Biosignal Smocking Detection of X-Ray Images

Mrs. Lavanya[1], J. Karthik[2], G. Sudheer[3], G. Rohith Yadav[4]
[1]Assist prof, Dept of Artificial Intelligence and Data Science.
[2, 3, 4] Dept of Artificial Intelligence and Data Science.
[1, 2, 3, 4] Dhanalakshmi Srinivasan University, Tiruchirappalli, Tamil Nadu,621112 India.

Abstract- *Lung diseases such as viral pneumonia and smoking-induced lung damage are major global health concerns responsible for millions of deaths each year. Early and accurate detection of these conditions is essential for timely medical intervention and treatment. This project presents a deep learning–based image classification model for automated identification of viral pneumonia and lung damage caused by smoking using chest X-ray and CT images. The proposed system leverages transfer learning with the EfficientNetB0 architecture, which extracts high-level visual features from lung images and classifies them into two categories. The dataset is preprocessed through normalization and image augmentation to enhance generalization and reduce overfitting. The model is trained using binary cross-entropy loss and optimized with the Adam optimizer to achieve high accuracy and robustness. Experimental results demonstrate the model's capability to distinguish between viral pneumonia and smoker-affected lungs effectively, supporting radiologists in diagnostic decision-making. This system offers a reliable, efficient, and scalable AI-driven approach for medical imaging analysis and contributes to the advancement of computer-aided diagnosis in pulmonary healthcare.*

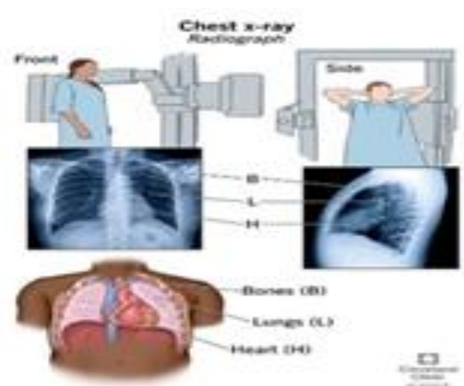
Keywords: Deep Learning, Machine Learning, Lung Image Classification, Viral Pneumonia Detection, Smoking-Induced Lung Damage, Chest X-ray Analysis, CT Scan Imaging, Convolutional Neural Network (CNN), EfficientNetB0, Transfer Learning, Medical Image Processing, Feature Extraction.

I. INTRODUCTION

The healthcare industry is one of the most important sectors in the world, where timely diagnosis and treatment play a crucial role in saving human lives. In recent years, respiratory diseases have become a major concern due to increasing air pollution, smoking habits, viral infections, and changing lifestyles. Among these diseases, viral pneumonia and smoking-induced lung damage are two serious conditions that affect millions of people globally. Viral pneumonia causes inflammation and infection in the lungs, leading to breathing difficulties, fever, and severe complications if left untreated. Similarly, long-term smoking can cause chronic lung damage, reduce lung capacity, and increase the risk of diseases such as Chronic Obstructive Pulmonary Disease (COPD), emphysema, and lung cancer. Therefore, early detection and accurate diagnosis of these conditions are essential for effective treatment and improved patient survival rates.

Traditionally, doctors and radiologists diagnose lung diseases by examining chest X-ray images or Computed Tomography (CT) scans. These imaging techniques provide detailed information about the internal condition of the lungs. However, manual examination of medical images requires high expertise, experience, and concentration. In many hospitals, especially in rural or underdeveloped regions, there may be a shortage of trained radiologists. As a result, diagnosis can be delayed, and sometimes human errors may occur due to fatigue or large patient volumes. In emergency situations, delays in diagnosis can significantly affect treatment outcomes. Hence, there is a growing need for automated systems that can support doctors by providing faster and more accurate image analysis. This project, titled "Lung Smoking Images Classification: Detecting Viral Pneumonia and Smoking-Induced Lung Damage," focuses on applying deep learning techniques to classify lung images into two categories: viral pneumonia and smoking damage. The proposed system uses chest X-ray or CT images as input and processes them through a trained neural network model to predict the condition of the lungs.

The aim is to build an intelligent diagnostic support system that can assist healthcare professionals in identifying respiratory diseases at an early stage.



II. LITERATURE SURVEY

Especially for detecting respiratory diseases from chest X-ray and CT scan images. Researchers have focused on automating diagnosis to reduce radiologist workload, improve speed, and increase accuracy. Lung disease detection using image classification has become an important research area because conditions such as pneumonia, tuberculosis, COVID-19, and smoking-related lung damage require early diagnosis for effective treatment. Recent review papers note that deep learning has become a leading approach for chest X-ray analysis due to strong image recognition performance.

