International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 06 | June - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

AUTOMATED CLASSIFICATION OF EMPHYSEMA USING CONVOLUTIONAL NEURAL NETWORKS

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***Abstract*: The analysis of CT scans for emphysema diagnosis can be formulated as a computer vision problem, where predefined patterns are used to automatically classify the images. This paper investigates a method for classifying emphysema subtypes in High-Resolution Computed Tomography (HRCT) scans using convolutional neural networks (CNNs). This classification is crucial for accurate diagnosis and management of emphysema, a chronic lung disease causing shortness of breath. Our approach leverages transfer learning to extract informative features from HRCT images labeled as centrilobular (CLE), paraseptal (PLE), panlobular (PSE), and non-emphysematous (NT). We evaluate various CNN architectures, with InceptionV3 demonstrating exceptional performance, achieving an accuracy of 98% while effectively distinguishing between all subtypes. The trained InceptionV3 model is then integrated into a user-friendly front-end application developed using Streamlit and ngrok. This application allows real-time emphysema classification from HRCT scans, potentially aiding clinicians in diagnosis and treatment decisions.**

Keywords:- Emphysema classification ,Transfer Learning,CNN,InceptionV3,Streamlit , Ngrok

I.INTRODUCTION

Chronic Obstructive Pulmonary Disease (COPD), characterized by progressive airway obstruction, significantly impacts patients' lives[1]. Emphysema, a major subtype of COPD, destroys air sacs in the lungs, leading to shortness of breath and exercise intolerance. Early and accurate diagnosis is crucial for timely intervention and improved treatment outcomes[7]. Currently, diagnosing emphysema relies on High-Resolution Computed Tomography (HRCT) scans interpreted by radiologists. However, this approach can be subjective and prone to inter-reader variability, potentially leading to misdiagnosis.

Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), offer exciting possibilities for automated medical image analysis[1]. CNNs excel at extracting complex patterns from images, making them ideal for tasks like classifying medical images, including HRCT scans[2]. Several studies have explored the application of CNNs for emphysema classification in HRCT scans, demonstrating their potential for improved accuracy and objectivity compared to traditional methods[4]. However, there remains room for further enhancing the performance, robustness, and generalizability of these deep learning models.

This research project investigates the performance of various CNN architectures on emphysema classification in HRCT scans. We aim to develop a robust and generalizable deep learning model for automated emphysema classification, potentially leading to earlier diagnosis and improved patient care[1]. Our research project tackles the challenge of automated emphysema classification in HRCT scans by investigating the performance of various, unexplored CNN architectures to potentially improve accuracy and generalizability. We will further enhance the model's robustness by employing data augmentation techniques to artificially expand the training dataset and address limitations of smaller datasets[10]. Finally, we explore the potential of incorporating weakly labeled learning approaches alongside traditionally trained CNNs for even higher accuracy and efficiency, ultimately aiming to develop a robust deep learning model for earlier diagnosis and improved patient care.

While this research focuses on the core development of the deep learning model, the potential for future implementation using web frameworks like Streamlit and deployment tools like ngrok is evident. A user-friendly front-end interface could be developed to facilitate interaction with the model, paving the way for its real-world application in clinical settings.

II. Literature Review

Automated Emphysema Classification Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), offer exciting possibilities for automated medical image analysis[1]. CNNs excel at extracting complex patterns from images, making them ideal for tasks like classifying medical images, including HRCT scans. Several studies have explored the application of CNNs for emphysema classification, demonstrating their potential for improved accuracy and objectivity compared to traditional methods.

Existing research has employed various CNN architectures for emphysema classification. Humphries et al. (2017) investigated a deep learning model utilizing a CNN integrated with a Long Short-Term Memory (LSTM) network for centrilobular emphysema classification[5]. While demonstrating the potential of deep learning, their approach faced challenges with memory requirements and overfitting. This highlights the need for exploring alternative CNN architectures that may address these limitations and potentially improve classification accuracy.

Some studies have explored approaches beyond traditional CNN architectures. Peña et al. (2014) proposed a weakly labeled learning method for emphysema detection. Their approach utilizes textural features extracted from lung parenchyma combined with multiple instance learning (MIL) classifiers trained on weak labels (e.g., pulmonary function tests)[6]. This method offers potential for reducing inter-observer variability but could benefit from incorporating fully labeled data for potentially higher accuracy.

