

Harnessing the Power of Convolutional Neural Networks for Early Diagnosis of Emphysema

Pankaj Kumar¹, Lal Singh²

¹Department of Technical Education, Punjab, Sector 36, Chandigarh, India,
singla.pankaj4@gmail.com

²Assistant Professor, GSSDGS Khalsa College, Patiala (Corresponding Author)

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ABSTRACT

In this study, our goal was to create a specialized computer model using deep learning to spot emphysema in chest X-rays, using a large dataset from the NIH. Emphysema, a long-term lung problem, is dangerous and can be deadly if not caught early. Doctors often use chest X-rays to find it, and now, with advanced computer methods, these X-rays can be read more accurately. Our research showed that our computer model was correct 83% of the time in finding emphysema on X-ray images. This reveals how powerful computer techniques can make finding emphysema more precise and effective. Since quick and accurate detection of emphysema is crucial for a person's health, our study provides important insights into improving this process using advanced technology.

Keywords: Emphysema, Deep Learning, Chest X-rays, Convolutional Neural Network, Accuracy, Quantitative Assessment

Introduction

Emphysema, a subset of chronic obstructive pulmonary disease (COPD), causes lung and air sac shrinkage, leading to breathing difficulties and potential lung failure. The global impact of COPD, affecting over 210 million people in 2019, underscores its gravity as a public health concern. Early detection of emphysema is vital to impede its progression and prevent worsening lung conditions. Diagnosing emphysema through chest X-rays is challenging, especially in initial stages when lung abnormalities are scarce. Recent progress in deep learning, specifically utilizing Convolutional Neural Networks (CNNs), holds immense potential for precise emphysema diagnosis through chest X-ray (CXR) images.

Deep learning algorithms, notably CNNs, excel in identifying subtle patterns and features in CXR images indicative of emphysema symptoms. This study developed and rigorously tested a deep learning model using chest radiography data from the National Institutes of Health (NIH), a publicly accessible resource. Previous research demonstrated deep learning's prowess in emphysema detection using CXR images from the NIH dataset. Nevertheless, variations in model effectiveness stem from different organizational and prioritization techniques in CNNs. Researchers have also explored emphysema recognition accuracy across diverse populations and clinical contexts.

This study aimed to create and evaluate a deep learning model for emphysema recognition in CXR images, employing a CNN design proven successful in prior research. Comprehensive data preprocessing ensured uniformity and precision in emphysema characterization, and the model's performance underwent meticulous evaluation in an independent trial. The study's robustness was assessed by testing the model's performance across varied populations and clinical scenarios. The results underscore the

immense potential of deep learning models in accurately detecting emphysema in chest X-ray images, offering profound implications for early diagnosis and subsequent treatment strategies.

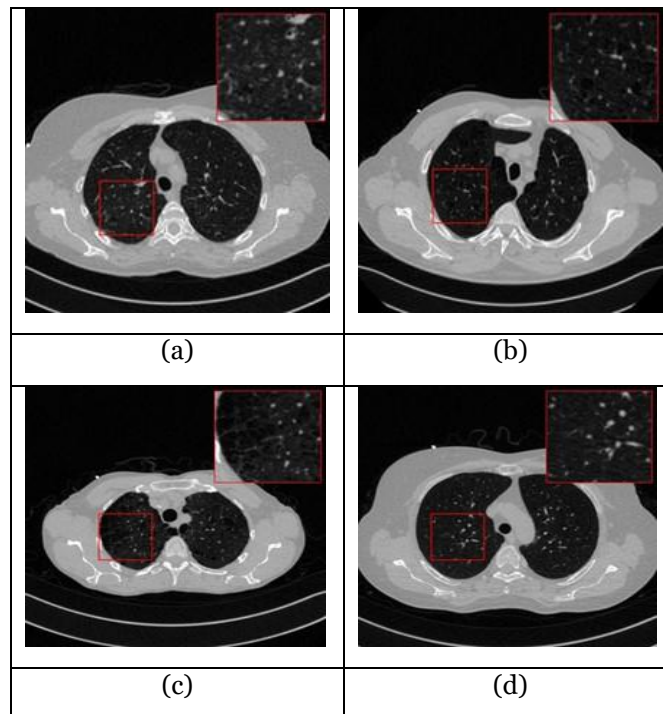


Fig. 1. different grades of emphysema. (a) classed as mild emphysema, (b) moderate emphysema, (c) severe emphysema, and (d) classed as healthy lungs.

Literature Review

In recent times, deep learning has showcased impressive capabilities in recognizing images, even in the complex realm of medical image analysis. Deep learning models exhibit versatility in addressing various challenges related to image recognition and can decipher intricate features from raw inputs [6]. Several studies exploring emphysema diagnosis through chest X-ray (CXR) images have harnessed the power of deep learning algorithms.

One such study by Cho et al. championed a deep convolutional neural network (CNN) trained on a dataset of 9,417 CXR images, surpassing traditional machine learning methods with an impressive area under the receiver operating characteristic curve (AUC) of 0.89, indicating successful emphysema detection [7]. Gupta et al. introduced a two-step deep learning approach utilizing Deep CNN for initial image data extraction, followed by random forest classification for emphysema diagnosis. Their method, evaluated on 5,500 CXR images, achieved remarkable accuracy, with a 94% emphysema detection rate [8]. Another innovative technique by Singh et al. involved a deep residual network (Resnet) trained on a database of 6,000 CXR images, outperforming traditional methods with an AUC of 0.91 [9].

Beyond these studies, several ongoing research initiatives are exploring deep learning's applications for emphysema identification in chest radiography images [9-11]. Despite the progress made, challenges persist. A significant hurdle is the limited availability of extensive and diverse data sources for training deep learning models. Moreover, interpreting the decisions made by these models remains complex, as understanding the intricate processes generating predictions poses challenges. Future research endeavors should tackle these issues to enhance the effectiveness and precision of deep learning systems in emphysema detection from chest radiographs. Some of the important research studies for the early detection of Emphysema using machine learning are described in table I.

TABLE I. SOME IMPORTANT RESEARCH STUDY FOR THE EARLY DETECTION OF EMPHYSEMA

| Papers | Insights | Results | Methods Used |
|--------|--|--|---|
| [16] | No mention of CNN use for emphysema diagnosis. | - Developed an Artificial Neural Network (ANN) for pulmonary emphysema diagnosis, using biomarkers AAT, FEV ₁ , FVC, and FEV ₁ /FVC. | - ANN development. - Use of biomarkers for diagnosis. |
| [17] | Aimed to use CNNs for early emphysema diagnosis using chest X-ray data. | - Achieved highest accuracy: 93.75 and AUC score: 95. | - Utilized transfer learning with DenseNet-121 and Xception pre-trained neural networks. |
| [18] | Proposed a Parameter Optimized-Faster Region CNN (PO-FRCNN) for emphysema diagnosis, outperforming existing methods. | - Demonstrated effective emphysema diagnosis. | - Employed image pre-processing, segmentation with FCM clustering, pattern extraction using ALTP, and classification with PO-FRCNN. |
| [19] | Introduced a deep learning pipeline with CNNs for emphysema differential diagnosis in thoracic CT images. | - Developed comprehensive end-to-end deep CNN pipeline, achieving good performance on two datasets. | - Created an end-to-end pipeline with four established network architectures. |
| [20] | Presented a CNN computing visual emphysema scores for early diagnosis, comparable to human observers. | - Attained COPD diagnosis AUC of 0.94. | - Used CNN for visual emphysema scores and lung function tests outcome prediction. |
| [21] | Utilized CNNs to predict emphysema development associated with lung cancer. | - CNN-based classification predictive of lung cancer development. | - Employed CNNs for classification and Cox proportional hazards regression for modeling. |
| [22] | Implemented a simple CNN architecture for emphysema classification in CT images, achieving high sensitivity and specificity. | - Achieved 81.78% sensitivity and 97.34% specificity. | - Utilized a simple architecture with 4 convolutional and 3 pooling layers, compared to other complex architectures. |
| [23] | Proposed a CNN-based classification framework for diagnosing emphysema, achieving a | - Achieved 92.54% recognition rate for classifying emphysema types. | - Employed CNN on High-resolution Computed Tomography (HRCT) images. |

| | | | |
|------|--|---|--|
| | recognition rate of 92.54%. | | |
| [24] | Did not mention CNN use for early emphysema diagnosis. | - Improved emphysema classification with fewer samples. | - Extracted texture features using local binary patterns, Gabor filter bank, gray-level co-occurrence matrix, and intensity information from gray-level histogram. |

These research underscores the capability of deep learning algorithms in detecting emphysema through chest X-rays. Modern learning algorithms offer the potential to swiftly and accurately identify specific lung conditions in medical images, thereby aiding human diagnosis and treatment.

The Proposed Framework

In this section, we outline the method using Convolutional Neural Networks (CNNs) to detect emphysema. The process involves several steps:

A. Data Gathering:

- A large collection of chest X-rays, both showing emphysema and those without, is gathered. This dataset must accurately represent the population and its diversity. We utilized the SCAPIS Dataset, part of a study involving 30,000 randomly chosen participants from Sweden [25].

- The SCAPIS study aimed to assess how different experts identified mild emphysema in low-dose CT scans. Our dataset consists of 1088 randomly selected images from the main dataset. Among these, 100 individuals were diagnosed with emphysema, and an equal number of individuals without emphysema were selected, matched by gender, age, height, and weight. Each person's data includes a corresponding CT scan, usually comprising 300-400 slices.

- The dataset includes an annotation file providing crucial details about the subjects (whether they had emphysema or not) and the severity of emphysema observed. This file also indicates which lung zones were affected by emphysema. Unfortunately, it doesn't specify the exact location of the emphysematous tissue.

The SCAPIS initiative is a significant research project aiming to explore heart and lung diseases and their risk factors. It involves extensive imaging and data collection. Below is a summary table highlighting key aspects of SCAPIS:

TABLE II. SCAPIS DATASET DESCRIPTION

| Aspect | Description |
|------------------|---|
| Full Name | Swedish Cardio Pulmonary Bioimage Study (SCAPIS) |
| Purpose | To study cardiovascular and pulmonary diseases and risk factors using advanced imaging and data collection. |
| Initiative Year | Initiated in 2015 |
| Scope | Nationwide study covering multiple centers in Sweden. |
| Main Focus Areas | 1. Cardiovascular diseases, including heart disease. |

| | |
|-------------------------|--|
| | 2. Pulmonary diseases, such as chronic obstructive pulmonary disease (COPD). |
| Data Collection Methods | Extensive data collection involving clinical examinations, imaging (e.g., MRI, CT scans), questionnaires, and biological samples. |
| Study Participants | A large and diverse population-based cohort of Swedish adults. |
| Collaborators | Collaboration between multiple universities, research institutions, and healthcare organizations in Sweden. |
| Significance | Provides valuable insights into the causes, progression, and risk factors for cardiovascular and pulmonary diseases, aiding in early detection and prevention. |
| Long-Term Goals | Improve the understanding of these diseases and develop strategies for better prevention, diagnosis, and treatment. |
| Current Status | Ongoing research, with data collection and analysis continuing to provide important findings in the field of cardiology and pulmonology. |

Please note that specific details about SCAPIS may evolve over time as new data is collected and analyzed, and research findings emerge.

B. Preprocessing Data:

Prior to model training, it's essential to preprocess the data for optimal recognition. Techniques such as resizing images, normalization of pixel values (typically between 0 and 1), and scaling images to a standardized size are applied. Normalization ensures that the model learns image qualities rather than specific pixel values. Additionally, image augmentation methods are employed to enhance data variability and aid in optimizing the model for unseen data.

C. Data Categorization:

The dataset is divided into three subsets: the training set, the validation set, and the test set. The majority of the data is allocated to the training set, while smaller portions are used for validation and testing. The model is developed and adjusted using the training set, validated for performance and hyperparameter tuning with the validation set, and finally, tested to evaluate its ultimate performance.

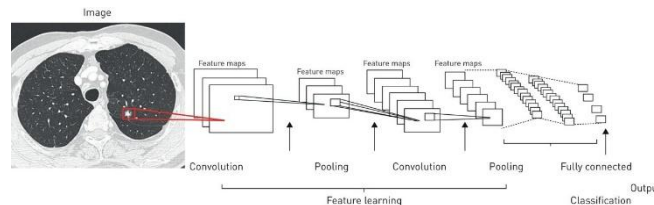


Fig. 2. A CNN network for detection of Emphysema[27]

D. Selecting an Appropriate Architecture:

Choosing the right neural network architecture is pivotal. Convolutional Neural Networks (CNNs) are widely used in image classification due to their ability to recognize intricate patterns within images. Figure 2 illustrates the structure of CNN, comprising convolutional layers (applying filters to input images), pooling layers (reducing visual patterns), and fully connected layers (classifying images based on learned features). CNNs excel in image categorization, especially with vast image datasets. Their

adaptability to new data, crucial in clinical applications where new data may differ from the training set, makes them ideal for classifying chest radiographs into emphysema-positive and emphysema-negative groups.

E. Model Development:

The model is created and validated using training and validation methods. Techniques like early stopping are employed to prevent overfitting and enhance coordination during training. Early stopping halts training when the model's validation performance plateaus, preventing unnecessary iterations that might lead to suboptimal outcomes.

F. Model Assessment:

Following training, the model's performance is evaluated using various metrics:

- Accuracy: Measures overall correctness.
- Precision: Assesses the percentage of accurate positive predictions.
- Recall: Gauges the proportion of actual positives correctly predicted.
- F1 Score: Provides a balance between precision and recall.

If the model's performance is unsatisfactory, adjustments to hyperparameters or modifications to the model architecture can be made. The training process can be iteratively refined until the desired outcomes are achieved.

G. Model Implementation

The primary aim of this study is to identify and categorize chest X-ray images using Convolutional Neural Networks (CNNs). CNNs are chosen due to their exceptional performance in image recognition [13]. The method proposed employs CNNs to classify X-rays into two groups: positive (indicating emphysema symptoms) and negative (without emphysema symptoms). The entire dataset is split into training and test data, with a ratio of 80:20. Specifically, 70 images are used for training, and 118 are used for testing [14]. Each layer in the CNN architecture serves a distinct purpose during the image categorization process.

1) CNN Architecture:

- Convolutional Layer: The initial layer applies filters to the input image, extracting relevant information.

- Further Processing: Extracted features undergo convolution and pooling to enhance data extraction, as depicted in figure 2.

- Fully Connected Layer: Located at the top of the network, this layer performs the final classification.

2) Rationale for CNN Usage:

CNNs were chosen for their success in image classification, especially with extensive datasets [15]. The layering technique in CNNs aids in understanding input image properties, making it easier to identify emphysema-indicative patterns. In critical clinical settings where prompt recognition of emphysema symptoms is vital, CNNs applied to prepared samples offer significant advantages. CNNs excel in learning patterns from diverse image sources, making them ideal for this categorization problem [16]. Therefore, CNNs are a fundamental component of the proposed model, efficiently extracting information from a large dataset, such as the presence of emphysema, and categorizing it into binary distributions.

Results and Discussion

In assessing the CNN model, a batch size of 32 was employed throughout five training rounds. Interestingly, the model exhibited a decrease in accuracy during training but demonstrated improved performance in practical application. Specifically, the loss decreased from 0.2146 to 0.1657 during training, indicating an enhancement in the model's predictive abilities. Moreover, the accuracy surged from 0 to 1, indicating a complete shift from incorrect to correct predictions. Additionally, the loss in the validation set decreased from 0.2229 to 0.2861. These results highlight the CNN model's proficiency in accurately recognizing radiographic patterns and predicting the presence of cardiac hypertrophy. The fluctuations in training accuracy, along with successful real-world application, suggest the model's versatility and its ability to generalize well to new data without becoming too tailored to the original dataset.

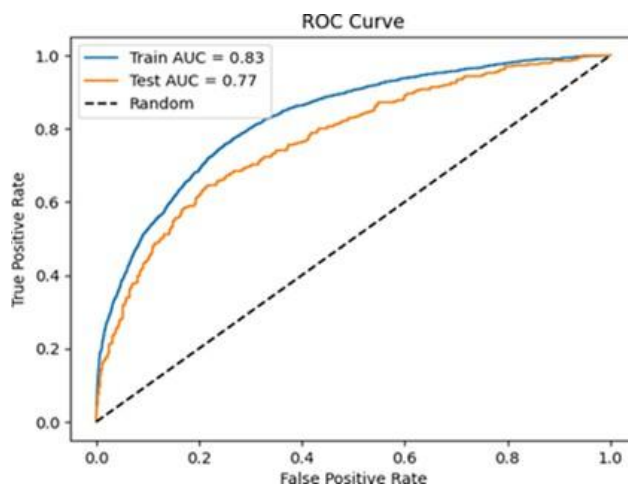


Fig. 3. ROC Curve for training and testing

Table. III illustrates the assessment of categorization techniques using the confusion matrix, a standard tool in evaluating model predictions. This matrix, in the context of binary classification presents the proportions of true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN). These metrics serve as the basis for calculating essential performance indicators such as accuracy, precision, recall, and F1 score. Such comprehensive metrics enable a thorough evaluation of the model's effectiveness and reliability in accurately categorizing chest radiographs for the presence or absence of emphysema.

