



PNEUMONIA TEXTURE ANALYSIS USING X-RAY IMAGES

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Abstract: Pneumonia is an acute pulmonary infection that can be caused by bacteria, viruses, or fungi and infects the lungs, causing inflammation of the air sacs and pleural effusion, a condition in which the lung is filled with fluid. It accounts for more than 15% of deaths in children under the age of five years [1]. Pneumonia is most common in underdeveloped and developing countries, where overpopulation, pollution, and unhygienic environmental conditions exacerbate the situation, and medical resources are scanty. Therefore, early diagnosis and management can play a pivotal role in preventing the disease from becoming fatal. Radiological examination of the lungs using computed tomography (CT), magnetic resonance imaging (MRI), or radiography (X-rays) is frequently used for diagnosis. X-ray imaging constitutes a non-invasive and relatively inexpensive examination of the lungs. Fig 1 shows an example shows an example of a pneumonic and a healthy lung X-ray. The white spots in the pneumonic X-ray (indicated with red arrows), called infiltrates, distinguish a pneumonic from a healthy condition. However, chest X-ray examinations for pneumonia detection are prone to subjective variability [2, 3]. Thus, an automated system for the detection of pneumonia is required. In this study, we developed a computer-aided diagnosis (CAD) system that uses an ensemble of deep transfer learning models for the accurate classification of chest X-ray images.

I. INTRODUCTION

Deep learning is an important artificial intelligence tool, which plays a crucial role in solving many complex computer vision problems [5, 6]. Deep learning models, specifically convolutional neural networks (CNNs), are used extensively for various image classification problems. However, such models perform optimally only when they are provided with a large amount of data. For biomedical image classification problems, such a vast amount of labeled data is difficult to acquire because it requires that expert doctors classify each image, which is an expensive and time-consuming task. Transfer learning is a work-around to surmount this obstacle. In this technique, to solve a problem that involves a small dataset, a model trained on a large dataset is re-used and the network weights determined in this model are applied. CNN models trained on a large dataset such as ImageNet [7], which consists of more than 14 million images, are frequently used for biomedical image classification tasks.

Ensemble learning is a popular strategy in which the decisions of multiple classifiers are fused to obtain the final prediction for a test sample. It is performed to capture the discriminative information from all the base classifiers, and thus, results in more accurate predictions. Some of the ensemble techniques that were most frequently used in studies in the literature are average probability, weighted average probability, and majority voting. The average probability-based ensemble assigns equal priority to each constituent base learner. However, for a particular problem, a certain base classifier may be able to capture information better than others. Thus, a more effective strategy is to assign weights to all the base classifiers. However, for ensuring the enhanced performance of the ensemble, the value of the weights assigned to each classifier is the most essential factor. Most approaches set this value based on experimental results. In this study, we devised a novel strategy for weight allocation, where four evaluation metrics, precision, recall, f1-score, and area under receiver operating characteristics (ROC) curve (AUC), were used to assign the optimal weight to three base CNN models, GoogLeNet, ResNet-18, and DenseNet-121. In studies in the literature, in general, only the classification accuracy was considered for assigning weights to the base learners [8], which may be an inadequate measure, in particular when the datasets are class-imbalanced. Other metrics may provide better information for prioritizing the base learners.

**LIBRARIES REQUIREMENT****Numpy**

A NumPy array is a multidimensional, uniform collection of elements. An array is characterized by the type of elements it contains and by its shape. For example, a matrix may be represented as an array of shape ($M \times N$) that contains numbers, e.g., floating point or complex numbers. Unlike matrices, NumPy arrays can have any dimensionality. Furthermore, they may contain other kinds of elements (or even combinations of elements), such as booleans or dates. Underneath the hood, a NumPy array is really just a convenient way of describing one or more blocks of computer memory, so that the numbers represented may be easily manipulated.

sklearn.model_selection

The train-test split procedure is used to estimate the performance of machine learning algorithms when they are used to make predictions on data not used to train the model. It is a fast and easy procedure to perform, the results of which allow you to compare the performance of machine learning algorithms for your predictive modeling problem. Although simple to use and interpret, there are times when the procedure should not be used, such as when you have a small dataset and situations where additional configuration is required, such as when it is used for classification and the dataset is not balanced.

matplotlib.pyplot :

matplotlib.pyplot is a collection of functions that make matplotlib work like MATLAB. Each pyplot function makes some change to a figure: e.g., creates a figure, creates a plotting area in a figure, plots some lines in a plotting area, decorates the plot with labels, etc.

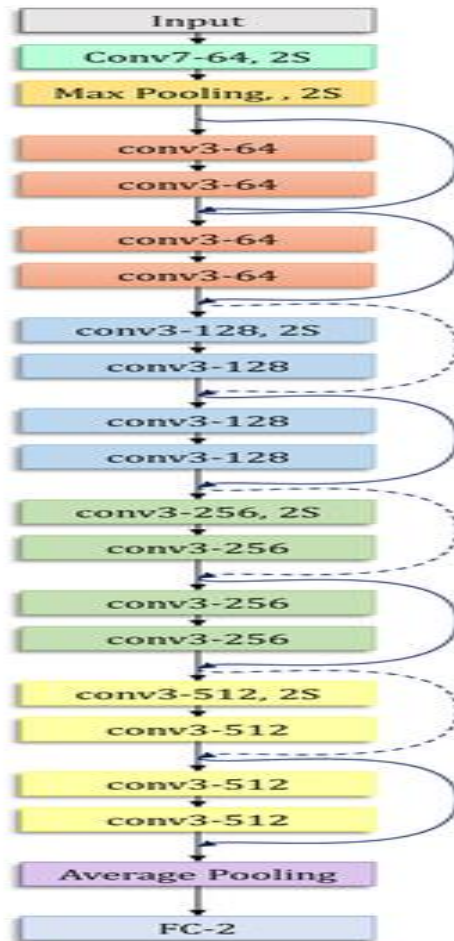
METHODOLOGY**Image Pre-Processing**

Keras preprocessing -The Keras preprocessing layers API allows developers to build Keras-native input processing pipelines. These input processing pipelines can be used as independent preprocessing code in non-Keras workflows, combined directly with Keras models, and exported as part of a Keras SavedModel.

With Keras preprocessing layers, you can build and export models that are truly end-to-end: models that accept raw images or raw structured data as input; models that handle feature normalization or feature value indexing on their own.

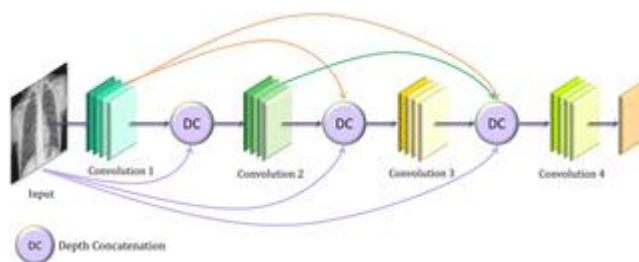
ResNet-18

The ResNet-18 model proposed by He et al. [35] is based on a residual learning framework, which increases the efficiency of deep network training. The residual blocks in the ResNet models facilitate the optimization of the overall network, which in turn improves model accuracy, unlike the original unreferenced mapping in monotonically progressive convolutions. These residuals or “skip connections” perform identity mapping, which neither adds parameters nor increases the computational complexity.



DenseNet-121

The DenseNet architectures proposed by Huang et al. [36] provide a rich feature representation while being computationally efficient. The primary reason is that, in each layer of the DenseNet model, the feature maps in the current layer are concatenated with those from all the preceding layers, as shown in Fig 6. Because fewer channels are accommodated in the convolutional layers, the number of trainable parameters is diminished, and thus, the model is computationally efficient. Furthermore, the concatenation of the feature maps from the previous layers with the current layer enhances the feature representation.



VGGNet

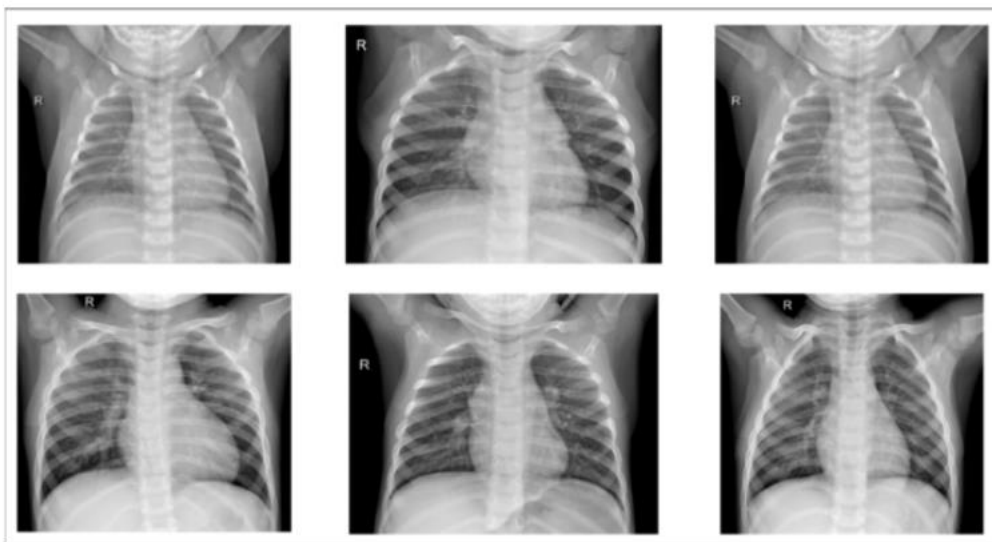
VGGNet is a CNN jointly developed by the Visual Geometry Group at the University of Oxford and Google DeepMind. As shown in Figure 3, VGGNet architecture can be considered an extended AlexNet, characterized by 3x3 convolutional



kernels and 2x2 pooling layers, and the network architecture can be deepened by using smaller convolutional layers to enhance feature learning. The two most common current VGGNet versions are VGGNet-16 and VGGNet-19

Training Datasets

We used an open-source dataset provided by the Kaggle data science competition platform for training (https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia accessed on 25 March 2018) [31]. The dataset comprised thoracic cavity images from child patients (1 to 5 years old) from the Guangzhou Women and Children’s Medical Center, China. These images were classified by two expert physicians and separated into training, test and validation sets. Figure 8 displays the dataset structure, with training sets including 1341 and 3875, test sets 234 and 390, validation set 8, and eight normal and pneumonia images, respectively. Figures 9 and 10 show examples of normal and pneumonia thoracic cavity X-ray images, respectively.

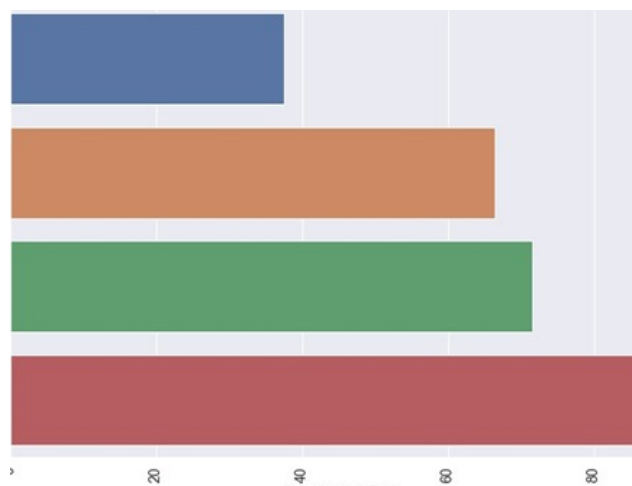


Outcomes

The models used are CNN based feature - extraction and supervised classifier algorithm and resulted in optimal solution for classifying abnormal (Pneumonia labeled) and normal Chest X-Ray images

The features should be extracted from various variants of pre-trained CNN models available such as CNN, VGG-16, ResNet-50, DenseNet-121 etc.

The performance of our proposed model, several comparisons of different input shapes and loss functions is provided.



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