Manikandan and Maheswari (2020) introduced a Multiscale Residual Network with Data Augmentation (MS-ResNet-DA) for automated emphysema classification[1]. They employed data augmentation techniques to address overfitting but further addressed the challenge of spatial dependence by proposing an Enhanced MS-ResNet-DA (EMS-ResNet-DA) model incorporating location data of emphysema pixels[1]. This approach highlights the importance of spatial information for accurate classification and emphasizes the need for models that can effectively capture these relationships within the image data.

While our research focuses on emphysema classification, related work by Gao et al. (2018) demonstrates the potential of deep learning for classifying interstitial lung diseases (ILD) patterns in CT images[7]. Their approach utilizes whole CT images as input, eliminating the need for manual region identification, and achieves state-of-the-art accuracy[8]. This aligns with the goal of developing fully automated systems for clinical settings, where streamlining workflows and reducing reliance on manual image processing can be beneficial.

This revised introduction focuses on the importance of early and accurate diagnosis of emphysema, while the literature review delves deeper into existing research, highlighting relevant studies and their contributions to the field of automated emphysema classification using deep learning. It emphasizes areas for improvement and introduces the motivation for your project's specific research goals.

III. Problem Statement

Emphysema is a chronic obstructive pulmonary disease characterized by the destruction of lung tissue, leading to difficulty in breathing and reduced lung function. Traditional methods of diagnosing emphysema rely heavily on manual interpretation of medical images, such as chest X-rays and CT scans, which can be time-consuming and prone to human error.This project aims to address the challenge of accurate emphysema diagnosis by developing an automated classification system using deep learning techniques, specifically Convolutional Neural Networks (CNNs). Emphysema is a chronic lung disease that requires precise identification through medical imaging such as chest X-rays and CT scans. By exploring different deep learning architectures and data augmentation strategies, the goal is to create a robust framework capable of accurately classifying emphysema from these medical images. This system will not only streamline the diagnostic process but also contribute to improving healthcare outcomes by enhancing diagnostic capabilities for pulmonary conditions, thereby advancing medical image analysis in the field.

IV. METHODOLOGY

This section outlines the comprehensive methodology utilized in the development of our deep learning model designed for automated emphysema classification via HRCT scan images. Our study capitalizes on a well-established dataset comprising diverse emphysema subtypes alongside healthy lung tissue to effectively train and evaluate the model. Furthermore, our objective extends to the creation of a user-friendly interface to facilitate real-world applications of the developed model. Detailed within subsequent sections are the specific methodologies employed for data preprocessing, model architecture selection, training procedures, and performance assessment. Additionally, we elucidate the process involved in developing a web application utilizing Streamlit and ngrok to streamline user interaction with the model.

A. Dataset Overview

At the outset of our dataset description, it's crucial to acknowledge the collaboration with the students from the School of Allied Healthcare Science within the Radiology Department. Their contribution of a dataset containing HRCT scan images has been pivotal for our project focusing on emphysema classification. This dataset comprises 447 images, each meticulously labeled and categorized into four distinct groups: Centrilobular (CLE), Panlobular (PLE), Paraseptal (PSE), and Normal Tissue (NT). These categories represent various lung conditions, providing our model with diverse examples to learn from during its training process. This diversity is essential for our model to accurately distinguish between different types of emphysema when analyzing new scan image.

B. Data Pre-processing

In the initial stages of our data preprocessing pipeline, we initiated by employing Python libraries to load the dataset. This foundational step enabled us to visualize the images and establish a rudimentary comprehension of the dataset's composition. Following the initial loading phase, we proceeded with resizing the images. Recognizing the prevalent input size prerequisites of Convolutional Neural Network (CNN) models, we uniformly resized all images to dimensions of (224, 224) pixels. This standardization not only aligns with the specifications of the chosen CNN architecture but also streamlines computational efficiency during the training phase.

