Introducing Novel Radon Based Transform for Disease Detection From Chest X-Ray Images

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***Abstract*—Medical imaging technologies, such as chest X-rays (CXR), have demonstrated their utility in predicting diseases with high accuracy using deep learning algorithms. These models are crucial for identifying critical lung conditions. Nevertheless, the challenge lies in the resemblance of disease patterns and symptoms, which may cause misdiagnoses and critical mistakes. In our research, we introduce a novel technique for feature extraction from CXR images using an advanced version of the Radon transform, named the RadEx Transform. This method, by integrating the extracted features with CXR images, significantly enhances the learning capability of the models. We focus our study on the COVID-19 radiography dataset. The results indicate that our approach of feature extraction markedly increases accuracy beyond that achieved with raw images alone, surpassing conventional techniques by significant margins in terms of x, y, and z. Our research underscores the effectiveness of augmenting RadEx features with images in elevating the accuracy of lung disease detection. This approach holds considerable promise for advancing medical image analysis and diagnostic processes, marking a significant step forward in the domain.**

***Index Terms*—Radiography, Pulmonary diseases, Transfer learning, RadEx Transform, Feature extraction, Convolutional neural networks**

I. Introduction

Chest X-rays (CXRs) are indispensable tools for radiologists, aiding in the diagnosis of critical conditions affecting the heart, blood vessels, bones, and particularly the lungs [1]. Deep learning (DL) techniques, especially through convolutional neural networks (CNNs) like MobileNet [2], EfficientNet [3] and ResNet [4], have significantly advanced the analysis of CXRs, particularly in disease detection. These DL models' efficacy is influenced by various factors including CNN architecture, data processing, and training methodologies. Despite the advancements, the classification of diseases through CXRs faces challenges due to the subtlety of lung disease patterns and the scarcity of comprehensive datasets, which may lead to model overfitting and diagnostic inaccuracies [5].

Addressing these challenges, this study introduces a novel feature extraction technique catered to images with lines and fissures that need to be detected and highlighted in order to understand their impact on the decision. We propose the RadEx Transform, an enhanced feature extraction strategy designed to improve disease detection in CXRs by refining data sources and extract meaningful information for more accurate disease classification. Our approach aims to support radiologists by providing a more efficient tool for identifying life-threatening lung diseases through enhanced visual analysis of CXR images. The rest of this manuscript is structured as follows. A review of recent literature relevant to the topic is provided in Section II. Section III provides an introduction to the Radon transform. Our proposed methodology is elaborated in detail in Section IV, encompassing the methods and tools utilized for development, as well as the dataset used for evaluation. Section V presents the findings and analysis from our investigation, followed by the conclusion and future prospects discussed in the final Section VI.

II. Literature Review

The advent of COVID-19 has placed unprecedented demands on global healthcare systems, necessitating rapid and accurate diagnostic solutions. In this context, Chest X-rays (CXRs) have emerged as vital tools for the screening and monitoring of COVID-19, given the virus's pronounced effects on pulmonary tissues. In this section, we delve into various deep learning strategies employed to enhance the detection and analysis of COVID-19 and other pulmonary diseases through CXRs.

A. COVID-19 Detection and Localization

A significant body of research has focused on leveraging Deep Learning (DL) for the automatic diagnosis of COVID-

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19 from CXR images. Despite achieving remarkable detection accuracy, these studies often rely on limited datasets, comprising only a few hundred COVID-19 samples. This limitation raises concerns about the reliability and generalizability of the resulting DL models. Moreover, many of these approaches lack the capability to precisely localize the infection or grade its severity, which is crucial for effective patient management and treatment planning. One innovative study proposes a systematic approach to address these challenges by creating the largest benchmark dataset to date, featuring 33,920 CXR images, including 11,956 COVID-19 samples. The study utilizes advanced segmentation networks like U-Net and Feature Pyramid Networks (FPN) for lung region segmentation and COVID-19 localization, achieving unprecedented performance metrics in both detection accuracy and infection quantification [6]. Alqahtani et al. [7] explored the potential of Deep Learning (DL) in addressing this diagnostic challenge by combining 1,504 CXR images from the Pediatric-CXR and COVID-19 chest X-ray datasets. The use of the Inception-V4 model, applying transfer learning techniques, resulted in the accurate identification of COVID-19 infections with an outstanding overall accuracy of 99.63%. Another innovative approach was presented in [8], where the authors developed a DL model named CovMnet, specifically designed to differentiate between normal and COVID-19 affected CXR images using the Pediatric-CXR dataset. Through a series of experiments aimed at refining model performance, including feature extraction and hyperparameter tuning, CovMnet achieved a notable accuracy of 97.40%. Furthermore, research conducted in [9] utilized the DenseNet-121 CNN model for the binary classification of COVID-19, leveraging a comprehensive dataset of 21,165 CXR images from various sources, including COVID-19 radiography and Pediatric-CXR datasets. The application of geometric data augmentation significantly enhanced the model's performance, culminating in a remarkable accuracy of 97%. These studies highlight the critical role of DL models in the rapid and accurate detection of COVID-19 through CXR imaging, offering promising strategies for combating the pandemic's effects on public health.

