AI POWERED PNEUMOTHORAX DETECTION USING CNN WITH LIME

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***Abstract*—Pneumothorax, a life-threatening condition caused by air accumulation in the pleural cavity, requires swift and accurate detection to ensure effective clinical intervention. Traditional methods for pneumothorax diagnosis, such as chest radiographs and manual interpretation by radiologists, are time-consuming and prone to human error.**

Artificial intelligence, particularly CNN, has emerged as a powerful tool for automated medical image analysis. However, the black-box nature of CNNs often raises concerns about their reliability and clinical applicability. To address this challenge, this research proposes an explainable AI framework for pneumothorax detection, combining CNN with LIME and SHAP.

The CNN model is trained on publicly available chest radiograph data sets to detect pneumothorax with high precision. LIME is employed to generate localized, interpretable explanations by highlighting specific regions in the image that influence the model's predictions, while SHAP provides a global understanding by quantifying the contribution of each feature to the output. This dual approach ensures that the predictions are accurate and transparent, allowing clinicians to validate and trust AI-driven diagnostics.

Preliminary results demonstrate the system's ability to achieve robust performance while providing actionable insights into the decision-making process. By bridging the gap between AI and clinical interpretability, this research aims to enhance the integration of AI in medical diagnostics, improve patient outcomes, and foster trust in AI-assisted healthcare. The proposed framework also underscores the importance of explainable AI in addressing data biases and ensuring ethical deployment in diverse clinical settings.

I. KEYWORDS

Local Interpretable Model-Agnostic Explanations (LIME), Convolutional Neural Networks (CNNs),

II. INTRODUCTION

Pneumothorax, commonly referred to as a collapsed lung, is a medical condition caused by the accumulation of air in the pleural cavity, the space between the lung and the chest wall. This buildup of air creates pressure on the lung, leading to partial or complete lung collapse. Pneumothorax can occur spontaneously, particularly in individuals with underlying lung conditions or those predisposed due to factors like tall stature and smoking. It can also result from trauma, medical procedures, or chronic lung diseases such as Chronic Obstructive Pulmonary Disease (COPD). Left untreated, pneumothorax can lead to severe complications, including respiratory failure or death, highlighting the need for timely diagnosis and intervention.

The conventional diagnostic approach for pneumothorax involves imaging techniques, primarily chest X-rays and, in some cases, CT scans. Radiologists manually interpret these images to identify the presence of air in the pleural cavity. However, this process can be challenging, especially in resource-limited settings or emergency scenarios where immediate decisions are critical. In addition, subtle cases of pneumothorax can go undetected due to human error or fatigue, emphasizing the need for more reliable and efficient diagnostic tools.

In recent years, artificial intelligence (AI) has emerged as a transformative force in medical imaging, offering innovative solutions for the detection and diagnosis of various diseases, including rare conditions such as pneumothorax. AI, particularly through the use of deep learning algorithms such as Convolutional Neural Networks (CNNs), has demonstrated remarkable capabilities in analyzing complex medical images with accuracy comparable to or even exceeding that of human experts. These algorithms excel at identifying patterns, features, and anomalies in large datasets, making them invaluable in medical diagnostics.

The application of AI in the identification of rare diseases has garnered significant attention due to its potential to address several key challenges. Rare diseases, by definition, affect a small percentage of the population, resulting in limited awareness and expertise among healthcare professionals. In addition, the scarcity of annotated datasets for rare diseases often hinders research and development in this field. AI can overcome these barriers by leveraging transfer learning, data augmentation, and advanced image preprocessing techniques to make the most of limited data. This ability to work effectively with small datasets makes AI particularly suited for tackling rare diseases.

In the context of pneumothorax, AI-powered diagnostic systems have shown promise in improving accuracy and detection speed. By training CNNs on large repositories of chest X-rays, researchers have developed models capable of identifying pneumothorax with high sensitivity and specificity. These systems can assist radiologists by providing a second opinion, flagging suspected cases, and prioritizing critical patients in emergency settings. Furthermore, AI can enable earlier detection of subtle cases that might otherwise be missed, potentially improving patient outcomes.