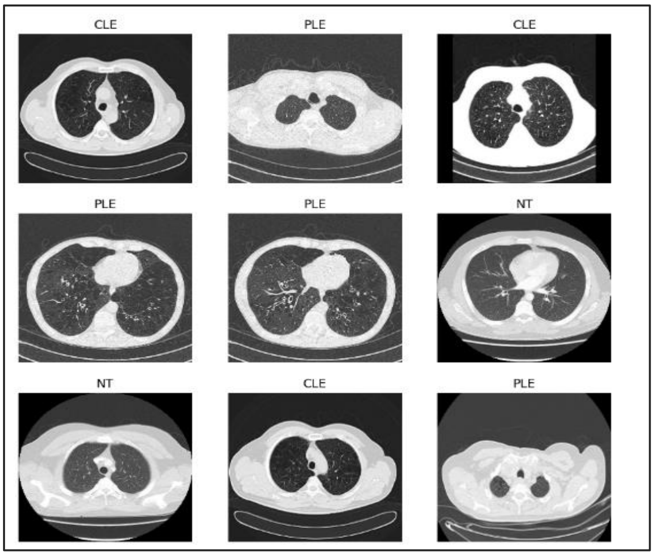

Fig. 1. Representative images after preprocessing and resizing.

C. Data Splitting

For the purpose of objectively evaluating our deep learning model, we conducted a systematic splitting of the dataset into distinct training and validation sets. Initially, utilizing the os library, we navigated through the directory structure of the dataset, identifying class folders for each emphysema subtype and retrieving their corresponding image file paths. Subsequently, employing the train_test_split function from scikit-learn, we executed a stratified split ensuring preservation of the original dataset's class distribution. With a test size of 20% designated for the validation set and a set random state for reproducibility, this procedure aimed to maintain balance across the classes in both sets. Following this split, we verified the efficacy of the process by printing the number of images in each set for every class, thus ensuring the establishment of balanced and representative training and validation sets devoid of biases towards any specific class.

D. Data Augmentation and Data Generators

To address the small size of our dataset , we employed data augmentation techniques to expand the training data artificially. Using Keras's ImageDataGenerator class, we defined augmentation parameters such as rescaling pixel values, applying random rotations, shifts, shearing, zooming, and horizontal flipping. These transformations introduce variations in image orientation and magnification, enhancing the model's ability to generalize to unseen data.

Data generators were created using ImageDataGenerator to streamline the training process. The training data generator (train_datagen) was configured with augmentation parameters and prepared batches of size 32 for efficient training. The validation data generator (val_datagen) only rescaled images to maintain the original data distribution. Both generators utilized pandas DataFrames to specify file paths and labels. The number of batches in each set ensured sufficient data for training and evaluation.

E.CNN Model Selection and Model Architecture

We evaluated the performance of four different CNN architectures for emphysema classification: a simple CNN, InceptionV3, ResNet50, and EfficientNet. After experimentation and evaluation, we determined that InceptionV3 achieved the highest accuracy on our dataset.

InceptionV3

InceptionV3 is a widely acclaimed pre-trained deep learning model renowned for its efficacy in image classification tasks. This model incorporates inception modules, which amalgamate convolutional filters of various kernel sizes to extract a comprehensive array of features from input images. By leveraging these modules, InceptionV3 effectively captures diverse information from High-Resolution Computed Tomography (HRCT) scans, thereby enhancing its capability to discern between different emphysema subtypes and healthy lung tissue.

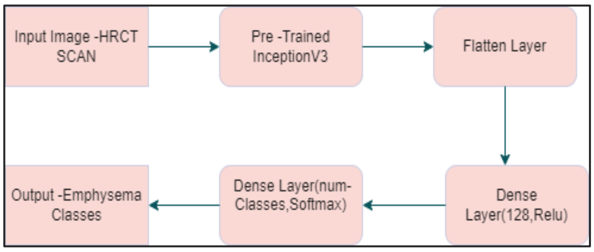

Fig. 2.InceptionV3 model for emphysema Classification.

Custom Layers Architecture

Upon the pre-trained InceptionV3 base, our model integrates a sequential arrangement of custom layers tailored for the emphysema classification task

1. *Flatten Layer*: This initial layer serves to transform the multi-dimensional output from InceptionV3 into a one-dimensional vector. The flattening operation enables the subsequent fully connected layers to process the extracted features efficiently.
2. *Dense(128, activation='relu') Layer:* Following the flattening operation, a dense layer comprising 128 neurons is added, employing the Rectified Linear Unit (ReLU) activation function. This fully connected layer plays a pivotal role in learning nonlinear relationships between extracted features, a crucial aspect in convolutional neural networks (CNNs).
3. *Dense(len(class_names),activation='softmax') Layer:* The final layer of the model consists of a number of neurons equal to the total emphysema classes, including healthy tissue. This layer employs the softmax activation function, ensuring that the output represents class probabilities that sum up to 1. Visualizations elucidating fully connected layers and softmax activation can be accessed online.

