**Pneumonia Detection**

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Introduction

This study focuses on the use of convolutional neural networks (CNN) and a comparison of pre-trained models in the creation of a powerful tool for the identification of pneumonia. Utilizing artificial intelligence technology developments, this study uses lung image data as its main input to detect cases of pneumonia with high accuracy. Such models can improve the speed and efficacy of doctors' diagnosis, boosting prompt treatment and possibly saving lives as AI technology becomes more mobile-friendly. This model's therapeutic relevance may be increased if it could accurately identify additional disorders like cancer, tumors, and bone fractures.

The project mainly enables us to implement some of the well-known models like VGG19, RESNET 152,200 as well as asks us to explore on how to build CNN models as well as how to adjust the hyper parameters to get more accuracy. This project was a dive into the current as well as past works of AI and ML that are being developed to detect Pneumonia.

Past Work

In recent years, significant work has been done in applying Convolutional Neural Networks (CNNs) to the field of medical imaging, particularly in disease detection. Here's a brief overview of some of the previous work relevant to this project:

1. **Pneumonia Detection Using CNN**: Several studies have demonstrated the efficacy of using CNNs for Pneumonia detection. For instance, a 2019 paper titled " Pneumonia detection based on deep neural network Retinanet" showed promising results by leveraging a CNN model.
2. **Pre-trained Models in Medical Imaging**: The use of pre-trained models, such as VGG16, VGG19, and ResNet, has been shown to be quite effective in medical imaging. In 2020, a paper titled " A novel transfer learning-based approach for pneumonia detection in chest X-ray images " demonstrated the successful application of transfer learning in detecting pneumonia.
3. **Leveraging Explainable AI (XAI) in Health**: The medical field has started to leverage XAI to understand AI decision-making, which is critical in health applications where interpretations are vital.

Architecture

## Data Collection

## We used the “Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images

## for Classification” created by University of California San Diego. The dataset consists of 5863 images that are each classified that accurately describe the image.

## Data Preprocessing

Clean and preprocess the dataset to remove noise, distortions, and other artifacts that may hinder the training process. The dataset was then split into 3 folders, separating them for training, testing and validation.

## Model Training

Here, as we said, we were going to compare some pre-trained models with our custom, self-made CNN model. The list of pre-trained models comprises of VGG 19, RESNET 50,152 and we also used ResNet 200, whose weights are not yet available, but we tweaked it a little and used it for our study. The CNN model that we built, comprises of layers, that are Conv2D layer, batch Normalization, Maxpooling, Flatten, Dense and Dropout. The reason we used these layers are:

1. Conv2D layers: These layers perform 2D convolutions over the input image, which can be thought of as a sliding window that moves across the image and performs element-wise matrix multiplication.
2. BatchNormalization layers: These layers normalize the activations of the previous layer at each batch. They maintain the mean activation close to 0 and the activation standard deviation close to 1. They are used here after each Conv2D layer.
3. MaxPooling2D layers: These layers down-sample the input representation by taking the maximum value over the window defined by pool size for each dimension along the features axis. The window is shifted by strides in each dimension.
4. Flatten layer: This layer is used to convert the 2D spatial features into a 1D vector. This is necessary for passing the output to fully connected Dense layers.
5. Dropout layer: This layer randomly sets a fraction (in this case, 50%) of input units to 0 at each update during training time, which helps prevent overfitting.
6. Dense layers: These are the fully connected layers where all neurons in a layer are connected to those in the next layer. In this model, there are two Dense layers.

## Model Testing

Evaluate the performance of the trained models on a test dataset to see if it accurately predicts Pneumonia or not. Here the training set is used for model training and the testing set is used for model evaluation. We evaluate the model performance using various metrics, including accuracy, precision, recall, and F1 score. The results of the evaluation help us understand about the efficiency and accuracy of the models.

A picture containing text

Description automatically generatedSurface chart

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Goals

The main objective of this project was to use convolutional neural networks (CNNs) and pre-trained models to create a high-performance, precise model for the detection of pneumonia. The study aimed to assist in the quick and accurate diagnosis of pneumonia by using lung scans as inputs, hence aiding immediate treatment.

The following were the main goals for this project:

1. Analyzing how well existing models, such VGG19, perform in detecting pneumonia.

2. Creating a CNN model that tries to achieve accuracies as good as these trained models.

3. Using a dataset of labelled chest X-ray pictures to implement and evaluate the developed model.

4. Making use of important parameters to evaluate the model's performance such as the F1 score and boost accuracy.

Discussion

In our endeavor to create an accurate Pneumonia detection model using Convolutional Neural Networks (CNN), we found that our custom CNN model did not outperform pre-existing models, namely VGG19, RESNET 152, and RESNET 200. These models demonstrated strong capabilities in image classification tasks, likely due to training on vast, diverse datasets. Our model's relative underperformance may be attributed to its complexity, the diversity of our training dataset, or the nature of the features learned. We also faced challenges with data imbalance during preprocessing, which could have affected our model's performance. Despite these hurdles, this project provided invaluable insights into the complexities of applying CNNs to medical imaging analysis. Moving forward, we aim to refine our custom model and explore strategies to better leverage the strengths of pre-existing models. Despite the current limitations, the potential of AI in enhancing healthcare solutions remains promising. Such models can improve the speed and efficacy of doctors' diagnosis, boosting prompt treatment and possibly saving lives as AI technology becomes more mobile-friendly. This model's therapeutic relevance may be increased if it could accurately identify additional disorders like cancer, tumors, and bone fractures.

Conclusion

Our project on developing a Convolutional Neural Networks (CNN) model for Pneumonia detection highlighted the potential and challenges of applying AI in medical diagnostics. Despite our efforts, the performance of our custom model did not exceed the accuracy of pre-existing models like VGG19, RESNET 152, and RESNET 200, underscoring the value of these comprehensive, pre-trained models in complex tasks like medical image classification. Data imbalance during preprocessing and possible shortcomings in our model's design and learning capabilities could have contributed to the observed performance gap.

**Future Works**

The findings from this project have set the stage for further exploration and improvements. We plan to refine our custom CNN model, enhancing its robustness and learning capabilities, potentially through deeper architectures or advanced training techniques. Additionally, we will explore strategies for a more effective fusion of our model with pre-existing ones, potentially via ensemble methods or transfer learning.

The project also underscored the importance of the dataset in model performance. Future work will focus on the acquisition of more diverse and balanced datasets, which may necessitate the use of advanced data augmentation techniques. Further, we intend to make our model more adaptable to variations in data quality, which is a crucial factor in real-world scenarios.

Finally, given a high degree of accuracy, we aim to expand the model's capabilities to detect other diseases, increasing its clinical applicability. This project has reinforced the significance of AI in healthcare, presenting a promising, albeit challenging, avenue for improving diagnostics and patient outcomes.

Results

Figure 1:

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*VGG 19 Result, we can see that we got an accuracy of 92%*

Figure 2:

A screenshot of a computer

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*ResNet 152, As we see, the model was only able to give 87% accuracy, this is because of the model complexity and the insufficient/ less data provided to the model.*

*Figure 3:*

A screenshot of a computer

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*ResNet 200, As we see, the model was only able to give 83% accuracy, this is because due to same reason as ResNet 152*

*Figure 4:*

Text

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*CNN model made by us, which was able to achieve 61% accuracy.*

Based on these results, we were able to conclude that the pre-trained models have a higher accuracy and the reason for such less accuracy for the CNN model was due to the dataset imbalance and the less big size of dataset that was used.

**References**

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