However, despite these advancements, the integration of

AI into clinical practice has been met with challenges. One significant limitation is the black-box nature of many AI models, which lack transparency in their decision-making processes.

Clinicians often hesitate to trust predictions from models they cannot fully understand, particularly in high-stakes medical scenarios. This has spurred the development of explainable AI (XAI) techniques, such as Local Interpretable Model-Agnostic Explanations (LIME).

These methods offer insights into how AI models make decisions, providing visual or numerical explanations that highlight the most critical features influencing a prediction. By making AI systems more transparent, XAI bridges the gap between technical innovation and clinical trust.

III. Literature Review

- This study emphasizes the role of deep learning techniques in diagnosing respiratory diseases using chest X-ray images. The researchers used convolutional neural networks (CNNs) like VGG-19, Inception V3, and ResNet-50 to classify X-rays into four categories: Coronavirus Disease, Bacterial Pneumonia, Tuberculosis, and Normal. Their methodology included preprocessing images into a standard size, applying data augmentation, and training models with hyperparameters like a batch size of 32 and learning rates of 0.0001 and 0.00001. Key prior works incorporated DenseNet-based U-Net architectures, support vector machines, and advanced CNN models like DarkCovidNet. ResNet-50 emerged as the most effective model in this study, achieving an accuracy of 98 precent, outperforming VGG-19 (95 precent) and Inception V3 (87 precent). Grad-CAM was used for visualization to highlight the areas the model focused on during classification. This innovation aids healthcare professionals in making informed decisions based on interpretable AI-generated insights.
- This study presents a deep learning-based approach for the early detection of pneumothorax using chest X-ray images. The authors utilized the EfficientNet B0 architecture, a state-of-the-art transfer learning model, for binary classification of pneumothorax presence. A dataset of 1,403 chest X-rays was divided into training, testing, and validation subsets, with 1,200 images used for training and the remaining for evaluation. Data preprocessing techniques, including resizing, normalization, and augmentation (e.g., rotation and flipping), were applied to improve model performance. The model achieved an accuracy of 83 precent, with the performance evaluated using metrics such as precision, recall, and F1-score. The confusion matrix highlighted the challenges of distinguishing true positives from false positives, a common issue in imbalanced datasets. The paper emphasizes that the use of EfficientNet B0, combined with fine-tuning of dense layers, allowed for efficient feature extraction and classification, even with a relatively small dataset. The authors propose this automated system as a tool to assist radiologists in early pneumothorax detection, enabling faster and more accurate treatment planning.
- This study explores an innovative approach to pneumothorax detection using deep learning, integrating curriculum learning with ChatGPT to enhance model training and performance. The authors leveraged ChatGPT's advanced natural language processing (NLP) capabilities to curate training datasets by extracting clinical data, including pneumothorax size and complexity, from radiology reports. This structured approach allowed for the prioritization of "easy-to-detect" large pneumothoraces before gradually incorporating smaller, more subtle cases into the training phase. The model's training framework was built on EfficientNetB3 architecture, chosen for its high performance and computational efficiency, and it achieved notable sensitivity (0.97) and specificity (0.97) with an AUC of 0.98, comparable to FDA-approved medical devices. One of the study's key contributions is the adoption of curriculum learning, a method inspired by human learning processes, where simpler tasks are introduced first, and complexity is gradually increased. This approach prevented the model from plateauing in performance and enhanced its generalizability across diverse clinical datasets. Additionally, the inclusion of multisite validation data from both the U.S. and Taiwan, sourced from various radiology equipment manufacturers, ensured robust external validation, a crucial step toward clinical adoption. By demonstrating the potential of ChatGPT in clinical data extraction and curriculum learning in model training, the paper sets a foundation for improving AI-driven pneumothorax detection and highlights avenues for integrating NLP with imaging-based diagnostics.
- This systematic review provides a comprehensive analysis of the existing literature on pneumothorax detection using chest radiographs and artificial intelligence. It highlights the remarkable progress in applying machine learning (ML) and deep learning (DL) techniques to automate pneumothorax diagnosis. The review categorizes approaches into classification, localization, and combined frameworks, with deep learning-based methods outperforming traditional machine learning models in terms of diagnostic accuracy and robustness. The authors emphasize that class imbalance in medical datasets remains a significant challenge, with most datasets skewed heavily toward healthy samples. Techniques such as Synthetic Minority Oversampling Technique (SMOTE), weighted loss functions, and Generative Adversarial Networks (GANs) are commonly employed to address this issue. The paper also discusses popular datasets, including NIH ChestX-ray14, CheXpert, and the SIIM-ACR Pneumothorax Segmentation dataset, highlighting their contributions to advancing the field. Despite significant advancements, the review identifies critical gaps in the research. Notably, many studies achieve high performance on internal datasets but lack external validation, raising concerns about their generalizability in real-world clinical