F. Model Compilation

Model compilation is a critical step that configures the training process by specifying essential components:

1. *Optimizer:* The optimizer algorithm dictates how the model updates its internal parameters (weights and biases) based on the errors encountered during training. For our model, we opted for the Adam optimizer due to its efficiency in handling gradients during training. The Adam optimizer computes adaptive learning rates for each parameter, ensuring faster convergence and efficient training.

Mathematically, the update rule for parameters θ using the Adam optimizer is expressed below

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{v_t + \epsilon}} m_t$$

where:

- θ_t represents the parameters at time step t.
- η is the learning rate.
- m_t is the exponentially decaying average of past gradients.
- v_t is the exponentially decaying average of past squared gradients.
- ϵ is a small constant to prevent division by zero.

Fig. 3. Update rule using Adam optimizer

2. *Loss Function:* The loss function quantifies the disparity between the model's predictions and the true labels. For our multi-class classification problem, where we aim to differentiate between various emphysema subtypes and healthy tissue, we selected categorical crossentropy as the loss function. Categorical crossentropy is well-suited for multi-class classification tasks, as it measures the dissimilarity between probability distributions, aligning with our objective of minimizing the discrepancy between predicted and actual class probabilities.

Mathematically, the categorical cross entropy loss function is given below in Fig 4.

$$\text{Categorical Crossentropy Loss} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C} y_{ij}\log(p_{ij})$$

where:

- N is the number of samples.
- C is the number of classes.
- y_{ij} is the indicator function that equals 1 if sample i belongs to class j and 0 otherwise.
- p_{ij} is the predicted probability of sample i belonging to class j.

Fig. 4.Cross Entropy Loss Function

G. Performance Assessment Metrics

Metrics serve as performance measures utilized to monitor the model's learning progress during training. In our project, we employed a combination of metrics to comprehensively assess the model's performance:

- *Accuracy:* Accuracy represents the overall percentage of correctly classified images by the model. It provides a general understanding of the model's effectiveness in making correct predictions across all classes.

- *Precision:* Precision measures the proportion of true positive cases among all the cases predicted as positive by the model. It indicates how many of the predicted positive cases were actually positive, thus reflecting the model's ability to avoid false positives.
- *Recall:* Recall, also known as sensitivity, measures the proportion of true positive cases that were correctly identified by the model out of all the actual positive cases. It signifies how many of the actual positive cases were identified correctly by the model, indicating its ability to avoid false negatives.

TABLE I

CNN Model Performance Metrics

Model	Accuracy	Precision	Recall
InceptionV3	98.98	98.88	98.88
Simple CNN	85.55	85.39	84.44
EfficientNet	14.44	14.44	14.44
ResNet50	84.44	85.22	83.33

V. Experimental Configuration

This section provides an overview of the hardware and software configurations utilized in the study to conduct experiments and train the emphysema classification model.

a) *Hardware Configuration:*
- In this study, the deep learning model was trained and evaluated using Google Colab, a cloud-based platform that provides free access to GPU accelerators. The experimental configuration utilized a virtual machine with GPU, offering significant computational power for training convolutional neural networks (CNNs) efficiently.
- The Tensor Flow and Keras frameworks were employed for model development and training, leveraging the parallel processing capabilities of the GPU to expedite training iterations. Additionally, data preprocessing , including image resizing and augmentation, was performed using Tensor Flow's built-in functionalities.
- These hardware resources facilitated the training of a robust CNN model for the classification of emphysema from HRCT scan images, demonstrating the scalability and accessibility of cloud-based GPU computing for medical image analysis tasks.

b) *Software Configuration:*
- In the software aspect of our research project, we utilized Streamlit, a Python library for building interactive web applications, to develop a user-friendly interface for our deep learning model.
- The Streamlit application, implemented in Python, allows users to upload HRCT scan images and receive real-time predictions for emphysema classification.
- Leveraging the capabilities of Streamlit, users can intuitively interact with the model without requiring prior expertise in machine learning or programming.
- Additionally, to share our Streamlit app securely over the internet, we employed Ngrok, a tunneling service that exposes local servers behind NATs and firewalls to the public internet. Ngrok facilitated the deployment of our Streamlit app, providing a temporary public URL for seamless access and collaboration.
- This software configuration enabled effective dissemination and utilization of our deep learning model for emphysema classification, enhancing accessibility and usability for healthcare practitioners and researchers alike.

