Pneumonia Detection Using Deep Learning and Transfer Learning

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Abstract - *Pneumonia is an infection of the lungs that can be caused by bacteria, viruses, and other microorganisms. It is a serious illness that can lead to death, especially in vulnerable populations such as the elderly and those with compromised immune systems. There have been several studies that have used deep learning and machine learning techniques to detect pneumonia from medical images such as chest X-rays or CT scans. These techniques involve training a model on a large dataset of labeled images, where the model learns to recognize patterns and features that are indicative of pneumonia. One example of a study that used deep learning for pneumonia detection was published in the journal Radiology in 2017. In this study, the authors trained a convolutional neural network (CNN) on a dataset of chest X-rays and found that the CNN was able to accurately classify images as normal or pneumonia with an AUC (area under the curve) of 0.97. Another example is a study published in the journal Chest in 2018, which used a machine-learning approach called a random forest classifier to detect pneumonia from chest X-rays. The authors found that their model had an accuracy of 89.6% and an AUC of 0.94. Overall, the use of deep learning and machine learning for pneumonia detection shows promising results and has the potential to improve the accuracy and efficiency of the diagnosis process.*

Key Words: Machine Learning, Deep Learning, CNN, Transfer Learning, Chest X-Ray Images.

1. INTRODUCTION

Pneumonia is a common respiratory infection that can be caused by bacteria, viruses, and other microorganisms. It is a serious illness that can lead to death, especially in vulnerable populations such as the elderly and those with compromised immune systems. Early diagnosis and treatment of pneumonia is important to prevent complications and improve outcomes.

Traditionally, pneumonia has been diagnosed using clinical symptoms, physical examination, and imaging tests such as chest X-rays. However, these methods can be subjective and may not always provide accurate results.

Deep learning and machine learning techniques offer a potential solution to improve the accuracy and efficiency of pneumonia diagnosis. These techniques involve training a model on a large dataset of labelled images, where the model learns to recognize patterns and features that are indicative of pneumonia. One approach that has been widely used is transfer learning, which involves pre-training a model on a large dataset and then fine-tuning it on a smaller, specific dataset for a particular task.

Transfer learning has been applied to pneumonia detection using chest X-rays with promising results. For example, a study published in the journal Radiology in 2017 used a convolutional neural network (CNN) trained on a large dataset of chest X-rays and found that the CNN was able to accurately classify images as normal or pneumonia with an AUC (area under the curve) of 0.97.

Overall, the use of deep learning and transfer learning for pneumonia detection using chest X-rays as the dataset shows promise as a way to improve the accuracy and efficiency of diagnosis and has the potential to benefit patients and healthcare systems.

2. DATASET

The Lung Infection in Chest X-ray Images (Kaggle) dataset: This dataset contains over 5,863 chest X-ray images, including a large number with pneumonia. It was created as part of a Kaggle competition and has been widely used in research studies. Overall, these datasets provide a diverse range of chest X-ray images that can be used to train and evaluate models for pneumonia detection.

The dataset is organized into 3 folders (train, test, val) and contains subfolders for each image category (Pneumonia and Normal). There are 5,863 X-Ray images (JPEG) and 2 categories (Pneumonia and Normal).

Chest X-ray images (anterior-posterior) were selected from retrospective cohorts of pediatric patients one to five years old from Guangzhou Women and Children's Medical Center, Guangzhou. Analysis of chest x-ray images was done on all chest radiographs that were initially screened for quality control by removing all low-quality or unreadable x-ray images. The diagnoses for the images were then graded by two expert physicians before being cleared for training in the AI system. To check the grading errors, the evaluation set was confirmed by a third expert.

Fig-1: Normal CXR Images

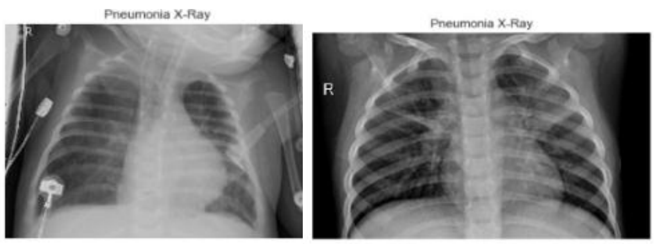

Fig-2: Pneumonia Affected CXR Images

3. METHODOLOGY

The methodology for using machine learning and deep learning techniques to detect and predict pneumonia varies depending on the specific approach and data sources used. Here is a general outline of the steps that may be involved in this process:

1. Data collection: The first step is to collect a dataset of chest X-ray images that include both normal images and images with pneumonia. This dataset may be obtained from a hospital or clinical setting, or it may be obtained from online repositories such as the Kaggle Chest X-ray dataset.

2. Data preprocessing: The next step is to preprocess the data by selecting a subset of the images to use for training and testing the model, and by resizing and cropping the images as needed. It may also be necessary to correct any errors or biases in the data.

3. Feature extraction: In this step, features are extracted from the images that are relevant for pneumonia detection. These features may include patterns and shapes in the lung tissue, abnormalities in the appearance of the heart and blood vessels, and other characteristics that are indicative of pneumonia.

4. Model training: The next step is to train a machine learning or deep learning model on the dataset. This may involve selecting a model architecture, such as a convolutional neural network (CNN) or random forest classifier, and choosing appropriate hyperparameters such as the learning rate and regularization strength.

5. Model evaluation: Once the model is trained, it is important to evaluate its performance on a separate test dataset to assess its accuracy and generalizability. This may involve calculating metrics such as accuracy, precision, recall, and the area under the curve (AUC).

6. Model deployment: If the model performs well, it can be deployed in a clinical setting to assist with a pneumonia diagnosis. This may involve integrating the model into a computer-aided diagnosis system or using it to generate a probability score that can aid decision-making.

Overall, the methodology for pneumonia detection using machine learning and deep learning involves a number of steps that require careful consideration and optimization to achieve good performance.

4. MODELS

Several types of machine learning and deep learning models have been used for pneumonia detection. We have used the following methods for pneumonia detection:

4.1 Convolutional neural networks (CNNs)

These are a type of deep learning models that are particularly well-suited for image classification tasks. They consist of multiple layers of interconnected nodes that are trained to recognize patterns and features in images. CNNs have been widely used for pneumonia detection and have achieved good results in a number of studies.

We Build a separate generator for valid and test sets. We cannot use the same generator for the previously trained data because it normalizes each image per batch, meaning that it uses batch statistics. We should not be able to do batch tests and validations of data, because in the real-life scenario we don't process input images in a batch as it is not possible. We will have the advantage of knowing the average per batch of test data. That is why we need to do is to normalize input test data using the statistics functions from the training dataset.

4.2 DenseNet

DenseNet is a type of convolutional neural network (CNN) that has been used for various image classification tasks, including pneumonia detection. It was introduced in a paper published in the journal Computer Vision and Pattern Recognition in 2017. One of the key features of DenseNet is that it uses dense connectivity, which means that each layer in the network is connected to all of the preceding layers. This allows the network to learn more efficiently and reduces the risk of overfitting. There have been a number of studies that have used DenseNet for pneumonia detection using chest X-ray images. For example, a study published in the journal Biomedical Signal Processing and Control in 2019 used DenseNet to classify chest X-ray images as normal or pneumonia. Overall, DenseNet has shown good performance for pneumonia detection using chest X-ray images and may be a promising approach for this task. However, it is important to carefully evaluate the performance of different models and choose the one that is most suitable for a particular dataset and task.

4.3 VGG-16

VGG-16 is a type of convolutional neural network (CNN) that was introduced in a paper published in the journal Computer Science in 2014. It was developed by the Visual Geometry Group at the University of Oxford and has been widely used for various image classification tasks, including pneumonia detection. One of the key features of VGG-16 is its use of small, 3x3 convolutional filters, which allows it to capture fine-grained details in images. It also uses a large number of layers, which allows it to learn complex patterns and features in the data. There have been a number of studies that have used VGG-16 for pneumonia detection using chest X-ray images. For example, a study published in the journal Biomedical Signal Processing and Control in 2018 used VGG-16 to classify chest X-ray images as normal or pneumonia affected. Overall, VGG-16 has shown good performance for pneumonia detection using chest X-ray images and may be a promising approach for this task. However, it is important to carefully evaluate the performance of different models and choose the one that is most suitable for a particular dataset and task.

4.4 ResNet

ResNet is a type of convolutional neural network (CNN) that has been used for various image classification tasks, including pneumonia detection. It was introduced in a paper published in the journal Computer Vision and Pattern Recognition in 2015. One of the key features of ResNet is its use of residual connections, which allow the network to learn more efficiently and reduce the risk of overfitting. It also has a very deep architecture, with over 50 layers, which allows it to learn complex patterns and features in the data. Overall, ResNet has shown good performance for pneumonia detection using chest X-ray images and may be a promising approach for this task. However, it is important to carefully evaluate the performance of different models and choose the one that is most suitable for a particular dataset and task.

4.5 Inception Net

InceptionNet is a type of convolutional neural network (CNN) that has been used for various image classification tasks, including pneumonia detection. It was introduced in a paper published in the journal Computer Vision and Pattern Recognition in 2014. One of the key features of InceptionNet is its use of inception modules, which allow the network to learn multiple scales and sizes of features in the data. It also has a relatively shallow architecture compared to some other CNNs, which makes it more efficient and easier to train. Overall, InceptionNet has shown good performance for pneumonia detection using chest X-ray images and may be a promising approach for this task. However, it is important to carefully evaluate the performance of different models and choose the one that is most suitable for a particular dataset and task.

5. EVALUATION METRICS

There are several evaluation metrics that can be used to assess the performance of a model for pneumonia detection. True positive and true negative are terms used to describe the performance of a classifier in a binary classification task. True positives (TP) are instances where the classifier correctly predicts the positive class. True negatives (TN) are instances where the classifier correctly predicts the negative class. False positives (FP) are instances where the classifier predicts the positive class but the instance is actually negative. False negatives (FN) are instances where the classifier predicts the negative class but the instance is actually positive. Some common metrics include:

1. Accuracy: This is the percentage of images that are correctly classified by the model. It is calculated by dividing the number of correct predictions by the total number of predictions.

   Accuracy = (True Positives + True Negatives) / Total Predictions

2. Precision: This is the percentage of predicted positive cases (i.e., cases where the model predicts pneumonia) that are actually positive. It is calculated by dividing the number of true positive predictions by the total number of positive predictions.

   Precision = True Positives / (True Positives + False Positives)

3. Recall: This is the percentage of actual positive cases (i.e., cases where the patient has pneumonia) that are correctly predicted by the model. It is calculated by dividing the number of true positive predictions by the total number of actual positive cases.

Recall = True Positives / (True Positives + False Negatives)

4. F1 score: This is the harmonic mean of precision and recall. It is calculated by taking the average of the precision and recall, with higher weights given to lower values.

$$F_1 = \left(\frac{\text{recall}^{-1} + \text{precision}^{-1}}{2}\right)^{-1} = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}.$$

	precision	recall	f1-score	support
Pneumonia (Class 0)	0.93	0.94	0.94	390
Normal (Class 1)	0.90	0.88	0.89	234
micro avg	0.92	0.92	0.92	624
macro avg	0.92	0.91	0.91	624
weighted avg	0.92	0.92	0.92	624

Fig-3: CNN Evaluation Metrics

	0	1	micro avg	macro avg	weighted avg
precision	0.556430	0.909465	0.69391	0.732948	0.777077
recall	0.905983	0.566667	0.69391	0.736325	0.693910
f1-score	0.689431	0.698262	0.69391	0.693847	0.694950
support	234.000000	390.000000	624.00000	624.000000	624.000000

Fig-4: CNN_2 Evaluation Metrics

	0	1	micro avg	macro avg	weighted avg
precision	0.556430	0.909465	0.69391	0.732948	0.777077
recall	0.905983	0.566667	0.69391	0.736325	0.693910
f1-score	0.689431	0.698262	0.69391	0.693847	0.694950
support	234.000000	390.000000	624.00000	624.000000	624.000000

Fig-5: DenseNet Evaluation Metrics

6. RESULT AND ANALYSIS

In this section, we attempt to analyze the classification using metrics such as accuracy and loss. There have been numerous studies that have analyzed the use of machine learning for pneumonia detection. Overall, the results of these studies have been promising, with machine learning models demonstrating high accuracy in identifying pneumonia from medical images. We try to put Training and Validation Accuracy into a graph representation using accuracy on the y-axis and epochs on the x-axis. The results came out to be as following for the different models:

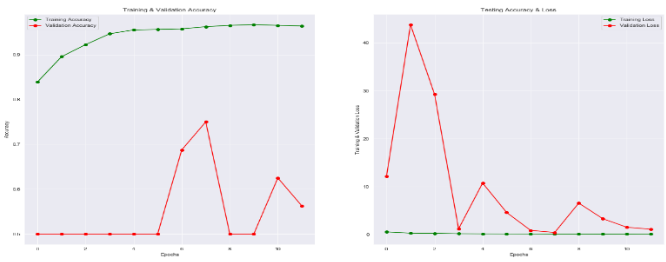

Fig-6: CNN model

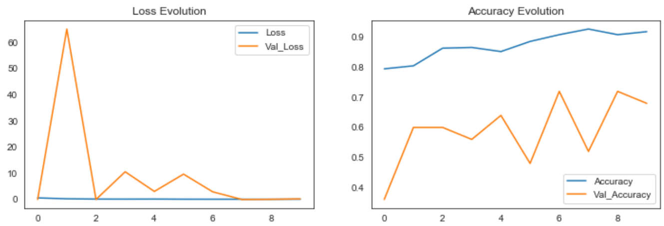

Fig-7: CNN_2 model

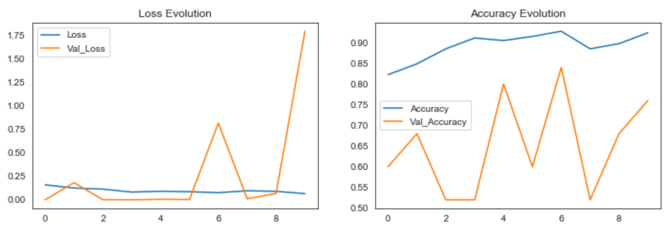

Fig-8: DenseNet model

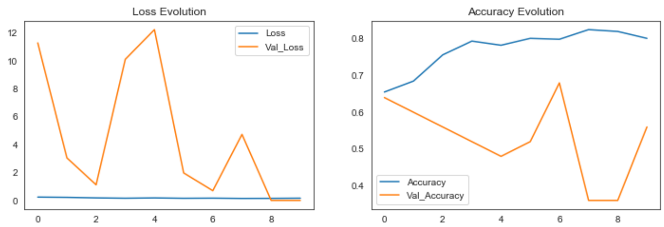

Fig-9: VGG-16 model

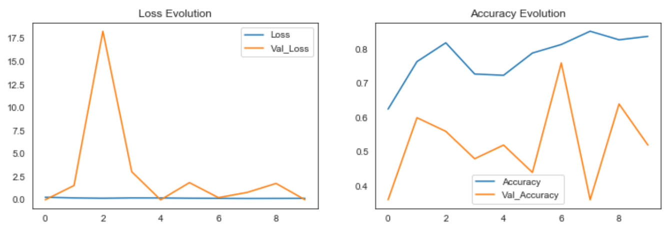

Fig-10: ResNet model

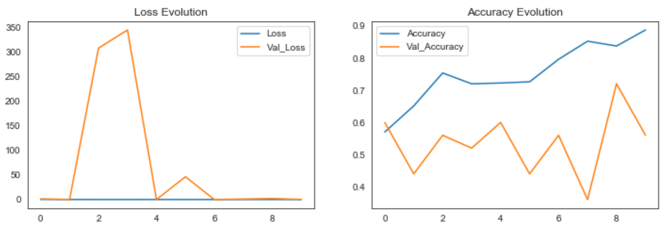

Fig-11: InceptionNet model

7. Comparisons of Different Models

In this section, we try to compare the different preprocessed models based on their performance such as accuracy and loss. Ultimately, the best model for pneumonia detection will depend on the specific characteristics of the dataset and the desired performance. It may be necessary to try several different models in order to find the one that works best. We are comparing the different models on testing and training accuracy. The accuracies came out to be as following:

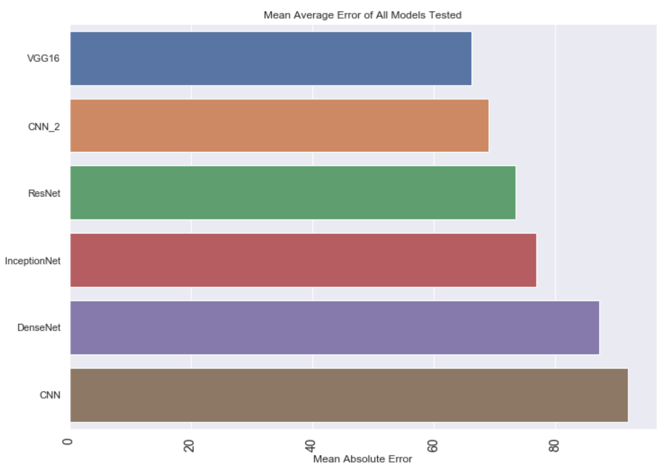

Fig-12: Mean Average Error of all models tested

CNN	91.98
CNN_2	68.91
DenseNet	87.18
VGG16	66.19
ResNet	73.40
InceptionNet	76.76

Fig-13: Accuracy of all models tested (in %)

8. Conclusions

We have proposed various models that detect pneumonia from chest x-ray images. We have made this model from scratch and all the models are purely based on transfer learning and CNN models. However, there are also some limitations to consider when using CNNs for pneumonia detection. One potential issue is the need for a large amount of annotated data to train the model, which can be time-consuming and expensive to collect. In the future, further research is needed to better understand the strengths and limitations of CNNs for pneumonia detection and to identify the most effective approaches for different types of datasets. This work can be extended for the classification and detection of the dataset of Dicom(.dcm) images. This would be our next approach to increase the accuracy using Dicom images.

9. Acknowledgement

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