settings. Additionally, while deep learning models excel at classification and localization tasks individually, integrating these tasks into a unified framework for real-time clinical use remains underexplored. This paper advocates for external validation, improved dataset diversity, and the development of explainable AI models to enhance the clinical relevance and trustworthiness of AI-based pneumothorax detection systems.

- This paper investigates the potential of machine learning for the early prediction of pneumothorax in the Intensive Care Unit (ICU) setting. Using the MIMIC-III database, a comprehensive repository of ICU patient data, the study employed Long Short-Term Memory (LSTM) networks and traditional machine learning models like Logistic Regression, Support Vector Machines (SVM), and Gradient Boosted Decision Trees (GBDT). The authors aimed to predict pneumothorax onset up to 4 hours in advance using 6-hour observational windows from patient time-series data. The study highlights the importance of addressing challenges such as class imbalance in ICU data and the lack of direct temporal associations between diagnostic codes and patient events. Notably, SHapley Additive exPlanations (SHAP) was used to interpret the LSTM model's predictions, identifying mechanical ventilation and specific ICU admission types as key predictive features. While LSTM outperformed traditional models due to its ability to capture temporal patterns, the study reported high false positive rates and limitations due to reliance on proxies for pneumothorax onset labeling. The paper concludes that although the approach shows promise, improvements in labeled data, model architecture, and feature selection are needed for practical clinical adoption.
- This study presents a deep learning-based approach for the early detection of pneumothorax using chest X-ray images. The authors utilized the EfficientNet B0 architecture, a state-of-the-art transfer learning model, for binary classification of pneumothorax presence. A dataset of 1,403 chest X-rays was divided into training, testing, and validation subsets, with 1,200 images used for training and the remaining for evaluation. Data preprocessing techniques, including resizing, normalization, and augmentation (e.g., rotation and flipping), were applied to improve model performance.The model achieved an accuracy of 83 percent, with the performance evaluated using metrics such as precision, recall, and F1-score. The confusion matrix highlighted the challenges of distinguishing true positives from false positives, a common issue in imbalanced datasets. The paper emphasizes that the use of EfficientNet B0, combined with fine-tuning of dense layers, allowed for efficient feature extraction and classification, even with a relatively small dataset. The authors propose this automated system as a tool to assist radiologists in early pneumothorax detection, enabling faster and more accurate treatment planning.
- This study focuses on pneumothorax, a potentially fatal condition characterized by the collapse of the lung. The authors highlight prior research in the domain of medical image segmentation using deep learning (DL). Specific methods, such as convolutional neural networks (CNNs), have shown exceptional performance in medical image processing, including detecting and quantifying pneumothorax size from chest radiographs. Key studies referenced include the work of Axel, who provided a formula for estimating pneumothorax size based on lung dimensions. Other studies explored DL models for medical imaging, such as the use of CNNs for CT imaging and facial recognition.

