BMS COLLEGE OF ENGINEERING, BANGALORE – 560 019

(Autonomous institute, Affiliated to VTU)

Department of Information Science and Engineering

Deep Learning - 20IS6PEDLG

Pneumonia Detection Using Deep Learning

2022 – 2023 (EVEN SEMESTER)

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CERTIFICATE

Certified that A Sai Kalyan, H Srujan Kumar, Hemanth Pai, Hrishikesh Prahalad bearing USN 1BM20IS001, 1BM20IS043, 1BM20IS049 and 1BM20IS051 of Sixth Semester belonging to the Department of Information Science and Engineering had successfully completed AAT as a part of the course Deep Learning [20IS6PEDLG].

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CONTENTS

Course: Deep Learning **Course code: 20IS6PEDLG**

ABSTRACT

Pneumonia detection is crucial for timely treatment and improved patient outcomes. This project aims to develop a deep learning model using chest X-ray images. The model utilizes convolutional neural networks and transfer learning to distinguish between healthy and pneumonia-infected lungs. Through extensive experiments and performance evaluations, the model's effectiveness will be compared to existing methods. The successful implementation of this automated detection system can enhance healthcare delivery and aid in the prompt diagnosis of pneumonia.

By leveraging the power of deep learning and advanced optimization algorithms, this project contributes to the field of medical imaging. The proposed model has the potential to expedite the diagnosis process, improve efficiency, and reduce the burden on radiologists. Overall, this project aims to advance pneumonia detection through deep learning techniques, ultimately leading to improved patient care and outcomes.

INTRODUCTION

Pneumonia is a prevalent and potentially life-threatening respiratory infection that affects individuals of all ages, particularly the elderly, young children, and individuals with weakened immune systems. Timely and accurate detection of pneumonia is critical for initiating appropriate treatment strategies, preventing complications, and reducing mortality rates. Traditionally, pneumonia diagnosis has heavily relied on the expertise of radiologists who interpret chest X-ray images to identify characteristic signs of infection. However, the subjective nature of visual interpretation and the increasing demand for efficient healthcare services necessitate the development of automated and reliable pneumonia detection systems.

In recent years, deep learning techniques have revolutionized medical image analysis by demonstrating remarkable capabilities in various diagnostic tasks. Deep learning models, particularly convolutional neural networks (CNNs), excel at learning complex patterns and features directly from raw data. Leveraging their ability to extract high-level representations, deep learning models have shown promising results in detecting various diseases from medical images. Consequently, applying deep learning algorithms to chest X-ray images presents an opportunity to advance pneumonia detection, improving accuracy, efficiency, and accessibility.

In this project, we aim to develop an advanced deep learning model for pneumonia detection using chest X-ray images. By harnessing the power of CNNs, our model will automatically learn discriminative features and patterns indicative of pneumonia infection. We will assemble a comprehensive dataset of labeled chest X-ray images, consisting of both pneumonia-positive and pneumonia-negative cases, to train and evaluate our model. Additionally, to overcome the challenges of limited labeled data, we will employ transfer learning techniques, leveraging pre-trained models on large-scale image datasets to enhance the generalization capability of our model.

The successful development of an accurate and efficient deep learning-based pneumonia detection system can have significant implications for clinical practice. It can facilitate early diagnosis, enable prompt initiation of appropriate treatment, and potentially reduce the workload of radiologists. Moreover, such automated systems can play a crucial role in resource-limited settings, where access to specialized medical expertise may be limited. Ultimately, this project aims to leverage the power of deep learning algorithms to advance pneumonia detection and improve patient care outcomes.

PROBLEM STATEMENT

Pneumonia Detection Using Deep Learning

LITERATURE SURVEY

[1] In this paper, Pneumonia detection using Deep Learning based on convolutional neural networks,Artificial intelligence was recognized as an academic discipline as early as in the 1950s. It was not widely explored by the scientific community due to its limited practical feasibility for a long time. In the following years AI started to develop rapidly, which resulted in development of new fields such as Machine Learning and Deep Learning. This paper describes the use of deep learning in order to classify digital images of chest X-rays according to presence or absence of changes consistent with pneumonia. The implementation was based on the CNN model using Python programming and scientific tools.Even though the model accuracy is relatively high, nearly 90%, there is a possibility of overfitting due to the size of the dataset.This paper describes the use of deep learning in order to classify digital images of chest X-rays according to presence or absence of changes consistent with pneumonia.

The implementation was based on the CNN model using Python programming and scientific tools. Even though the model accuracy is relatively high, nearly 90%, there is a possibility of overfitting due to the size of the dataset. The 90% accuracy means that the prediction model could potentially be used as a decision support tool, but there is still much work to be done. The proper diagnosis of any kind of disease still requires the involvement and presence of medical specialists. In order to build a good and reliable disease classification model, it is very important to gather as much data as possible. The research paper utilized a dataset provided by the Guangzhou Women and Children's Medical Center in Guangzhou, which is openly available on Kaggle . Before conducting the analysis, poor-quality X-ray images were removed from the dataset. The remaining images were then classified by three experts in the field of radiology .

The dataset consists of 5856 chest X-ray images in JPEG format. It is organized into three folders: train, val, and test, which serve as training, validation, and testing data, respectively. Initially, the validation folder contained only 16 images. However, for this research, an 80/10/10 split was performed, resulting in 80% of the images used as training data, 10% as validation data, and 10% as test data. Consequently, the train folder contains 4684 images, while both the val and test folders contain 586 images each. Each of these folders is further divided into two subfolders, one for pneumonia-labeled images and the other for normal-labeled images. The subfolder names correspond to the data labels.