VI. Result and Discussion

The results of our study demonstrate the effectiveness of the InceptionV3 model in classifying emphysema from HRCT scan images with a remarkable accuracy of 98.88%. The model exhibited exceptional performance, yielding perfect predictions for the tested dataset. This high accuracy indicates the robustness and reliability of the deep learning approach employed in our study. Furthermore, the deployment of the Streamlit web application facilitated seamless interaction with the model, allowing users to upload images and receive instantaneous predictions. The integration of Ngrok for secure public access ensured the accessibility of our application, enabling healthcare practitioners and researchers to utilize the model conveniently. The output screens generated by Ngrok provided users with a user-friendly interface to interact with the model, enhancing the usability and practicality of our solution.

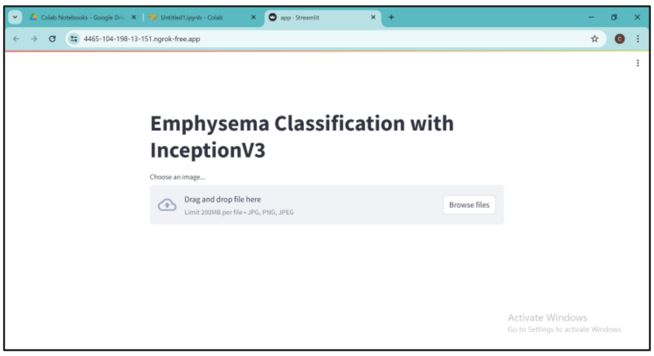

Fig. 5. Streamlit interface for uploading HRCT scan images.

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Volume: 08 Issue: 06 | June - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

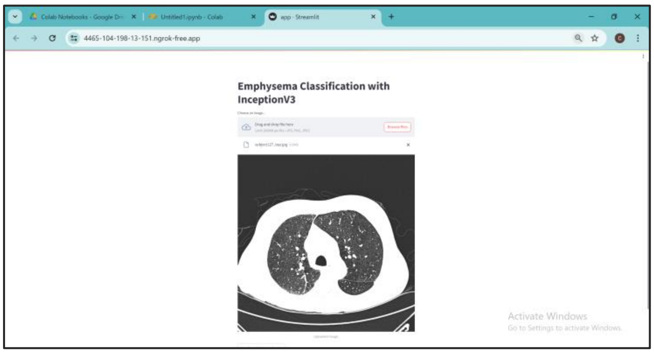

Fig .6. Uploaded Image Display Screen

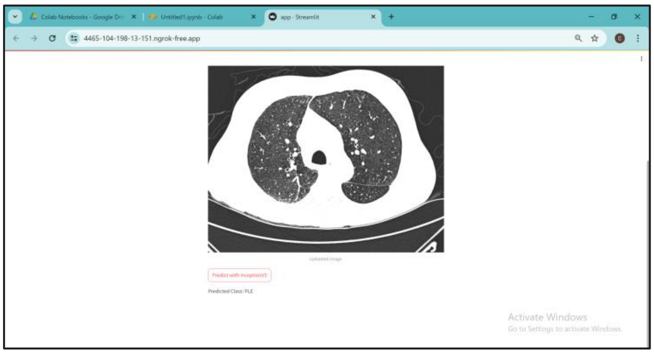

Fig. 7. Prediction Result Screen

VII. Conclusion And Future Scope

In conclusion, our research demonstrates the effectiveness of utilizing deep learning techniques, specifically the InceptionV3 model, for accurate classification of emphysema from HRCT scan images. Achieving a high accuracy of 98.88% underscores the potential of machine learning in aiding medical diagnosis and treatment planning. Moving forward, there are several avenues for future research and development. Expanding the dataset to include more diverse cases and incorporating advanced deep learning architectures could further improve model performance. Additionally, integrating real-time monitoring and feedback mechanisms into the application could enhance its utility in clinical settings. Moreover, exploring transfer learning techniques and ensemble methods may yield even more robust and generalizable models for emphysema detection. Overall, our study lays a foundation for leveraging artificial intelligence in pulmonary healthcare, paving the way for enhanced diagnostic accuracy and patient care.

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