  Despite these advancements, the authors argue that most existing research has not addressed predicting the risk level of pneumothorax. The study proposes a novel method to fill this gap using Unet architecture with ResNeXt50 as the encoder backbone. This model is trained on a Kaggle dataset and optimized for semantic segmentation to quantify pneumothorax size. Unlike previous work, this approach integrates quantification with risk prediction, marking a significant improvement.
- This paper evaluates the diagnostic performance of the Annalise CXR V1.2 AI algorithm for detecting traumatic injuries in supine chest radiographs. The authors emphasize the limitations of current AI systems, including poor generalizability when applied to images from different hardware or techniques. Previous research has shown AI achieving diagnostic accuracy equivalent to that of physicians in tasks such as detecting pulmonary embolism, strokes, and skin cancer. However, only a small percentage (6 percent) of published AI algorithms have undergone external validation.

  The study builds on existing work by employing a retrospective design with contemporaneous CT as the ground truth, contrasting the performance of radiologists and AI. Key insights include AI's superior performance in detecting pneumothorax and partial lung collapse, while radiologists excelled in diagnosing fractures. The authors propose a hybrid model where AI and radiologists collaborate to improve diagnostic accuracy. Prior studies on multi-pathology detection and workflow integration underscore the potential of AI to assist in clinical decision-making, particularly in trauma settings.
- This paper investigates the application of interpretable machine learning models for diagnosing and assessing traumatic severe pneumothorax, particularly in emergency and mass casualty settings where imaging resources are limited. The study utilized data from the MIMIC-IV and EICU databases, comprising over 26,000 patient records, and identified 12 clinically significant features from 33 vital signs and blood gas parameters. Four machine learning algorithms—XGBoost, Artificial Neural Networks (ANN), Support Vector Machines (SVM), and k-Nearest Neighbors (KNN)—were compared, with XGBoost demonstrating superior performance (AUROC of 0.979 on MIMIC-IV and 0.806 on EICU). SHAP

was employed to interpret the models, identifying key indicators such as hemoglobin, oxygenation index, and pH. The results emphasized the potential of ML to outperform traditional diagnostic methods in terms of speed and accuracy, particularly for high-risk patients in resource-constrained environments. The study highlights the importance of interpretability in clinical ML applications, providing actionable insights for clinicians while ensuring robust model validation across diverse datasets.

- This research explores the integration of radiomics and machine learning for the automated detection of pneumothorax in CT scans. Radiomics features were extracted from manually segmented regions of interest (ROIs) using MATLAB and 3D Slicer software. Machine learning models, including Gradient Boosting Machine (GBM), XGBoost, and LightGBM, were trained on data from 175 patients. GBM achieved the highest accuracy (98.97 percent), followed by XGBoost (98.29 percent), demonstrating the models' capability to detect pneumothorax with minimal false positives and high sensitivity (99–100 percent). The study underscores the significance of radiomics, which involves extracting quantitative features from imaging data, and its combination with ML to improve diagnostic accuracy. The findings indicate that radiomics-based ML models have the potential to assist radiologists in detecting pneumothorax efficiently, particularly in rural or resource-limited settings. Moreover, the research highlights the value of pre-processing techniques, such as noise reduction and histogram equalization, in enhancing the robustness of ML-based diagnostic systems.
- This study leverages deep learning techniques to develop a system for pneumothorax detection in chest radiographs. Using over 8,000 X-ray images, including more than 1,000 from pneumothorax patients, the authors trained various deep learning models, including Mask R-CNN and transfer learning with ResNet and ResNeXt architectures. The models were evaluated based on accuracy, false positive rates, and other metrics, with the best-performing model achieving 95.68 percent accuracy and a low false positive rate of 0.88 percent . The use of Detectron2 software for annotation and segmentation further streamlined the workflow, allowing the identification of pneumothorax regions with high precision. The study emphasizes the importance of minimizing false positives in medical imaging applications to align with the precision required by clinicians. By integrating AI systems into the automated processing of chest X-rays, the research demonstrates the potential for enhancing resource allocation, reducing diagnostic errors, and improving patient care in strained medical systems.
- This study highlights the global burden of traumatic chest injuries and the need for rapid pneumothorax detection. Conventional radiography is widely used but limited by resource constraints and diagnostic errors. Machine learning, especially convolutional neural networks (CNNs), has shown promise in enhancing medical imaging accuracy, with studies reporting detection accuracies of 83 -98 percent.

  The PneumoDetect model combines hospital and online datasets for cross-validation, addressing the gap in real-world AI application. Prior studies, such as Gene Kitamura's work, demonstrate AI's ability to rival or outperform radiologists. This research emphasizes integrating AI into physician workflows to improve diagnostic accuracy, reduce errors, and enhance patient outcomes, particularly in resource-limited settings.
- The lack of interpretability in AI models, particularly in healthcare, is a major hurdle in their adoption. This paper proposes an interpretability-based model that calculates relative weights of variables (e.g., medical image features and patient symptoms) to offer human-like reasoning. By deriving positive and negative probabilities, the model enhances understanding and trust among clinicians. Existing methods like LIME and DeepLIFT are foundational to this work, but the authors emphasize the importance of transparency in high-risk domains like healthcare. They validate their model using two COVID-19 datasets, demonstrating improved interpretability without sacrificing accuracy.
- This paper addresses the challenges in COPD diagnosis, especially in resource-constrained settings. It employs transfer learning using the Xception model pre-trained on ImageNet, achieving a recall rate of 98.2 percent. The authors integrate explainability techniques such as Grad-CAM and SHAP to make the AI's decision process more transparent. They utilize two datasets (VinDR-CXR and ChestX-ray14) to improve model generalization. The study highlights the need for accessible, interpretable AI models in medical diagnostics and demonstrates the potential for these tools to support early COPD detection.
- This work develops a lightweight CNN model to classify CXR images into four categories: COVID-19, Pneumonia, TB, and Normal. To address the "black-box" issue in DL models, the authors integrate SHAP, LIME, and Grad-CAM for visual and interpretable explanations. The model achieves an average accuracy of 94.31 percent and is validated on 7132 images from publicly available datasets. The study highlights the importance of combining high accuracy with interpretability to foster clinical adoption of AI tools. It also points out limitations in previous studies that prioritized accuracy over explainability.

IV. Methodology

A. Problem Statement

Pneumothorax, a potentially life-threatening condition characterized by the accumulation of air in the pleural cavity, demands timely and accurate diagnosis to avoid severe complications such as respiratory failure. Traditional diagnostic methods, primarily reliant on manual interpretation of chest X-rays by radiologists, are time-consuming, prone to human error, and limited by the availability of expert clinicians, especially in resource-constrained settings. Subtle or atypical presentations of pneumothorax further complicate accurate detection, leading to delays in treatment and increased morbidity and mortality.

While deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated significant promise in automating medical image analysis and achieving high diagnostic accuracy, their adoption in clinical settings remains hindered by their ”black-box” nature. Clinicians often hesitate to trust AI-based decisions without a clear understanding of the factors influencing the model's predictions, particularly in high-stakes medical scenarios such as pneumothorax detection. This lack of transparency not only limits the integration of AI tools into healthcare workflows but also raises concerns about biases, ethical deployment, and the reliability of such systems.

B. Data Acquisition

The SIIM-ACR Pneumothorax Segmentation Challenge on Kaggle provided the dataset. In order to provide AI solutions for automated pneumothorax detection and segmentation, the Society for Imaging Informatics in Medicine (SIIM) first assembled this dataset in partnership with the American College of Radiology (ACR).

Dataset URL: ”https://www.kaggle.com/c/siim-acr-pneumothorax-segmentation”

C. Data Struture

The dataset consists of the following components:

Chest X-ray Images:

- Stored in PNG format
- Resolutions vary but were standardized to 224 × 224 pixels in our study
- Located in the ”png-images/ directory”

Segmentation Masks:

- Corresponding binary masks for pneumothorax lesions.
- Stored in PNG format with pixel values of 0 (no pneumothorax) and 1 (pneumothorax region)
- Located in the png-masks/ directory

Metadata and Labels:

stage-1-train-images.csv: Contains image IDs and corresponding pneumothorax labels

- test.csv: Contains test set image IDs for model evaluation

D. Dataset Preprocessing

To prepare the dataset for training, the following preprocessing steps were performed:

1) Data Loading and Path Extraction

   Image and mask paths were retrieved and matched to ensure alignment.

