№3 (4), 2022 ISSN: 2682 – 9517 (print) ISSN: 2683 – 0930 (online)

INSTITUTE OF INFORMATICS AND INNOVATIVE TECHNOLOGIES

COMBINATION OF GABOR FILTER AND CONVOLUTIONAL NEURAL NETWORK IN DETECTING ABNORMAL SIGNS IN LUNG BASED ON X-RAY

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Abstract: **In recent years, X-ray has been applied in diagnosing lung abnormalities, the sooner gets diagnosed the lower the risk of death caused by pulmonary diseases. Consequently, the automatic detection of lung abnormalities for early treatment is necessary. There are many proposed methods to have the work done. Over the last few years, methods based on deep learning techniques have been receiving many interest for their efficiency as well as being cost-effective in detecting lung abnormalities through X-ray images. However, not every model can provide high accuracy. In this paper, we propose combining the Gabor Filter and the Convolutional Neural Network to detect abnormal lung signs caused by pneumonia. We use Gabor Filter as an initial solution to clarify the lung's traits. Next, we use Convolutional Neural Network to train and test the data which contains Tawsifur Rahman's 832 images. The output of the experiment indicates that our suggested model is quite sanguine when compared with other approaches, with an accuracy of 94.4%.**

Keywords: **Convolutional Neural Network, Gabor filter, X-ray.**

I. INTRODUCTION

Early detection of irregular signs in the lung is vital. It helps us discover lung illness as well as have proper treatments and decrease the possibility of severe complications and death. The most well-known and simplest method to detect lung abnormal symptoms is by X-raying the chest area. Every lung illness creates abnormal signs on X-ray images. Some cues can be observed by bare eyes, such as blur spots on the image, white lung, lung consolidation, pneumothorax, bronchiectasis,… which are pointed out in Figure 1. Based on X-ray images, researchers have suggested applying high-tech methods to soon discover unusual signs in the lungs and decrease pressure on the health industry.

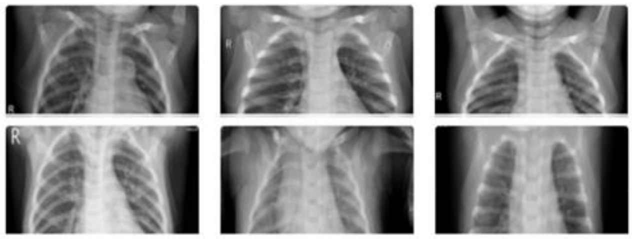

Fig. 1. Chest X-ray figures (Row 1: Image of normal lung, Row 2: Image of pneumonia lung.)

As a result of analyzing both X-rays and image processing technology, Ioannais Livieris's research group has proposed a new semi-observing algorithm to classify lung abnormal signs based on a synthetic thesis [1]. To detect irregular signs caused by pneumonia, it is advised to combine AlexNet and SVM, PCA technique to implement sorting out distinctive and subclasses, the accuracy has been raised better than the traditional models [4]. Some research groups had used the YOLO model with a considerable set of data to discover anomalies in chest X-ray images [5]. In 2021, Saleh Albahli's team has conducted research and proposed three models: DenseNet121, InceptionResNetV2, and ResNet152V2 to classify 14 different ill lung symptoms, the data is extended by rotating every 10 degrees upon lung X-ray images. Qiao Ke's research team has used the DNN deep learning model paired with the Ant Lion and Moth-Flame algorithm to detect lung degeneration by X-rays [7]. Ho & Gwak (2019) has used the DenseNet121 model combined with a distinctive sorting technique to determine 14 lung related illness [8]. In [9], the authors have designed three convolutional neural network models: GoogLeNet, ResNet-18, and DenseNet-121, A weighted average ensemble technique was adopted, wherein the weights assigned to the base learners were determined using a novel approach. The proposed method achieved accuracy rates of 98.81% and 86.85% and sensitivity rates of 98.80% and 87.02% on the Kermany and RSNA datasets. In 2020, the authors suggested ResNet-50 and DenseNet-161 models discover pneumonia, the accuracy has been enhanced by increasing dataset technique [10].

In this paper, we introduce a brand-new approach that improves the performance of detecting lung abnormalities. It is proven that the Gabor filter is an effective tool for texture analysis [11]. The output shows high performance in increasing the contrast of images. Therefore, we use the Gabor filter to clarify X-rays' distinctiveness, and then CNN is adopted to detect lung abnormalities, due to the effectiveness of CNN in classification problems [12]. Based on the output of the experiment, our proposed method is more effective than other approaches methods with an accuracy of more than 94%.

II. Combination of Gabor Filter and CNN

A. Gabor filter

In image processing, a Gabor filter is a linear filter used for texture analysis, which means that it basically analyzes whether there is any specific frequency content in the image in specific directions in a localized region around the point or region of analysis [11], [13-14]. The Gabor Filter is said to have a similar image analysis capability to the human visual system. The Gabor Filter is designed by the following formula

$$g(x, y, \lambda, \Theta, \varphi, \sigma, \gamma) = e\left(\frac{x'^2+\gamma^2 y'^2}{2\sigma^2}\right)e\left(i\left(2\pi\frac{x}{\lambda}+\varphi\right)\right)$$

where x' = xcosΘ + ysinΘ and y' = -xsinΘ + ycosΘ

In the above equation, λ represents the wavelength of the sinusoidal factor, θ represents the orientation of the normal to the parallel stripes of a Gabor function, ϕ is the phase offset, σ is the standard deviation of the Gaussian envelope and γ is the spatial aspect ratio and specifies the ellipticity of the support of the Gabor function. The Gabor Filter is accustomed to separating distinctive edges and highlighting the image's contrast. Consequently, the Gabor Filter is considered a great method that can distinguish characteristics between normal lungs and pneumonia lungs in X-rays.

B. Convolutional Neural Network

In this paper, after preprocessing the dataset and using the Gabor Filter to distinguish characteristics between images, we proceed to train with model CNN. The CNN model which we discuss in this article is VGG16. VGG-16 contains some enhancements in terms of architecture, including 13 layers of two-way convolutional, layers of CNN and max pooling instead of intercalating only one layer of CNN, and max pooling. VGG-16 only uses filters with a small size of 3*3 which helps decrease the number of parameters for the model and shows greater efficiency in computation [14]. Based on VGG-16, we built layers of CONV which put input image with parameters: Convolutional layer with a size of 3x3, padding = 1, stride = 1, max pooling layer with a size of 2x2. The parameters of the layers are described in Image 2. At the input layer, we use 3 filters, each with a size of 3x3. On account of each filter having a weight of 3x3, as a consequence, the weight will be (3*3*3+1)*64 = 1792. There are 64 filters in the first layer, and 1792 of weight could be trained. The second CONV layer has 64 filters, each of which is 3x3, and the input is the previous CONV, resulting in a total of (3*3*64+1) *64 = 36928 of the weight that can be trained. Next, in the third layer, the max pooling function is applied to decrease the input matrix's dimensions by a window which has a size of 2x2, therefore, this layer has no weight. Other layers can be created similarly. After going through the all layers, we receive a model which can detect lung abnormal cues through X-ray images with 2 outputs for healthy and sick lungs.

III. Experimental Results

A. Data Preprocessing

In this paper, we use Tawsifur Rahman's dataset and some images collected by us, a total of 1832 images, which contains 916 healthy lung X-rays and 916 pneumonia lung X-rays. The data were preprocessed and labeled before being divided by two, with 80% of the images used for training and the remaining images used for testing. Training data will be preprocessed by converting it into grayscale to decrease the dimension of the input matrix, changing the images' size to 224x224 since the initial size was not the same. After that, we use the Gabor filter to highlight the characteristics of healthy and ill lung X-rays. At the end of the experiment, we gathered a model which is proposed to classify lung abnormalities based on X-rays.

B. Results

Our system is built on a computer with the following configuration, environment and framework: CORE I7-10700 2.9GHZ, 16GB RAM, Windows 10 OS, Python 3.6 and TensorFlow. In this work, we set the Learning Rate to 1e-4, batch_size=32, epochs = 100. The output not only affirms that we chose an adequate number of images in the dataset with proper parameters to avoid overfitting but also proves that our combination of Gabor Filter and CNN gave excellent and stable accuracy more than CNN. Figure 2 describes the CNN model's accuracy in training with 100 epochs. During

ISSN: 2682 – 9517 (print) ISSN: 2683 – 0930 (online)

the first 30 epochs, the model's accuracy was not stable, but from the 31st epoch, the accuracy started to become more consistent and achieved 92.6%.

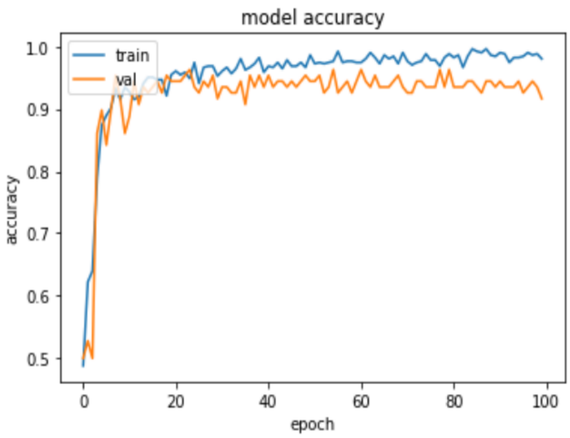

Fig. 2. The accuracy of the CNN model

With our proposed combination of the Gabor Filter and CNN, the model achieved an accuracy of 94.44%. Figure 4 depicts the accuracy of the method of combining the Gabor filter with CNN during training with 100 epochs. In the first 20 epochs, the accuracy of the model is unstable. But at subsequent epochs, the accuracy of the model gradually stabilizes and converges.

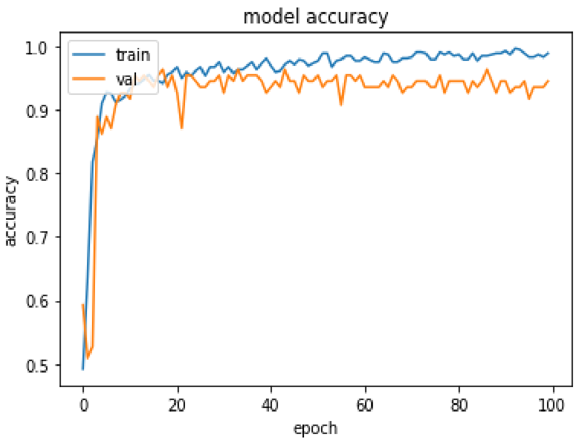

Fig. 3. The accuracy of the combination of the Gabor Filter and CNN model

In order to further clarify the efficiency of the combined method of Gabor Filter and CNN, we use the Confusion matrix to display the classification performance more intuitively. Accordingly, the vertical axes of the matrix are the actual labels corresponding to the two classes of abnormal and normal lungs. The horizontal axes are the labels according to the predictive model, which also corresponds to the two classes above.

In the CNN model, the Confusion matrix is demonstrated in Figure 4, the model accurately expected more than 95% of healthy lung cases and mistook healthy lungs for abnormal lungs at a percentage of 4. The model achieved an accuracy of 89% for predicting abnormal lungs, and the percentage of mistakes is greater than 10%.

In the combined model of the Gabor filter and CNN, the Confusion matrix is demonstrated in Figure 5, the model prediction achieved an accuracy of more than 98% of healthy lung cases, and only mistook for abnormal cases at a rate of 1%. For expecting abnormal cases, the model's accuracy is nearly 92%, and being mistaken for healthy cases is more than 9%.