B. Enhancing COVID-19 Detection through Image Enhancement

The role of image enhancement techniques in improving COVID-19 detection from CXRs has also been explored. Recognizing the limitations posed by small datasets, one study compiled a substantial dataset (COVQU) containing 18,479 CXR images. It investigated the impact of various image enhancement methods, such as Histogram Equalization (HE) and Gamma Correction, on detection efficacy. Notably, the gamma correction technique showed superior performance, highlighting the potential of image processing in enhancing diagnostic accuracy, especially when applied to segmented lung images [10].

C. Infection Map Generation for COVID-19

Generating accurate infection maps from CXR images represents another avenue of research aimed at enhancing COVID-19 diagnosis. Despite the utilization of deep networks in previous studies, the accuracy of localizing actual infestations remained suboptimal. Addressing this gap, a novel method was introduced for joint localization, severity grading, and detection of COVID-19, supported by the compilation of a dataset comprising 119,316 CXR images. This approach significantly outperformed traditional activation map techniques, offering a reliable tool for clinical application [11].

D. AI Screening for Viral and COVID-19 Pneumonia

The potential of Artificial Intelligence (AI) in screening for COVID-19 and viral pneumonia through CXRs has been a subject of intensive investigation. One study highlighted the utility of pre-trained deep CNNs in distinguishing between normal, viral, and COVID-19 pneumonia cases, using a diverse database of CXR images. By applying transfer learning and image augmentation techniques, the study achieved classification accuracies upwards of 99.7%, underscoring the efficacy of AI in rapidly and accurately detecting COVID-19 from CXRs [12]. Khoiriyah and colleagues [13] evaluated the effectiveness of a tailored Convolutional Neural Network (CNN) for distinguishing between normal and pneumonia-affected CXRs within the Pediatric-CXR dataset, comprising 5856 images. By applying data augmentation techniques, they achieved a notable accuracy of 83.38% in identifying pneumonia. Singh et al. [14] introduced a CNN model enhanced with an attention mechanism for the binary classification of CXRs into normal or pneumonia categories. Utilizing the ResNet50 architecture equipped with attention mechanisms and trained on the Pediatric-CXR dataset [9], they reported a high accuracy of 95.73%, demonstrating the potential of attention-based models in pneumonia detection. Another study [15] explored the application of transfer learning on the RSNA-Pneumonia-CXR dataset using two CNN architectures, ResNet-50 and Inception-V4, for binary classification. The findings indicated that the Inception-V4 model surpassed ResNet-50, with a validation accuracy of 94.00%, compared to ResNet-50's 90.00%. Although these studies successfully tackled pneumonia detection using binary classification frameworks, they were limited by the binary nature of their approach, categorizing CXR images strictly into either normal or COVID-19 affected groups. Recent research efforts, however, are shifting towards more nuanced multi-class and multi-label classification techniques, aiming for a more detailed analysis despite the relatively small size of the datasets used when benchmarked against larger, publicly available CXR datasets [16].

III. Background

In this section we talk briefly about Radon transform as our feature extraction method has been inspired from the same.

A. The Radon Transform

Radon transform, initially conceptualized for its application in seismics, is often referred to as slant stacking [17]. We explore the discrete version of the Radon transform and examine its several characteristics. Its utility lies in focusing on the extraction of straight lines from digital imagery. The Radon transform is adept at extracting line parameters, even amidst noisy conditions. The discrete Radon transform performs a transformation from a complex global task in the image domain to a simpler local peak identification challenge in the parameter domain, thus facilitating the retrieval of line parameters through methods like thresholding [18]. It's important to note that in scenarios characterized by noise, conventional algorithms may falter. An alternative approach involving local detection algorithms, such as edge detection filters, followed by pixel linking and parameter estimation via linear regression, often struggles with intersecting lines and stabilizing in high noise environments. Unlike these methods, the Radon transform exhibits resilience to these challenges [19]. The Radon transform encapsulates the process of stacking or integrating the values along inclined lines, determined by specific line parameters, namely the slope (p) and offset. This process, referred to as slant stacking or the p-transform in seismics, leverages the integration of values along lines to deduce the transform of a two-dimensional function into a function within a two-dimensional (p,)-space, known as Radon or parameter space.

$$R(g)(p,\tau) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x,y)\, \delta(y - px - \tau)\, dx\, dy$$

The Radon transform $R(g)(p,\tau)$ of a two-dimensional function $g(x,y)$, where integration is performed over the entire plane, constrained along lines defined by the slope p and intercept τ through the use of the Dirac delta function δ.

