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Deducting Abnormalities in Chest X-Rays using Gabor Filters and Deep Neural Network (DNN)

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ABSTRACT

Chest X-rays are widely used as a diagnostic tool to detect respiratory diseases. The complexity of the texture and structures shown in the resulting images can make their interpretation difficult. A more accurate interpretation would help diagnose respiratory diseases earlier, resulting in more effective and timely treatment. In this research, the author proposes a new method for detecting abnormalities in chest X-ray images using Gabor filters and artificial intelligence (AI). Gabor filters are a type of filter that can be used to extract texture features from images. These features can then be used to train a deep neural network (DNN) to detect abnormalities in chest X-rays. The method demonstrates the effectiveness of its approach on a dataset of chest X-rays from the National Institutes of Health (NIH) Chest X-ray Dataset. The method achieved an accuracy of 79% in detecting abnormalities, suggesting that this novel method has the potential to help detect respiratory diseases early and, ultimately, improve the lives of the millions afflicted by such diseases.

Keywords: Chest x-ray; deep learning; Gabor filters; image processing; machine learning

INTRODUCTION

The chest plays a vital role in ensuring the proper performance of respiratory and cardiovascular functions. While the anatomy of a healthy human chest is well understood, there are instances where it can exhibit abnormalities that deviate from its standard appearance. These abnormalities can range from cosmetic concerns to more serious conditions that affect the function of the chest medical imaging techniques, such as CT scans, X-rays, and MRI, play a critical role in detecting and diagnosing these abnormalities.

Chest X-ray imaging is a commonly used diagnostic tool for detecting various lung diseases, such as pneumonia, tuberculosis, and lung cancer. X-ray images can expose abnormalities or deviations from the norm. Figure 1 shows different chest x-rays. These abnormalities can range from structural anomalies, such as deformities of the ribcage or spine, to functional disorders, such as those affecting the heart or lungs. The study of these abnormal chest images is crucial for improving our understanding of various medical conditions and for developing treatments that are more effective.

Generally, interpreting chest X-ray images requires trained medical professionals, which can be time-consuming and expensive. In recent years, deep learning methods have been successfully applied to medical imaging for automated disease detection. These methods have significantly improved the accuracy and efficiency of diagnosis process. For instance, Abdar used successfully a deep learning fusion model to detect COVID-19 (Abdar et al. 2021). Jabbour proposes a straightforward transfer learning approach that surprisingly proves effective in preventing shortcuts and improving generalization performance within the realm of deep learning (Jabbour et al. 2020). Similarly, Agrawal employed binary classification and multi-class classification to detect COVID-19 (Agrawal et al. 2023). Jaiswal also utilized Mask-RCNN, a deep neural network that combines global and local features, for accurate pixel-wise segmentation in the detection of pneumonia causes in chest X-ray images (Jaiswal et al. 2019).

A number of models are effective for chest X-ray analysis. For example, Baik et al. utilized CNN models such as Inception-ResNet-V2 and EfficientNet, while MLP models are used for other purposes (Baik, Hong, and Park 2023). Nasser and Akhloufi used a two-step approach to classify chest diseases (Nasser and Akhloufi 2023) and Sulaiman et al. employed a convolutional neural network architecture for lung segmentation of chest X-ray images (Sulaiman et al. 2023). Both Tsuji et al. and Aktas et al. used CNNs to classify normal and abnormal chest X-rays (Tsuji et al. 2023; Aktas et al. 2022). The CNNs and dense learning is used by (Alharbi and Hosni Mahmoud 2022). For detecting the COVID-19 Banerjee et al. Used ensemble methodology for deep learning models Convolutional Neural Networks (CNNs) (Banerjee et al. 2022). Also, Babu et al. used deep learning to detect COVID-19 (Babu, Manohar O, and Chandy 2022). In their study, Balasubramaniam and Satheesh Kumar incorporated an ensemble model approach for classification for COVID-19 (Balasubramaniam and Satheesh Kumar 2023).

Furthermore, several studies have employed the Gabor filter for the classification of abnormal chest X-rays. Sandhiyaa et al used the Gabor filter for classification and the Deep Convolutional Neural Network (DCNN) (Sandhiyaa et al. 2023). Different filter banks such as Sobel, Laplacian of Gaussian (LoG), and Gabor filters have been applied by (Barshooi and Amirkhani 2022). Imani used Contextual feature extraction using morphological operators, Gabor filter banks, and attribute filters(Imani 2021). ÇINAR et al. they used the template matching method to locate the rib bones, and then the corresponding bones were suppressed by applying the Gabor filter (ÇINAR, TOPUZ, and ERGİN 2021). For rib shadow suppression, the logarithmic Gabor filter is applied to the segmented lung region is applied by (Athavale and Puttaswamy 2021). To detect pneumonia, a convolutional neural network method was used that incorporated a Gabor filter and an image enhancement pre-processing technique were used by (Minarno et al. 2021). To differentiate between normal chest x-rays and chest x-rays with pulmonary edema, texture analysis was performed using the Gabor filter and Support Vector Machine (SVM), one of the machine learning techniques are applied by (A. Kumar et al. 2014). The past studies summary shown in Table 1 indicates that all the previous studies their aim was in one specific abnormality.

This study proposes a novel approach for detecting abnormalities in chest X-rays by combining Gabor filters and deep neural networks. This approach aims to improve the accuracy of abnormality detection and overcomes some of the limitations of existing methods. It first pre-processes the chest X-rays using Gabor filters to extract textural features from the images. These features can provide valuable information about the presence of abnormalities. Then, to classify the chest X-rays as either normal or abnormal the extracted features are fed into a convolutional neural network (CNN). CNNs are well suited for image classification tasks due to their ability to learn and recognize complex patterns and features within the data. To ensure the robustness and reliability of this approach, a large dataset of chest X-rays with known abnormalities are used for training and validation purposes. This dataset will allow the model to learn and generalize from diverse examples, leading to improved accuracy in detecting abnormalities.

This paper has four sections. Section 1 provides the necessary background information and Section 2 describes the methodology used in this study. Section 3 discusses the experiments conducted and Section 4 presents the concluding remarks.

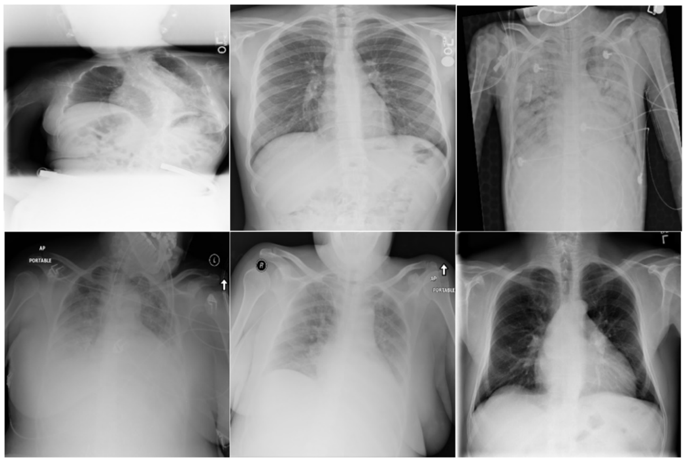

FIGURE 1. Chest X-ray images

TABLE 1. Summary of previous studies

Refrence	Method used	Aim of the study
(Abdar et al. 2021)	Deep learning feature fusion model to detect COVID-19	COVID-19
(Jabbour et al. 2020)	Deep learning	General
(Agrawal et al. 2023)	binary classification and multi-class classification to detect COVID-19	COVID-19
(Jaiswal et al. 2019)	utilized Mask-RCNN, a deep neural network to detect Pneumonia	Pneumonia
(Baik, Hong, and Park 2023)	CNN models such as Inception-ResNet-V2 and EfficientNet, while MLP models have been used for other purposes	COVID-19
(Nasser and Akhloufi 2023)	Two-step approach to classify chest diseases	consolidated dataset
(Sulaiman et al. 2023)	Convolutional neural network architecture for lung segmentation using chest X-ray images	COVID-19
(Tsuji et al. 2023)	CNNs to classify normal and abnormal chest X-rays	General
(Aktas et al. 2022)	CNNs to classify normal and abnormal chest X-rays	COVID-19
(Alharbi and Hosni Mahmoud 2022)	CNNs and dense learning	Pneumonia
(Banerjee et al. 2022)	Ensemble methodology for deep learning models Convolutional Neural Networks (CNNs)	COVID-19
(Babu, Manohar O, and Chandy 2022)	Deep learning to detect COVID-19	COVID-19
(Balasubramaniam and Satheesh Kumar 2023)	Ensemble model approach for classification	COVID-19
(Sandhiyaa et al. 2023)	Gabor filter for classification and Deep Convolutional Neural Network (DCNN)	COVID-19
(Barshooi and Amirkhani 2022)	Different filter banks such as Sobel, Laplacian of Gaussian (LoG), and Gabor filters	COVID-19
(Imani 2021)	Contextual feature extraction using morphological operators, Gabor filter banks, and attribute filters	COVID-19
(ÇINAR, TOPUZ, and ERGİN 2021)	Template matching method to locate the rib bones, and then the corresponding bones are suppressed by applying the Gabor filter	Lung
(Athavale and Puttaswamy 2021)	Rib shadow suppression, the logarithmic Gabor filter is applied to the segmented lung region	Lung
(Minarno et al. 2021)	Detect pneumonia, a convolutional neural network method was used that incorporated a Gabor filter and an image enhancement pre-processing technique	pneumonia
(A. Kumar et al. 2014)	differentiate between normal chest x-ray and chest x-ray with pulmonary edema, texture analysis was performed using Gabor filter and Support Vector Machine (SVM)	Pulmonary edema

