Machine learning techniques in Pneumonia Detection

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Abstract: *Pneumonia is a symptom which has increased in these few years and since the Covid-19. Therefore, this research is an important topic that could solve problem for healthcare system, for some cases, Pneumonia is hard to see with human's eyes, so implementation deep learning in Pneumonia could help healthcare system to detect Pneumonia with the precise prediction. Moreover, in this research, many models have been training with Pneumonia, and VGG-16 is the best so far comparing to the other models. It works well with Pneumonia dataset that are obtained from Kaggle.*

Keywords: Pneumonia; Convolutional Neural Network; X-ray images; Transfer Learning;

1. INTRODUCTION

Pneumonia is an infection of both or one of the lungs caused by viruses, bacteria or fungi. It is a serious infection in which the air sacs fill with pus and other liquid. The purpose of this research is aimed to detect Pneumonia in X-ray images using deep learning. Pneumonia has rapidly increased throughout the years since the pandemic era. Therefore, the research is conducted to solve and enhance the detection of Pneumonia in the healthcare field and to deeply understand which model has the best performance on detecting Pneumonia.

2. METHODOLOGY

2.1 Data Source and Structure

The data set is captured from kaggle (Chest X-Ray Images (Pneumonia)) that were selected from Medical Center of GuangZhou and published in 2018-01-06. It contains 3 folders (train,test,val) with 5,863 X-Ray images (JPEG) and 2 categories (Pneumonia/Normal).
For train directory, it has 3875 images are pneumonia and 1341 images are normal. For testing, 234 images are normal and 390 images are pneumonia. For validation, it contains only 16 images.

2.2 Data Preproccesing

All images were processed with OpenCV to convert them to RGB, resized to 224×224 dimensions with 3 channels, and batched into groups of 100 using PyTorch DataLoader. Data augmentation techniques were applied to enhance diversity and improve model generalization.

```python
from torchvision import transforms
train_transforms = transforms.Compose([
    transforms.ToTensor(),
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.RandomRotation(degrees=30),
    transforms.Normalize([0.485, 0.456, 0.406],
                         [0.229, 0.224, 0.225])
])
val_N_tes_transforms = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                         [0.229, 0.224, 0.225])
])
```

For training data, PyTorch's torchvision.transforms were used to apply ToTensor() (scaling pixel values to [0,1] and reshaping images to [C, H, W]), horizontal flipping (50% probability), random rotation (±30°), and normalization with predefined means and standard deviations. Validation and testing sets were only scaled and normalized.

2.3 Model

For this project, I used three CNN architectural models: ZFNet, which was built from scratch, and ResNet and VGG-16, which were implemented using transfer learning.

2.3.1 ZFNET

ZFNet, designed by Zeiler and Fergus (2013), has five convolutional blocks and a fully connected block, outputting two classes from an input of 224×224×3. The first convolutional layer uses a 7×7 kernel, a stride of 2, ReLU activation, max-pooling, batch normalization, and 10% dropout, producing 96 output channels.

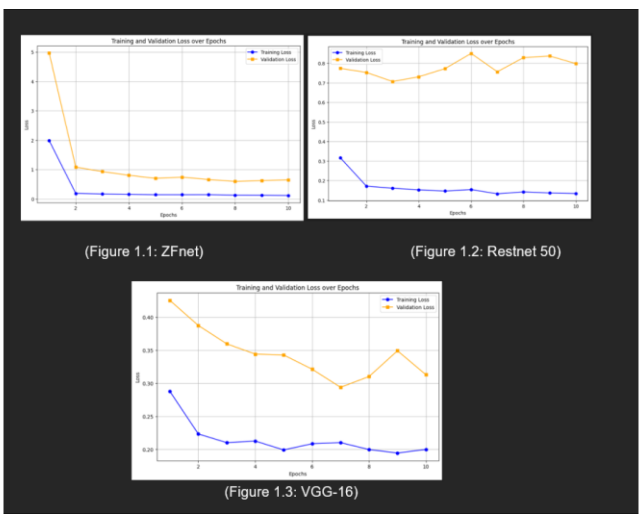
2.3.2 RestNet50

ResNet50 comprises convolutional layers, identity and convolutional blocks, and fully connected layers. Transfer learning loads pre-trained weights, modifying the fully connected block with two layers, ReLU activation, and a 2-class output.

2.3.3 VGG-16

This study uses VGG-16 with transfer learning, featuring 13 convolutional layers (3x3 kernels, stride 1, padding), max-pooling (2x2, stride 2), ReLU activation, and a fully connected block with 2 layers, ending with a softmax function.

3. RESULTS AND DISCUSSION



(Figure 1.1: ZFnet) (Figure 1.2: Restnet 50)

(Figure 1.3: VGG-16)

The plot shows that ZFNet performed well, with both training and validation losses consistently decreasing toward zero. The other two models also performed well on the training set but were less effective on the validation set, with loss values below 1 but not close to zero.

Table 1. Evaluation Matric

	Accuracy	Precision	Recall	F1-Score
ZFNET	86.21%	84.08%	96.15%	89.71%
RESTNET 50	82.25%	78.73%	98.71%	87.59%
VGG-16	88.3%	87.82%	94.35%	90.96%

VGG-16 are the best performance compared to the two models, with an accuracy of 88.3%, precision of 87.82%, recall of 94.35%, and F1-score of 90.96%. ZFNet followed closely with 86.21% accuracy, but its precision (84.08%) was lower, while its recall (96.15%) was high. ResNet50 had the lowest accuracy (82.25%) and precision (78.73%), but its recall (98.71%) was the highest among the three, resulting in an F1-score of 87.59%.

4. CONCLUSIONS

From the results, CNN architectural models perform well with X-ray image data (pneumonia), showing very high accuracy on recall, which indicates the model is almost perfect at identifying patients with pneumonia. However, there are several limitations that need improvement. Due to the dataset being imbalanced (74.29% of the samples are pneumonia cases), the model tends to be biased, often predicting pneumonia rather than normal cases. Additionally, the model's compilation process should be enhanced, as modern techniques like Early Stopping and Learning Rate Schedulers can significantly aid in training the model.

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Models Architecture and Details:
ZFNet:https://medium.com/@ibtedaazeem/a-brief-overview-of-zfnet-architecture-c56aa015d20f
Restnet50:
https://medium.com/@nitishkundu1993/exploring-resnet50-an-in-depth-look-at-the-model-architecture-and-code-implementation-d8d8fa67e46f
VGG-16:
https://medium.com/@mygreatlearning/everything-you-need-to-know-about-vgg16-7315defb5918
Dataset:
https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia