Pneumonia Detection from Chest X-Rays (CNN & ResNet)

Group Members

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a. Convolution Neural Network Model.
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INTRODUCTION

What is the central question your project seeks to answer?

Pneumonia is an infection that inflames the air sacs in one lung. The air sacs may fill with fluid or pus (purulent material), causing cough with phlegm or pus, fever, chills, and difficulty breathing. A variety of organisms, including bacteria, viruses, and fungi, can cause pneumonia. Chest X-ray, blood tests, and sputum culture may help confirm the diagnosis. The disease may be classified by where it was acquired, such as community or hospital-acquired. This project will culminate in a model that can predict the presence of pneumonia with human radiologist-level accuracy. We trained models to diagnose chest x-ray images if the patient has pneumonia or not.

Provide a brief motivation for your project question. Why is this question important? What can we learn from your project?

When it comes to pneumonia, chest X-rays are the best available method for diagnosis. More than 1 million adults are hospitalized with pneumonia, and around 50,000 die from the disease every year in the US alone. The high prevalence of pneumonia makes it a good candidate for the development of a deep learning application for two reasons:

- Data availability in a high enough quantity for training deep learning models for image classification
- Opportunity for clinical aid by providing higher accuracy image reads of a difficult-to-diagnose disease and reducing clinical burnout by performing automated reads of very common scans.

Briefly describe the data source(s) you have used in your project. Where is the data from? How big is the data in terms of data points and/or file size? If the data was not already available, how did you collect the data?

The dataset is gathered from Kaggle pneumonia chest x-rays. The dataset is organized into three folders (train, test, Val) and contains subfolders for each image category (Pneumonia/Normal). The data set is 2.5GB. Processed the images and resize them to the preferred size. 5216 training images, of which 3875 are of pneumonia and 1341 are normal images. 624 testing images, 390 are of pneumonia, and 234 are normal.

SUMMARY OF EDA

What is the unit of analysis?

The main objective of this model is to recognize the future images and give the prediction result of the patient x-rays if they have pneumonia or not so that the person can get treatment as soon as possible. Deep Learning models which are trained correctly by using suitable datasets can be helpful for doctors. The CNN can train the images of chest X-rays and then predict with high accuracy.

How many observations in total are in the dataset?

There are 5,863 X-Ray images (JPEG) and two categories (Pneumonia/Normal).

How many unique observations are in the dataset?

Pneumonia x-rays total 3875, normal x-rays are 1341 removing these two there are 2534 x-rays.

What time period is covered?

The time period covered in our dataset was for one year.

Briefly summarize any data cleaning steps you have performed:

Processed the images and resize them to the preferred size. 5216 training images, of which 3875 are of pneumonia and 1341 are normal images. 624 testing images, 390 are of pneumonia, and 234 are normal.

Visualization technique:

Matplotlib.pyplot and seaborn will be used to produce plots for visualization. Libraries: Keras, TensorFlow. NumPy and pandas are used to manipulate data.

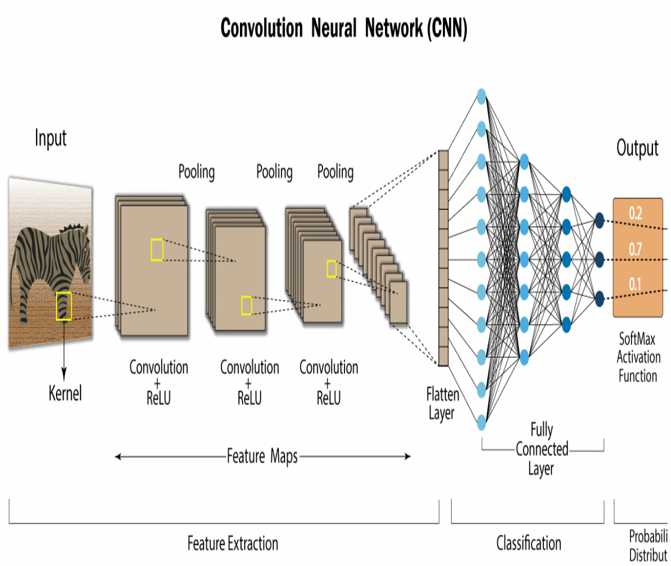
Key Predictors:

Histograms are preferred to determine the underlying probability distribution of data. On the other hand, Box plots are more useful when comparing several data sets. They are less detailed than histograms and take up less space. Scattered boxplots may be a powerful tool for expressing results in a way that is both visually appealing and useful to the audience. Boxplots depict the distribution of results by displaying the median value, interquartile range, and other skewness and symmetry-related characteristics.

Summary of Machine Learning Models

Justify your model choices based on how your response is measured and any observations you have made in your EDA.

The first model we will train on is a simple CNN (Convolution Neural Network). CNN can be the best model because of its extensive data handling and automatically detecting of significant features without human supervision. Fine-tuning can be performed by freezing your chosen pre-built network and adding several new layers to the end to train, or by doing this in combination with selectively freezing and training some layers of the pre-trained network. You may choose or need to do preprocessing before feeding images into your grid for training and validating. This may conform to your model's architecture and augment your training dataset to increase your model performance. When performing image augmentation, consider augmentation parameters that reflect real-world differences that may be seen in chest X-rays.



After the model is constructed, we compile the neural net using a categorical cross-entropy loss function and Adam optimizer. So, this loss function is used since it's just the one commonly used in the multiclass classification task. Meanwhile, I choose Adam as the optimizer since it's just the best to minimize loss value in most neural network tasks.