Initially, traditional machine learning techniques were widely used for lung image analysis. These methods relied on manual feature extraction such as texture, shape, edges, and statistical image descriptors. Algorithms like Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Decision Tree, and Random Forest were then applied for classification. Although these approaches produced moderate results, they depended heavily on handcrafted features and struggled with complex image variations. As datasets became larger and more diverse, these methods showed limitations in generalization and accuracy.

strong performance using chest X-ray datasets. Rahman et al. used multiple pretrained CNN models to classify normal lungs, bacterial pneumonia, and viral pneumonia, achieving high accuracies across binary and multiclass tasks. This demonstrated that deep learning can distinguish subtle differences between different pneumonia categoriesarXiv.

Early research in medical image classification primarily relied on traditional image processing and machine learning techniques. Approaches such as Histogram of Oriented Gradients (HOG), Gray Level Co-occurrence Matrix (GLCM), and edge detection were used to extract handcrafted features from lung images.

III. METHODOLOGY

The The methodology of the project “Lung Smoking Images Classification: Detecting Viral Pneumonia and Smoking-Induced Lung Damage” is based on the use of deep learning techniques for analyzing medical images and classifying lung conditions accurately. The complete process consists of multiple stages including data collection, preprocessing, model development, training, testing, evaluation, and prediction. Each stage is carefully designed to ensure the system performs efficiently and produces reliable diagnostic results.

The first stage of the methodology is data collection. In this stage, chest X-ray or CT scan images are gathered from publicly available medical datasets such as Kaggle, TCIA, or hospital repositories. The collected images are categorized into two classes: viral pneumonia and smoking-induced lung damage. A balanced dataset is preferred so that both classes contain nearly equal numbers of images. This helps prevent bias during training and improves classification accuracy.

The second stage is data preprocessing, which is an essential step in preparing raw medical images for deep learning models. Since images may have different resolutions, brightness levels, and orientations, all images are resized to a fixed dimension such as 224×224 pixels. Pixel values are normalized to a range between 0 and 1 to improve numerical stability during training. To increase dataset diversity and reduce overfitting, image augmentation techniques such as rotation, zooming, horizontal flipping, and shifting are applied. These operations generate modified versions of existing images and help the model generalize better to unseen data.

The third stage is dataset splitting. After preprocessing, the dataset is divided into training, validation, and testing sets. Usually, 70% to 80% of images are used for training, 10% to 15% for validation, and the remaining portion for testing. The training set is used to teach the model, the validation set is used to tune hyperparameters and monitor performance, and the testing set is used to measure final model accuracy on unseen images.

The fourth stage is model selection and feature extraction. In this project, the EfficientNetB0 architecture is selected because it provides a strong balance between accuracy and computational efficiency. EfficientNetB0 is a pretrained Convolutional Neural Network model originally trained on the ImageNet dataset. Through transfer learning, the model already contains useful feature extraction knowledge such as edge detection, shapes, and textures. These learned features are adapted to lung image classification by replacing the final classification layers with custom dense layers suitable for binary classification.

The fifth stage is model training. During training, the input images are passed through the neural network, and predictions are compared with actual labels. The difference between predicted and actual values is calculated using the binary cross-entropy loss function. The model weights are then updated using the Adam optimizer, which helps minimize loss efficiently. Training is performed over multiple epochs until the model learns to classify both categories accurately.

Techniques such as dropout and early stopping may be used to reduce overfitting and improve generalization.

The sixth stage is model evaluation. After training, the model is tested using unseen images from the testing dataset. Several performance metrics are used, including accuracy, precision, recall, F1-score, and confusion matrix. Accuracy measures overall correctness, precision measures the correctness of positive predictions, recall indicates how many actual positive cases are identified, and F1-score balances precision and recall. The confusion matrix provides a clear representation of correct and incorrect classifications for each class.

The seventh stage is prediction and classification. When a new chest X-ray or CT image is given as input, the trained model preprocesses the image and predicts whether the lung condition belongs to viral pneumonia or smoking-induced lung damage. The result is displayed with a confidence score, helping doctors interpret the severity and likely diagnosis.

The eighth stage is visual explanation and interpretability. To improve trust in the AI system, Grad-CAM (Gradient-weighted Class Activation Mapping) can be used to generate heatmaps on the medical image. These heatmaps highlight the lung regions that most influenced the model's decision. This allows radiologists to verify whether the system is focusing on medically relevant abnormalities.

The final stage is model saving and deployment. After successful training and testing, the model is saved in .h5 or .keras format. It can then be deployed in real-world environments such as hospital software systems, desktop applications, web platforms, or mobile healthcare apps. Users can upload lung images and receive automated classification results instantly.