IV. Proposed Approach

This segment offers a summary of our approach, starting with the choice of a suitable dataset, followed by an explanation of the RadEx transform.

A. Dataset Selection

The COVID-QU-Ex Dataset, developed by Qatar University researchers, comprises a comprehensive collection of 33,920 chest X-ray (CXR) images. This dataset includes:

- 11,956 images of COVID-19 cases,
- 11,263 images of Non-COVID infections (either Viral or Bacterial Pneumonia), and
- 10,701 images categorized as Normal.

Accompanying the entire dataset are ground-truth lung segmentation masks, marking the creation of the largest dataset of its kind for lung mask data.

This study is pioneering in its application of both lung and infection segmentation techniques for the detection, localization, and quantification of COVID-19 from X-ray imagery. It offers unprecedented support to healthcare professionals in assessing the severity of COVID-19 pneumonia and monitoring disease progression with enhanced accuracy.

Our research utilizes the COVID-QU-Ex dataset further segmented into training, validation, and testing subsets:

1) **Lung Segmentation Data**: This includes the complete COVID-QU-Ex dataset, encompassing all 33,920 CXR images along with their respective ground-truth lung masks.

We now look into the novel RadEx transform and understand its process.

B. RadEx Transform

Our novel transformation technique involves a strategic overlay of lines across an image, followed by aggregation of pixel intensities along these lines into a distinct matrix. To enhance the continuity and address the issue of sparsity within this transformed space, we employ a variety of interpolation methods, aiming to fill in intermediate values and create a more cohesive representation.

Central to this method is a fundamental equation:

$$y = \frac{N}{2}\left(\frac{e^{b(x-a)} - 1}{e^{b(x-a)} + 1} + 1\right)$$

Here, N represents the dimensionality of the image, with a and b serving as adjustable parameters, and x indicating the horizontal position within the image matrix.

However, direct application of this equation may result in noticeable gaps within the final transformed image. To counteract this, we employ an inverse function that calculates the corresponding x values for given y coordinates, effectively bridging these gaps:

$$x = a + \frac{1}{b}\left(\log\left(\frac{y}{N-y}\right)\right)$$

This ensures a more uniform and comprehensive coverage across the image, enhancing the visual clarity and integrity of the transformation.

Moreover, to accommodate the entire range of the image, especially focusing on the upper half, we determine the potential b values that satisfy when y extends from $N/2$ to N, as delineated by:

$$b = \frac{1}{x-a}\log\left(\frac{y}{N-y}\right)$$

Through this systematic approach, combining direct and inverse equations along with strategic parameter selection, our transformation method not only illuminates the intrinsic patterns and intensities across the image but also pioneers a comprehensive framework for image analysis and enhancement.

We show below two cases where the image coverage has been sparse and complete respectively. by changing the parameters like a, b and we can generate different granularity of image processing.

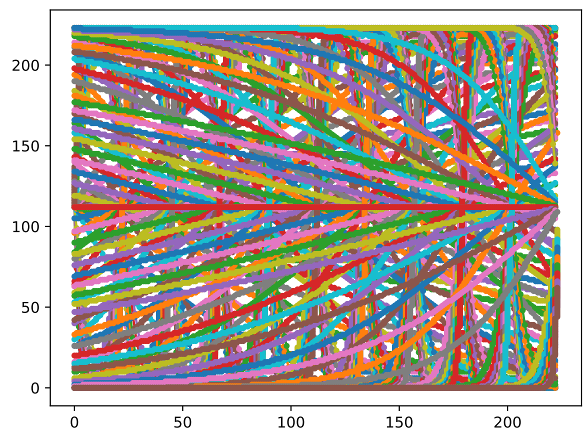

Fig. 1. Image coverage with sparsity

Figure 1 highlights the case when there are gaps in computation and as a result some lines are missed. Figure 2 shows the case where we increase the resolution and compute all possible polynomials within the domain that can be drawn and aggregate the pixel values on each curve.