ResNet:

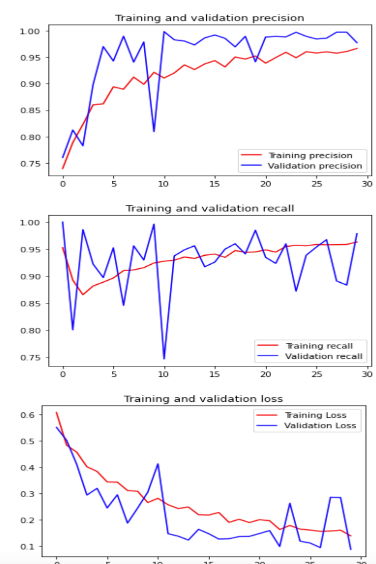
ResNet is a new neural architecture for reducing the complexity and solving the degradation while maintaining good performance. To reduce complexity, fewer parameters need to be trained and spend less time on training.

Report the results from at least two different models

Model 1:

Convolution Neural Network:

CNN can be the best model because of its extensive data handling and automatically detecting of significant features without human supervision. As this is the case of medical diagnosis, accuracy cannot be the only metric to evaluate. It is essential to predict the actual values correctly in medical diagnosis. We cannot incorrectly diagnose a patient as a regular event after the accurate diagnosis report shows that patient has pneumonia. So along with higher accuracy, we need higher recall.



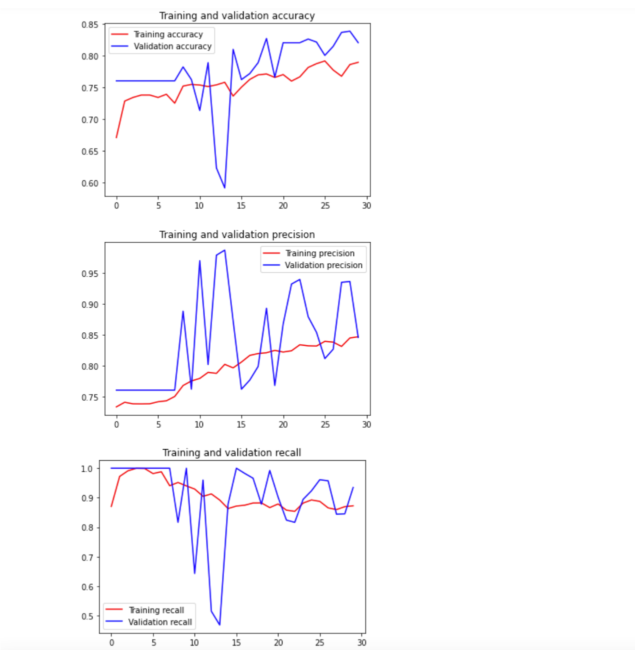
```
loss  : 0.5112326741218567
accuracy  : 0.8766025900840759
Precision : 0.8380129337310791
Recall : 0.9948717951774597
```

We can say that the model's performance keeps improving, even though both the testing accuracy and loss value fluctuate within these 30 epochs. We can see here that accuracy on train and test data is 79% and 80%, respectively, at the final iteration.

Model 2:

ResNet:

ResNet model in Keras takes in the input of exactly three input channels, but our input image is of grayscale. So, to avoid a mismatch of shape, we'll let our Image data generator use the default color_mode, i.e., RGB, instead of specifying it to be grayscale.




```
loss  : 0.5058506727218628
accuracy  : 0.7467948794364929
Precision : 0.727450966835022
Recall : 0.9512820243835449
```

Briefly discuss which model fits the data better?

Model 1 performed best with accuracy=0.8766 and recall=0.9949 on the test set, so we'll save this model from being the best to give out the results.

Based on the estimated test error rate, discuss how well the model fits the data:

As this is the case of medical diagnosis, accuracy cannot be the only metric to evaluate. In medical diagnosis, it is essential to predict the actual values correctly. We cannot incorrectly diagnose a patient as a regular event after the accurate diagnosis report shows that patient has pneumonia. So along with higher accuracy, we need higher recall. Compared to our model 1, it gives only 74% accuracy on test and train data.

Summary and Conclusion

Going back to the question that has motivated your project, how would you answer that question given the results of your analysis?

Pneumonia is responsible for a large percentage of patient morbidity and mortality. Pneumonia must be diagnosed and treated as soon as possible to avoid serious complications, including death. Chest X-rays are the most common imaging examination technique used in practice, with over 2 billion operations each year. They are crucial for screening, diagnosing, and treating several disorders, including pneumonia. We devise a method for detecting pneumonia in frontal-view chest X-ray pictures. We expect this technology to improve healthcare delivery by automating at the expert level and extending access to medical imaging expertise in areas where qualified radiologists are scarce. Adding new layers to our model can improve it, but this will introduce even more hyperparameters that need to be modified. We plan to use deep learning and computer vision techniques to extend our model architecture to additional areas of medical imaging. The models suggested in this study, which use CNN and Transfers learning techniques to detect pneumonia on frontal chest x-ray pictures, exhibit remarkable results. Several studies on the same dataset have recently been published. On the other hand, our models have exceeded earlier research results to achieve state-of-the-art status. Models for efficiently extracting information from an x-ray image and predicting the presence or absence of pneumonia were developed using neural networks.

Think about domain experts in the field you have analyzed. What can they learn from your project? How could the results of your analysis inform their work?

This can help them better analyze the other models, VGG16 and DenseNet, and InceptionNet.

Identify one way that your project could be improved if you had more time and resources to work on this project. For example, what additional data would you gather? What alternative data cleaning decisions would you make? What additional models would you estimate?

Suppose we would have extra time to finish up more additional work. In that case, we will finish other models like VGG16, InceptionNet, and DenseNet for better accuracy and precision details in pneumonia detection.