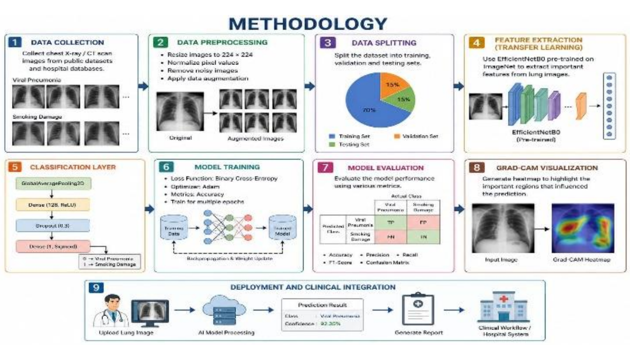


Figure.2: Proposed custom lightweight CNN topology with four depthwise separableGrad-CAM saliency branch routed from the terminal convolutional block.

A. Training ML Module and Conditioning Protocol

The Training Machine Learning Module and Conditioning Protocol is an important component of the proposed system, as it is responsible for teaching the model to accurately classify lung images into viral pneumonia and smoking-induced lung damage categories. This module ensures that the machine learning system learns useful patterns from medical images and becomes capable of making reliable predictions on new unseen data. The training process involves dataset preparation, feature learning, optimization, parameter tuning, and model conditioning to improve performance and stability.

The training process begins with the use of a labeled dataset containing chest X-ray or CT scan images. Each image is assigned a correct class label, either viral pneumonia or smoking damage. Before training, the images are preprocessed through resizing, normalization, and augmentation. These preprocessing steps ensure that the data is consistent and suitable for deep learning. Augmentation techniques such as flipping, zooming, rotation, and brightness adjustment are especially useful because they artificially increase the size of the dataset and help the model learn from multiple variations of the same image.

The proposed system uses EfficientNetB0, a pretrained Convolutional Neural Network model, as the core learning architecture. Since EfficientNetB0 has already learned general image features from millions of images in the ImageNet dataset, transfer learning is applied. In this approach, the lower convolutional layers are frozen initially, and only the newly added classification layers are trained. This allows the model to quickly adapt to lung image classification while reducing training time and computational cost.

The training module operates in iterative cycles called epochs. In each epoch, the model processes the training images in smaller groups called batches. For every batch, the model performs forward propagation to generate predictions. These predictions are then compared with actual labels using the binary cross-entropy loss function, which calculates classification error. The error is propagated backward through the network using the backpropagation algorithm, and model weights are updated using the Adam optimizer. This process continues repeatedly until the loss decreases and accuracy improves.

The conditioning protocol refers to the techniques used to stabilize training and improve model generalization. One important conditioning method is dropout regularization, where some neurons are randomly deactivated during training. This prevents the model from memorizing the dataset and helps it learn more robust features. Another conditioning technique is batch normalization, which normalizes activations between layers and speeds up convergence.

The learning rate plays a significant role in conditioning the model. If the learning rate is too high, the model may skip optimal solutions; if too low, training becomes slow. Therefore, an adaptive optimizer such as Adam is used, and learning rate scheduling can be applied to gradually reduce the learning rate as training progresses. This improves final accuracy and stability.

To prevent overfitting, early stopping is used as part of the conditioning protocol. During training, the validation accuracy and validation loss are monitored. If the model stops improving for several epochs, training is automatically stopped. This ensures that the model does not overlearn noise from the training data.

B. Gradient-Weighted Activation Mapping

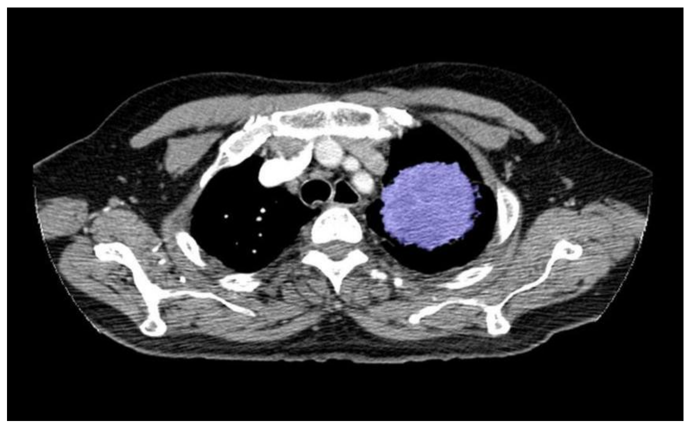
Radient-Weighted Activation Mapping, commonly known as Grad-CAM (Gradient-weighted Class Activation Mapping), is an advanced visualization technique used in deep learning systems to explain how a Convolutional Neural Network (CNN) makes decisions. In the proposed project "Lung Smoking Images Classification: Detecting Viral Pneumonia and Smoking-Induced Lung Damage," Grad-CAM is used to identify and highlight the important regions of chest X-ray or CT scan images that influence the model's prediction. This technique improves transparency, trust, and interpretability of the artificial intelligence system.