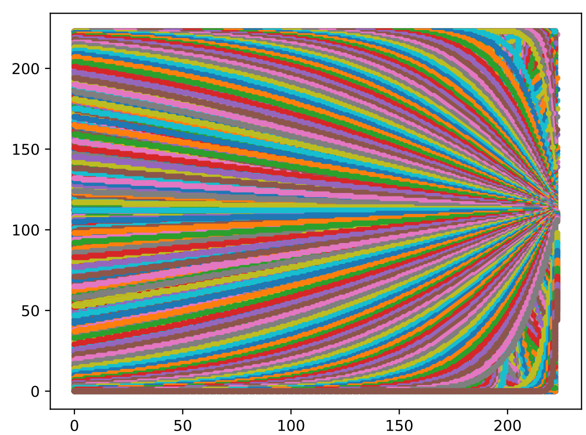

Fig. 2. Image coverage with sparsity

The output images on using the same technique can be seen in the Figures 4 and 3.

Figure 3 shows the after effect of RadEx transform on an X-Ray with covid infection. THe bottom half of the image is the original X-ray and the top half is the result of our novel Radex transform. Figure 4 shows the same effect but on a non Covid infected X-ray image. We perform this transformation on all the images in the dataset and perform transfer learning on three Convolution Neural Networks - MobileNet [2], EfficientNet [3] and ResNet [4]. We prepare two sets of data - one comprising of the origianl images and the second consisting of images as shown in Figures 3 and 4. We then train the three models for 20 epochs on the two sets of data and check the performance on raw images as well as transformed images.

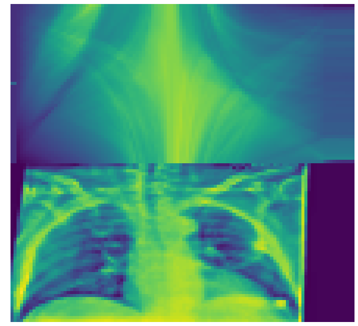

Fig. 3. X-Ray with covid

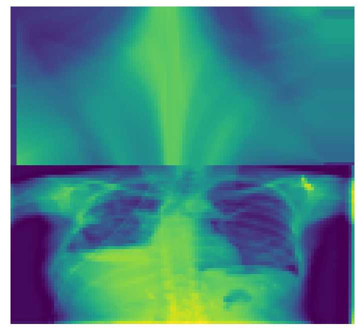

Fig. 4. X-Ray with no covid

V. Results And Discussions

TABLE I
Comparison of Model Performance on RadEx and raw Images for the Lung Segmentation Data

Model	RadEx Approach			Raw Images		
	Precision	Recall	F1 - Score	Precision	Recall	F1 - Score
resnet 34d	0.918	0.916	0.917	0.839	0.844	0.839
mobilenet v2	0.873	0.872	0.871	0.854	0.850	0.849
efficientnet v2	0.883	0.871	0.862	0.857	0.855	0.851

Table I compares the performance of Resnet34d, Mobilenet v2, and Efficientnet v2 models for lung segmentation using RadEx (Radiomics-Enhanced) and raw image approaches. With the RadEx approach, Resnet34d achieves the highest precision, recall, and F1-score, followed closely by Efficientnet v2. However, when using raw images, Efficientnet v2 outperforms the other models, showing the highest precision, recall, and F1-score. Generally, all models perform better with the RadEx approach compared to raw images, indicating the efficacy of our novel feature engineering method.

A. Discussion

Time Complexity: Once the list of x and y co-ordinates are identified it takes 0(n**2) time to complete the feature extraction process where n is the size of the square image. On a system with 64 GB RAM and Intel(R) Xeon(R) CPU E5-2620 v4 @ 2.10GHz with 16 processors, time taken to extract features from a single 224X224 image was approximately 0.1 second. Consequently, processing the entire database of 33,920 images in the Lung Segmentation Data took a total approximate time of 56 minutes.

VI. Conclusion

In this study, we introduced RadEx, an innovative feature extraction technique designed for medical imaging data. Initial findings demonstrate its potential, showing a notable improvement in accuracy for models trained on combined image data and extracted features compared to those trained solely on images. Moving forward, we aim to expand our research by increasing both the duration of training, through additional epochs, and the diversity of data utilized.

Future investigations will explore the application of RadEx to other types of medical imagery, such as retina scans and fundus photographs, to assess its versatility and effectiveness across various domains. Moreover, evaluating the impact of RadEx in conjunction with vision transformers presents an exciting avenue for further research, potentially broadening the method's applicability and enhancing its benefits in medical imaging analysis.

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