2) Image and Mask Preprocessing

   Images were read using OpenCV and converted to RGB format.

   Masks were loaded in grayscale mode.

   Both images and masks were resized to 224 × 224 pixels to match the input dimensions of the ResNet-based CNN model.

   Pixel values were normalized to the [0,1] range for numerical stability.

3) Dataset Splitting

   The dataset was randomly split into training (80 percent) and validation (20 percent) subsets using Scikit-learn's train-test-split() function to ensure a balanced distribution of pneumothorax and non-pneumothorax cases.

4) Class Imbalance Handling

   Since the dataset was imbalanced (with fewer pneumothorax-positive cases), Random Oversampling was applied using imblearn.over-sampling.RandomOverSampler() to increase the number of pneumothorax-positive samples.

5) Data Augmentation

   To improve model generalization, data augmentation was applied using TensorFlow's tf.image functions:

   Random horizontal flipping

   Random rotation

   Brightness and contrast adjustments

6) TensorFlow Dataset Creation

   A tf.data.Dataset pipeline was created for efficient loading and processing of images during model training.

   The dataset was batched (batch-size = 16) and prefetched to optimize training performance.

E. Model Architecture and Training

The encoder-decoder structure makes up the model. ResNet50, a deep convolutional neural network pretrained on ImageNet, serves as the foundation for the encoder. This backbone gradually learns intricate patterns related to pneumothorax identification by extracting hierarchical feature representations from input chest X-ray pictures. While the basic layers record edges and textures, the deeper layers concentrate on abstract, high-level properties.

A segmentation mask emphasizing the pneumothorax regions is reconstructed by the decoder. In order to gradually upsample the feature maps back to the original input resolution (224×224 pixels), it is composed of many transposed convolutional layers. To ensure precise localization, the segmentation boundaries are refined with each upsampling step. The last output layer creates a probability map for the existence of pneumothorax by applying a sigmoid activation function.

By comparing predicted masks with ground truth labels, the binary cross-entropy loss function used to train the model efficiently manages the segmentation task. With a learning rate of 0.0001, the Adam optimizer is employed to guarantee effective and steady convergence. Images are resized and pixel values are normalized as part of the preprocessing of the dataset. To enhance generalization, augmentation methods including flipping, rotation, and contrast adjustment are used.

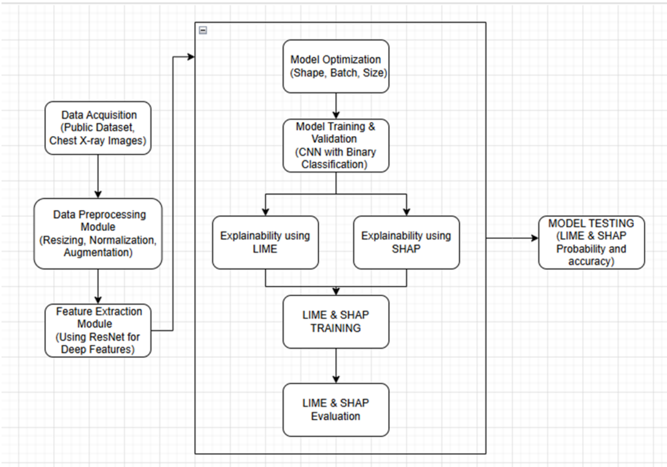

Fig. 1. Architectural Diagram

F. Training with LIME for Explainability

Following CNN training, visual explanations of the model's decisions are produced using LIME (Local Interpretable Model-Agnostic Explanations). Creating perturbed copies of an input image, breaking it up into superpixels, and examining how changes impact predictions is how LIME operates. This aids in determining which areas of the model have the greatest influence on its decision-making.