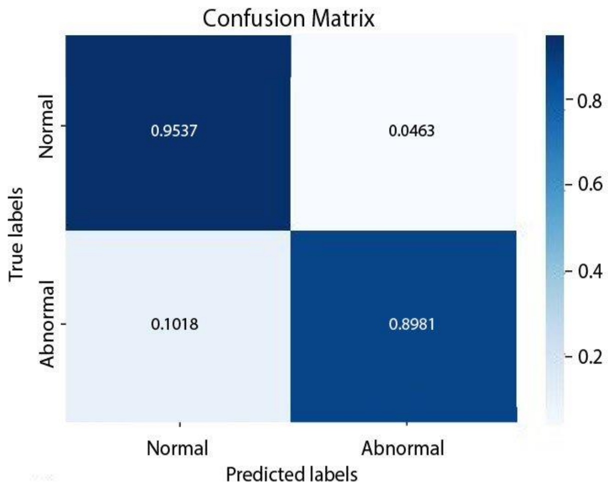

Fig. 4. Confusion matrix of CNN model

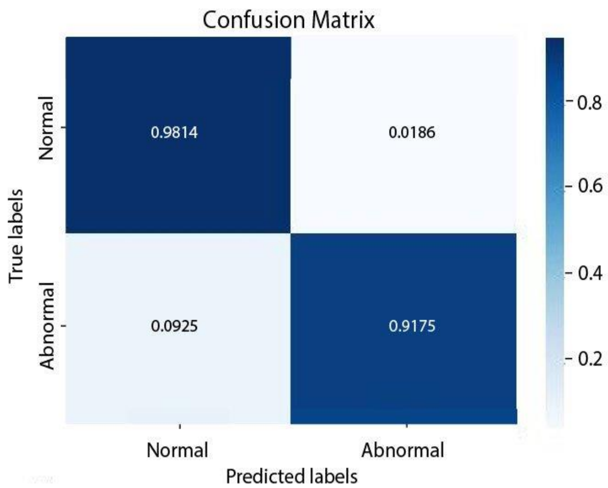

Fig. 5. Confusion matrix of the combination of Gabor Filter and CNN model

In terms of comparing and rating deep learning models, we process to static and compare four values after training the models: Precision, Recall, F1-score, and Accuracy. The Accuracy value is the ratio of the precisely predicted data to the total number of testing data [15]. The precision value is the proportion of correctly recognized data in a class to the total amount of data in the classes. The Recall value is the ratio of the precisely recognized data in a class to the total number of data in the classes. The F1-score value is a harmonic mean which is determined based on Precision and Recall values. The results of comparing the accuracy in detecting lung abnormalities between the algorithms are shown in table 1 and table 2.

Table 1. Comparing the accuracy between algorithms of healthy lung classes

Models	Acc	Precision	Recall	F1-Score
Gabor Filter and CNN	94.44	91.37	98.14	94.63
CNN	92.6	90.35	95.37	92.79

Table 2. Comparing the accuracy between algorithms of abnormal lung classes

Models	Acc	Precision	Recall	F1-Score
Gabor Filter and CNN	94.44	97.9	90.74	94.18
CNN	92.6	95.09	89.81	92.37

CONCLUSIONS

Early detection of abnormal lung signs is a pressing demand. This article introduces a new method to detect lung abnormalities based on X-rays by combining the Gabor filter and convolutional neural network (CNN). The Gabor filter has succeeded in increasing the contrast and highlighting abnormal lung distinctive compared with healthy lungs. The result of our proposed method is great and stable. In comparison to normal CNN, the performance of our method is more sanguine and has the potential to be further investigated. In the future, we will develop and improve deep learning network models to improve their accuracy and enable them to be used in the early detection and diagnosis of lung diseases.

ACKNOWLEDGEMENTS

This research was supported by the University of Transport and Communications under grant number T2022-CN-004.

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