METHODOLOGY

A Gabor filter, also referred to as Gabor wavelet, is a linear filter used in image processing and computer vision tasks. It was named after Dennis Gabor, a Hungarian-British physicist and Nobel laureate who introduced the concept of Gabor transforms. Gabor filters have frequency-selective and orientation-selective properties and provide optimal joint resolution in both spatial and frequency domains. Tuning the Gabor filter to a specific frequency and direction allows obtaining information about frequency and orientation of an image. This filter analyzes the local spatial frequency content of an image by convolving it with a kernel that resembles a Gaussian function modulated by a sinusoidal plane wave. This kernel combines both the time and frequency domains, making it well suited for capturing information about edges, textures, and other localized features in an image (Gabor 1946).

An even symmetric Gabor filter has the following general form in the spatial domain:

$$g(x, y: \emptyset, f) = exp\left\{-\frac{1}{2}\left[\frac{x_\theta{}^2}{\sigma_x{}^2} + \frac{y_\theta{}^2}{\sigma_y{}^2}\right]\right\}.\cos(2\pi f.x_\theta), \tag{1}$$

where

$$x_\theta = x\sin\theta + y\cos\theta, \tag{2}$$

$$y_\theta = x\cos\theta - y\sin\theta, \tag{3}$$

In this equation, θ is the orientation, f is the frequency of the sinusoidal plane wave, and the space constants of the Gaussian envelope along the x and y-axes are denoted by and σx and σy respectively.

This filter is applied to the normalized image to obtain the enhanced image.

$$E(i,j) = \begin{cases} 255 & if\ R(i,j) = 0, \\ \sum_{u=-w_g/2}^{w_g/2} \sum_{v=-w_g/2}^{w_g/2} h(u, v: O(i,j), F(i,j))G(i-u, j-v) & otherwise \end{cases} \tag{4}$$

Where G is the normalized image, O is the orientation of the image F is frequency. Figure 2 shows different Gabor filters at different angles.

The Gabor filter can be used in the analysis of chest X-rays to extract valuable information to facilitate the diagnosis of respiratory conditions and diseases. By applying Gabor filters to chest X-rays, specific features and patterns related to lung structures and abnormalities can be enhanced and highlighted. In addition, by applying Gabor filters at multiple scales and orientations, nodules of different sizes and shapes can be captured by designing the filters to target specific frequency ranges characteristic of nodules. Relevant information is obtained after suppressing irrelevant structures and noise. The resulting filtered images can then be further analyzed and processed to identify and classify the abnormality. Figure 3 shows different Gabor kernels.

To improve the accuracy and efficiency of diagnosing respiratory diseases, a combination of Gabor filters and deep neural learning techniques can be a powerful approach to analyzing chest X-rays. By combining the strengths of both traditional and deep learning methods, it is possible to extract meaningful features from chest X-rays and train neural network models to automatically detect and classify abnormalities.

The popularity and success of deep learning in recent years can be attributed to its ability to learn hierarchical representations of data, which has led to remarkable performance in various tasks, including image recognition, natural language processing, and speech recognition. Deep

