AUC is also 1.000. The precision vs recall curve and the receiver operating characteristic (ROC) curve is provided in Fig. 3. In Fig. 4 and Fig. 5, the confusion matrix is provided and the training and validation accuracy & loss curve is provided.

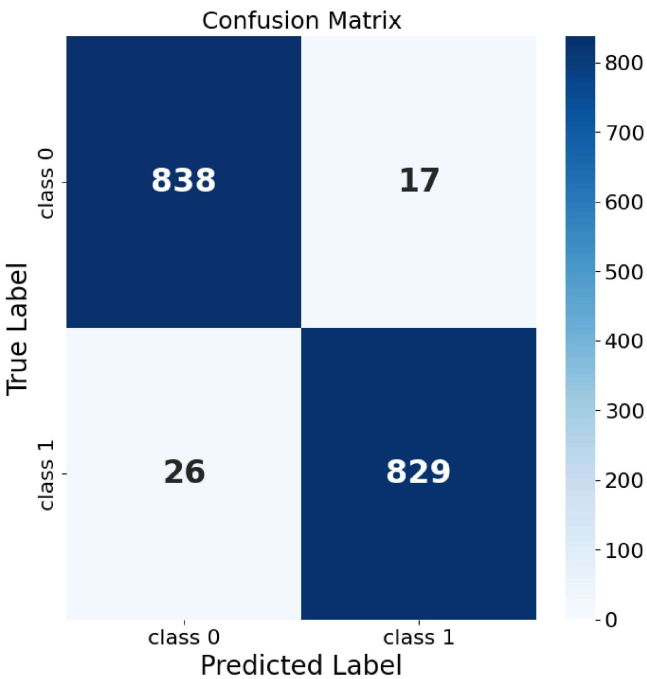

Fig. 4. Confusion Matrix

*a) **Limitations**:* The deep feature extraction and model training processes require significant resources and time. Pre-trained models, such as DenseNet169, might not effectively capture the intricacies of medical engineering. Furthermore, complex models can lead to memory overflow issues. There is also a restricted adaptability for larger datasets and various imaging modalities. Potential biases in the data, along with a lack of comprehensive validation, can hinder the readiness for deployment.

*b) **Future Work**:* In the future, larger and more diverse datasets will be utilized to enhance robustness. To reduce costs, we will explore lightweight architectures and transfer learning techniques. Real-life medical trials will be conducted to assess efficiency and reliability. It is essential to address biases in training data for ethical deployment. Additionally, models will be adapted for edge devices to enable real-time diagnostics in low-resource settings.

V. Conclusion

This research presents an effective approach using advanced deep learning techniques for medical image analysis for the diagnosis of pneumonia through chest x-ray. By employing advanced preprocessing techniques, such as CLAHE and Laplacian filtering, alongside feature extractors and classification,

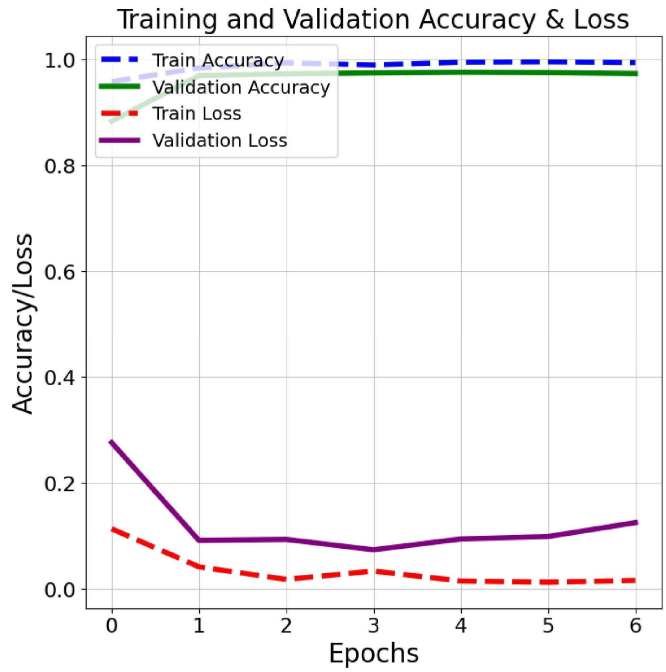

Fig. 5. Training and Validation Accuracy & Loss Curve

the framework achieved significant accuracy in medical image analysis. Performance metrics demonstrated the model's effectiveness in classification accuracy, precision, recall, and AUC. However, the study acknowledged limitations, such as reliance on dataset quality and high computational demands. Future work will focus on enhancing scalability, integrating data, and validating the framework to improve practical applicability.

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