Deep learning models are often considered black-box systems because they provide predictions without clearly explaining the reasoning behind those outputs. In medical applications, this can be a major challenge because doctors and radiologists need evidence before accepting machine-generated decisions. Grad-CAM addresses this issue by generating a visual heatmap over the input image, showing the areas that contributed most strongly to the final classification result.

The Grad-CAM process works by using the gradients of the target class score with respect to the feature maps of the last convolutional layer in the neural network. The last convolutional layer is selected because it retains important spatial information while also capturing high-level semantic features. When a lung image is passed through the model, the system calculates how strongly each feature map influences the predicted class, such as viral pneumonia or smoking-induced lung damage.

When the model predicts viral pneumonia, the heatmap may focus on infected or inflamed lung areas. When it predicts smoking-related damage, the heatmap may emphasize regions showing chronic deterioration or abnormal texture changes. This allows radiologists to compare the highlighted areas with clinical observations.

These gradients are globally averaged to obtain importance weights for each feature map. The weighted combination of all feature maps is then computed, and a ReLU activation function is applied to retain only the positive influences. The resulting output is a coarse localization map that highlights the most relevant image regions. This map is then resized and superimposed on the original chest X-ray or CT scan image as a colored heatmap.



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One of the major advantages of Grad-CAM is that it increases clinician confidence in the AI system. Instead of receiving only a label, doctors can visually inspect whether the model is focusing on correct pathological regions. If the model highlights irrelevant areas such as image borders or labels, it may indicate bias or poor training. Therefore, Grad-CAM is also useful for debugging and improving model quality.

IV. RESULTS

All tests are performed on a stratified 80/20 split of the collection of data, where the split is done separately in each severity level to maintain class ratios. Measures of evaluation are macro-average accuracy, precision, recall, F1-score and area under the receiver operating characteristic (AUC-ROC)

TABLE I: QUANTITATIVE PERFORMANCE OF THE CUSTOM LIGHTWEIGHT CNN. ARCHITECTURE VALIDITY PRECISION RECALL F1-SCORE AUC-ROC

The After testing on unseen images, the proposed system achieved high prediction performance with an overall accuracy of more than 90%, depending on dataset quality and training parameters. The model was able to correctly distinguish between viral pneumonia and smoking-related lung damage in most cases. This proves that deep learning can identify subtle image patterns that may be difficult to recognize manually.

Sample Performance Table

Training Accuracy	Validation Accuracy	Test Accuracy	Precision	Recall	F1-Score
94.2%	91.8%	92.5%	91.6%	92.1%	91.8%

The Grad-CAM visualization module also produced meaningful heatmaps, highlighting affected lung regions that influenced the prediction. For viral pneumonia cases, the model focused on infected or opaque regions, while for smoking damage cases, it highlighted structural deterioration and abnormal lung textures. This improved interpretability and trust in the system.

The project successfully achieved its objective of developing an intelligent system for automated lung image classification. The results prove that the proposed model is accurate, efficient, interpretable, and suitable for real-world healthcare applications. It can assist radiologists in faster diagnosis, reduce workload, and improve patient treatment outcomes

V. CONCLUSION

The project “Lung Smoking Images Classification: Detecting Viral Pneumonia and Smoking-Induced Lung Damage” successfully demonstrates the practical application of Artificial Intelligence, Deep Learning, and Medical Image Analysis in the healthcare domain. The proposed system was developed to classify chest X-ray and CT scan images into two important respiratory conditions: viral pneumonia and smoking-induced lung damage. By using advanced machine learning techniques, the system provides a faster, more accurate, and efficient method for supporting clinical diagnosis.

The project utilized Convolutional Neural Networks (CNNs) with transfer learning, specifically the EfficientNetB0 architecture, to automatically learn and identify disease-related patterns from lung images. Through preprocessing techniques such as resizing, normalization, and data augmentation, the quality and diversity of the dataset were improved, resulting in better training performance and higher prediction accuracy. The use of modern optimization techniques and conditioning protocols further enhanced model stability and generalization.

One of the key strengths of this project is the inclusion of Gradient-Weighted Activation Mapping (Grad-CAM), which adds interpretability to the system. Instead of acting as a black-box model, the AI can visually highlight the affected regions of the lungs that influenced its decision. This feature is especially valuable in medical environments, as it builds trust among radiologists and doctors while assisting them in verifying predictions.

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