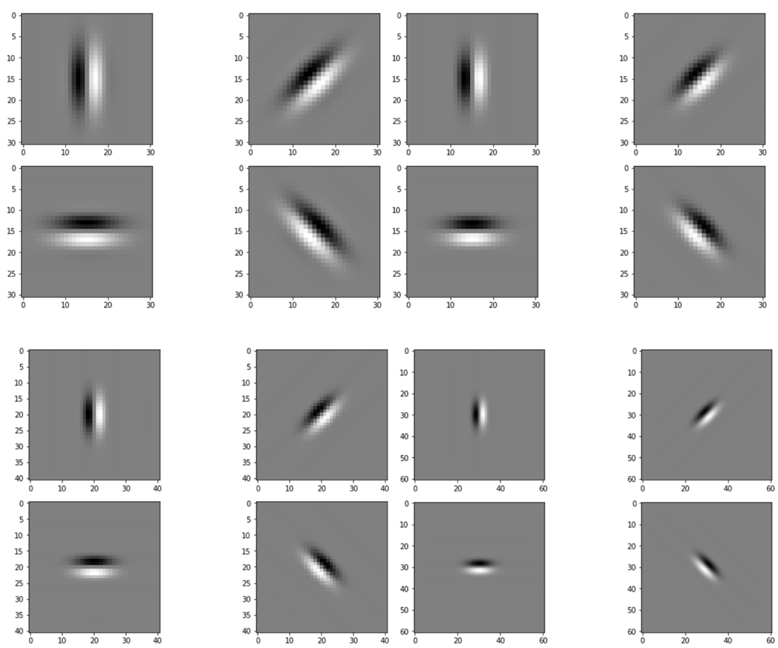

FIGURE 2. Gabor filters at different angels

learning is a subfield of machine learning that focuses on training artificial neural networks to learn from large amounts of data and make predictions based on that learning (K. Kumar et al. 2023).

Artificial neural networks are modeled on the structure and function of the human brain. These networks consist of interconnected layers of artificial neurons, also called nodes or units, organized into input, hidden, and output layers. Each neuron receives input signals, processes them, and generates an output signal based on an activation function(Ajantha Devi & Naved 2021)

The power of deep learning lies in its ability to learn complex representations of data through multiple layers of abstraction. This is achieved by training the neural network using a technique called backpropagation. During the training process, the network is presented with labeled training examples where the input data is paired with the desired output. The network's initial predictions are compared to the actual outputs, and the difference between the two is measured using a loss function, such as the mean squared error or cross entropy (Eloranta & Boman 2022).

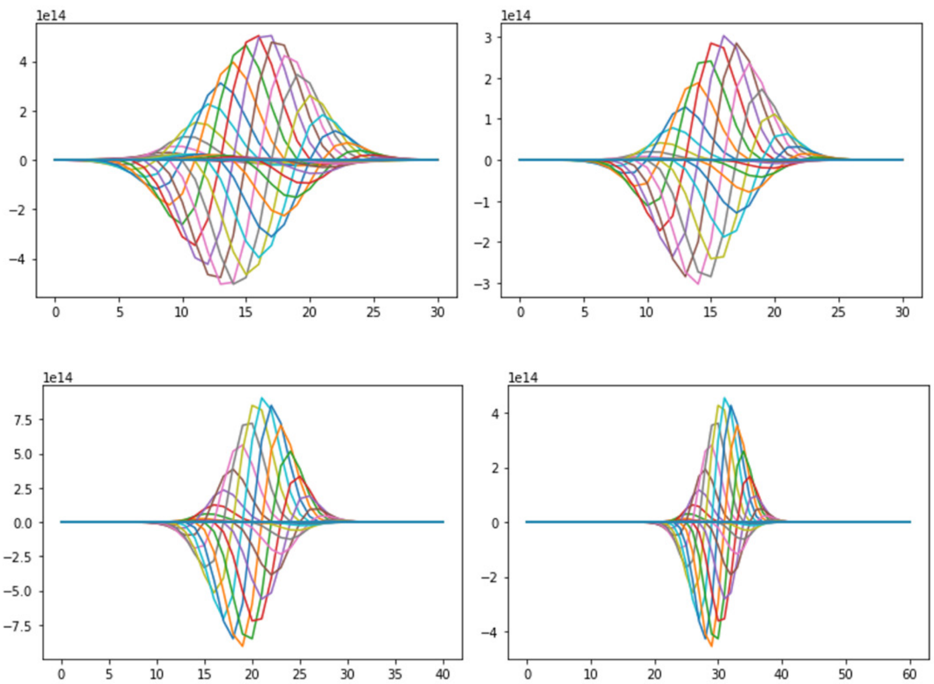

FIGURE 3. Different Gabor filter kernels

RESULTS AND DISCUSSION

The chest x-ray NIHCC dataset (Dataset 2018) contains 112,120 images and was evaluated on a hold-out test set consisting of 8,016 images. The dataset used for the experiment is small due to the limitations of the equipment used. Each image is loaded and preprocessed by resizing it to 224x224 pixels and normalizing it to values between 0 and 1. Figure 4 shows the processed images.