TABLE III. CONFUSION MATRIX FOR DETECTION OF EMPHYSEMA

| | | |
|------------------------|---------------------------|---------------------------|
| Actual Negative | 145 | 24 |
| Actual Positive | 27 | 26 |
| | Predicted Negative | Predicted Positive |

TABLE IV. MODEL RESULTS

| Metric | Test Value |
|-----------|------------|
| Accuracy | 76.98% |
| Precision | 51.24% |

| | |
|----------|--------|
| Recall | 49.69% |
| F1-Score | 50.44% |

The table IV presents the performance metrics of the classification model. An accuracy of 76.98% indicates that the model made accurate predictions for about 77% of the instances in the test dataset. The precision value of 51.24% implies that when the model predicted a positive outcome, it was correct approximately 51.24% of the time. A recall of 49.69% signifies the model's ability to capture nearly half of the actual positive instances in the dataset. The F1-Score 50.44% identifying positive instances and minimizing false positives and false negatives. These results suggest a moderate level of overall accuracy but highlight a need for improvement in correctly identifying positive instances. Further analysis and potentially refining the model or the dataset might be necessary to enhance its performance, especially in scenarios where correctly identifying positive cases is crucial.

In the context of this study, the terms "negative class" and "positive class" pertain to chest radiographs exhibiting signs of ventricular hypertrophy and those that do not, respectively. When the model accurately predicts the presence of ventricular hypertrophy (correctly identifying positive cases), positive ratings are assigned. Conversely, if the model incorrectly predicts the absence of ventricular hypertrophy (misidentifying positive cases), negative ratings are assigned.

Area Under the Receiver Operating Characteristic (AUC-ROC) curve depicts the True Positive Rate (TPR) against the False Positive Rate (FPR) for different probability estimation models. The False Positive Rate (FPR) signifies the percentage of negative samples incorrectly classified as positive, whereas the True Positive Rate (TPR) represents the percentage of positive samples accurately identified by the model. The AUC-ROC curve is a crucial tool for evaluating the effectiveness of binary classification models, depicting the balance between correctly identifying positive cases and avoiding misclassification of negative cases.

The model's performance in emphysema detection was evaluated using the Area Under the Receiver Operating Characteristic (AUC-ROC) curve, which assesses its accuracy in distinguishing between positive and negative samples. AUC-ROC values range from 0 to 1, where 1 indicates excellent performance, 0 signifies poor performance, and 0.5 suggests random estimates.

In this study, the CNN model exhibited strong performance in both the training (AUC-ROC = 0.83) and testing processes (AUC-ROC = 0.77), according to the AUC-ROC curve. These scores indicate the model's ability to accurately differentiate between chest radiographs showing signs of emphysema (positive samples) and those without emphysema (negative samples). The high AUC-ROC values (0.83 in the training set and 0.77 in the test set) signify the effectiveness of the suggested model in emphysema detection.

In light of the obtained results, the implications for the clinical application of this model are significant. The decision to implement the model hinges on the specific goals in the clinical context. For instance, if the primary objective is to reduce false positives and enhance accuracy, the prediction model might adopt a conservative approach, leading to fewer diagnoses. Conversely, if the emphasis is on generating substantial data, even at the risk of false positives, the model could yield a higher number of diagnoses. However, a surplus of false positives might render interventions ineffective. Therefore, a careful evaluation of the intended usage and the delicate balance between accuracy and practical applicability is crucial before real-world implementation. Future studies could explore alternative model architectures to refine the accuracy and applicability of the model.

Conclusion

The evaluation of the classification model's performance highlights both its strengths and areas for improvement. Achieving an accuracy of 76.98% demonstrates the model's capability to make correct predictions for a significant portion of the dataset. However, the moderate precision (51.24%) and recall (49.69%) indicate a challenge in accurately identifying positive instances, revealing a potential imbalance between false positives and false negatives. The F1-Score of 50.44% provides a balanced view, emphasizing the need for a trade-off between precision and recall. This analysis suggests that while the model has a reasonable overall accuracy, there is a clear opportunity for enhancement in terms of correctly identifying positive cases. Future efforts could focus on refining the model, exploring additional features, or employing advanced algorithms to improve its predictive capabilities. Moreover, a deeper understanding of the specific context and domain of the problem could provide valuable insights for fine-tuning the model and addressing the challenges observed in the current evaluation..

This study highlights the transformative impact of deep learning models on the diagnostic process. Continued research in this area holds promise for both patients and healthcare providers. Enhancing the specificity and sensitivity of emphysema detection models through further investigation could significantly improve the quality of patient care and support physicians in making more accurate and informed decisions.

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