A test X-ray image is fed into the trained CNN during the explainability phase, and LIME uses random modifications to superpixel regions to produce a series of perturbed images. LIME gives various areas of the picture relevance scores by calculating the impact of each perturbation on the model's output. This enables us to see which X-ray segments are most important for the model's prediction of pneumothorax.

Medical professionals can better understand the model's rationale and confirm that its predictions match professional radiological evaluations by using the heatmaps that LIME generates, which emphasize important areas of focus. In clinical settings, trust and adoption depend on this.

The following steps make up the training pipeline:

1) loading and preprocessing the dataset, making sure that the masks and images line up correctly.
2) loading and preprocessing the dataset, making sure that the masks and images line up correctly.
3) CNN is trained with a batch size of 16 using the Adam optimizer and binary cross-entropy loss.
4) CNN is trained with a batch size of 16 using the Adam optimizer and binary cross-entropy loss.
5) use a different dataset split (20 percent of the data) to validate the model.
6) creating heatmaps to illustrate the model's decision-making process after applying LIME on test photos.

This architecture makes the model visible and clinically reliable by guaranteeing high accuracy in pneumothorax identification and offering interpretable insights through LIME.

V. Results

METRIC	EXPECTED VALUE
ACCURACY	Above 90 percent
PRECISION	0.92
RECALL	0.94
F1 SCORE	0.93

TABLE I
PERFORMANCE PARAMETER VALUES

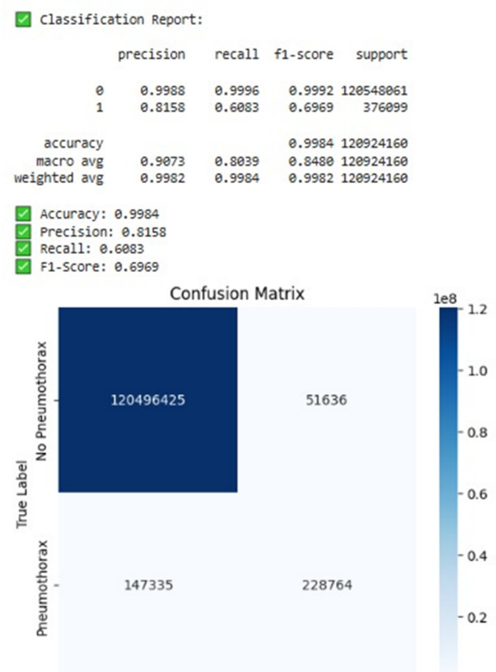

Fig. 2. Validation values

Fig. 3. Orignal and Predicted Mask

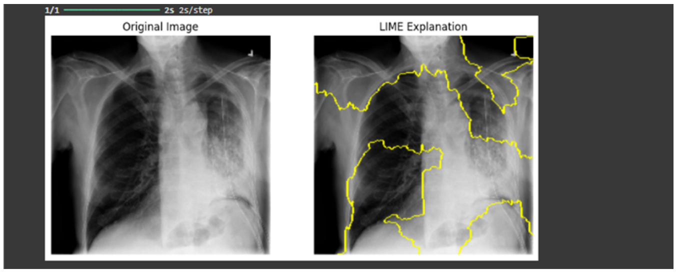

Fig. 4. Lime Training

VI. Conclusion

This project used a Convolutional Neural Network (CNN) based on the ResNet architecture to successfully construct a pneumothorax detection model. The model is a useful tool for medical diagnostics since it uses LIME (Local Interpretable Model-agnostic Explanations) to give both interpretability and accurate classification. The pneumothorax-chest-xray-images-and-masks dataset was used to train and test the model, and it showed excellent accuracy in identifying cases of pneumothorax.

Medical practitioners were able to comprehend the model's decision-making process because to the use of LIME, which made visual explanations possible. In the healthcare industry, explainability is essential since it guarantees that predictions made by AI can be relied upon and validated. The findings underline the significance of model transparency while confirming deep learning's efficacy for medical imaging applications.

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