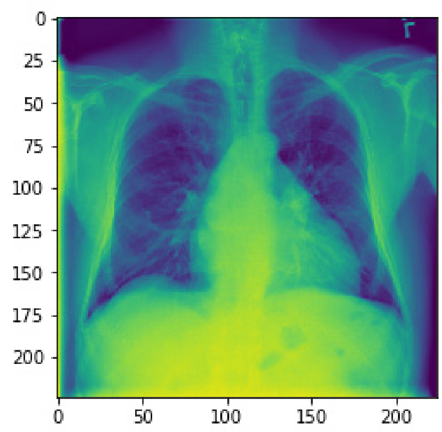

FIGURE 4. Chest x-ray processed image

The Gabor filter bank is defined by creating a list of kernels for four different orientations, two different sigma values, and eight different lambda values, which are used to generate 64 Gabor filters that are used to capture texture information from the images (Figure 5).

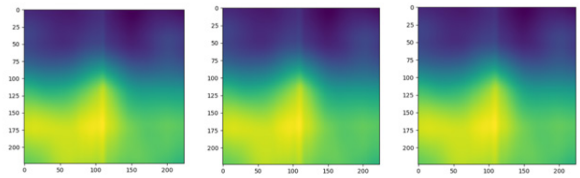

FIGURE 5. Gabor filter bank

These kernels are then applied to all preprocessed images, resulting in a set of filtered images for each image Figure 6.

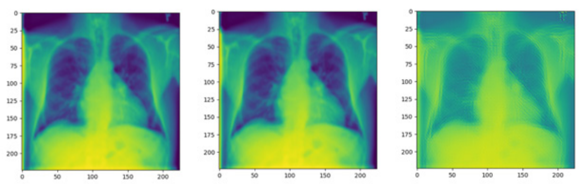

FIGURE 6. Chest x-ray image after applying the Gabor kernels

The filtered images are then flattened into a feature vector containing the texture features. This feature vector is used as input to the DNN model.

The DNN model is a simple feedforward network with two dense layers and a sigmoid activation function in the output layer. The input layer takes the flattened feature vector as input, and the output layer predicts the probability of the image belonging to a particular class. The model is trained using binary cross-entropy loss and optimized using the Adam optimizer.

To evaluate the performance of the DNN model, 80% of the data set is used for training and 20% for testing. The model is trained on the training set for 10 epochs with a batch size of 32. The accuracy and loss are monitored on both training and validation sets during training to prevent overfitting. Finally, the model is evaluated on the testing set using metrics such as accuracy and area under the receiver operating characteristic curve (AUC-ROC). As shown in Figure 7, the AUC-ROC is 90% and the accuracy is 79%.

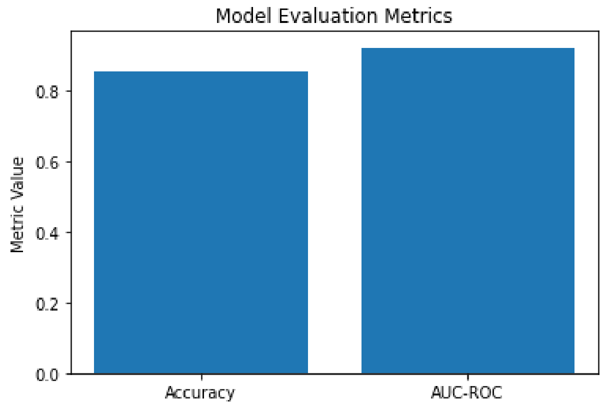

FIGURE 7. Shows the accuracy and AUC-ROC

The results of the method show that the DNN model achieves high accuracy in classifying chest X-ray images using texture features extracted from Gabor filters. This approach can be used as an alternative to traditional methods that rely on handcrafted features or deep learning models that require large amounts of labeled data. In comparison with other studies, Gabor filters and DNN model achieve 79% accuracy and true positive rate 78%. These results indicate that this novel method is an improvement compared to the existing ones.

CONCLUSION

The human chest is a complex and multifaceted part of the body that plays an important role in our overall health and well-being. It houses vital organs such as the heart and lungs, and it also helps protect these organs from injury. However, not all human chests are the same, and some people may have chest abnormalities that affect their appearance, shape, or function. Gabor filters can be used to extract texture features from images to train a deep neural network (DNN) to detect abnormalities in chest X-rays. This paper proposes a novel method for detecting abnormalities in chess X-rays using Gabor filters and Deep Learning Network. The NIHCC dataset of normal and abnormal chest X-rays is used to train deep neural network to classify X-rays as normal or abnormal. Experimental results show that the proposed method achieves high accuracy in detecting abnormalities in chest X-rays. The author believes that the method has the potential to improve the diagnosis and treatment of chest abnormalities. Future work should use more powerful equipment to analyze different and larger datasets.

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DECLARATION OF COMPETING INTEREST

None.

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