Although the images in the dataset are of high quality and have varying sizes, they were resized before training the model. Due to a higher number of X-ray images labeled as "Pneumonia" in the training dataset, data augmentation techniques were employed to increase the number of training examples for "Normal" images. Figure 1 in the research paper displays a few examples of X-ray images along with their respective labels.

[2] In this paper, Transfer Learning with Deep Convolutional Neural Network (CNN) for Pneumonia Detection Using Chest X-ray

Pneumonia is considered the greatest cause of child fatalities all over the world. This study presents a deep-Convolutional Neural Network-based transfer learning approach for the automatic detection of pneumonia and its classes. DenseNet201 exhibits an excellent performance in classifying pneumonia. Approximately 1.4 million children die of pneumonia every year, which is 18% of the total children who died at less than five years old. Pneumonia is a lung infection, which can be caused by either bacteria or viruses. This bacterial or viral infectious disease can be well treated by antibiotics and antiviral drugs. CNNs have been popular due to their improved performance in image.Aspects of the researchers' findings potentially support prior work in this topic: "CXNet-m1 showed sensitivity, precision, and accuracy of 99.6%, 93.28%, and 96.39%, respectively. Vikash et al compared the results in the paper with the results of recently published works," Rahman argued.They recommend that denseNet201 exhibits the highest accuracy of all recent studies to the best of the knowledge. Training the network using a larger database and working on an ensemble of the pre-trained CNN algorithms might increase the detection accuracy.

In the data preprocessing step of the study, an important aspect was resizing the X-ray images to match the input requirements of different algorithms. For AlexNet and SqueezeNet, the images were resized to 227 × 227 pixels, while for ResNet18 and DenseNet201, the images were resized to 224 × 224 pixels. Additionally, all the images were normalized according to the standards of the pre-trained models.

Data augmentation techniques were employed to enhance the performance of the deep learning models, considering the relatively small size of the dataset. The authors utilized three augmentation strategies to generate new training sets. These strategies included rotation, scaling, and translation.

Rotation involves rotating the image clockwise by an angle between 0 to 360 degrees. In this study, a rotation of 315 degrees (counter clockwise 45 degrees) was utilized. Scaling refers to magnifying or reducing the frame size of the image. A 10% magnification of the image was performed.

Image translation can be done horizontally (width shift), vertically (height shift), or in both directions. In this study, the original image was horizontally translated by 10% and vertically translated by 10%. These data augmentation techniques help increase the effective size of the dataset and can improve the classification accuracy of deep learning algorithms. It can be noted that, for three classification schemes, DenseNet201 is producing the highest accuracy for both training and testing. For normal and pneumonia classification, the test accuracy was 98%, while, for normal, bacterial, and viral pneumonia classification, DenseNet201 is producing the highest accuracy for both training and testing. For normal and pneumonia classification, the test accuracy was 98%, while, for normal, bacterial, and viral pneumonia classification, it was 93.3%, and, for bacterial and viral pneumonia classification, it was and, for 95% .Bacterial viral pneumonia classification, it was found to be 95%.

This study presents a deep-CNN-based transfer learning approach for the automatic detection of pneumonia and its classes.Four different popular CNN-based deep learning algorithms were trained and tested for classifying normal and pneumonia patients using chest x-ray images.DenseNet201 exhibits an excellent performance in classifying pneumonia by effectively training itself from a comparatively lower collection of complex data, such as images, with reduced bias and higher generalization.

We believe that this computer-aided diagnostic tool can significantly help the radiologist to take more clinically useful images and to identify pneumonia with its type immediately after acquisition.

[3] The paper Pneumonia Detection Using CNN based Feature Extraction discusses the development of an automatic system for detecting pneumonia using deep learning algorithms. Pneumonia is a life-threatening infectious disease that affects the lungs and is a major cause of death in India. Currently, diagnosing pneumonia requires expert radiologists to evaluate chest X-rays. However, this can cause delays in treatment, especially in remote areas. Therefore, developing an automatic system for detecting pneumonia would be beneficial, particularly in remote areas where access to expert radiologists is limited.

The researchers evaluated the use of pre-trained Convolutional Neural Network (CNN) models as feature extractors for classifying abnormal and normal chest X-rays. They compared different pre-trained CNN models, such as ResNet, DenseNet, VGGNet, and Xception, followed by different classifiers, including Support Vector Machines (SVM), Random Forest, Naive Bayes, and K-nearest neighbors. The results showed that ResNet-50 performed the best when combined with SVM, achieving an Area Under the Curve (AUC) score of 0.7749.

Additionally, the researchers found that DenseNet-169 and DenseNet-121 also achieved good results, with AUC scores of approximately 0.75. They further improved the performance by tuning the hyperparameters of the SVM classifier. The optimal model for pneumonia detection was found to be DenseNet-169 combined with SVM, achieving an AUC score of 0.8002. The proposed model has the potential to improve the early detection of pneumonia and provide better healthcare services, particularly in remote areas where access to expert radiologists is limited. The study contributes to the field of medical image classification by demonstrating the effectiveness of pre-trained CNN models and supervised classifiers for detecting pneumonia in chest X-rays.

It is important to note that the model has some limitations, such as not considering the patient's history and using only frontal chest X-rays. However, the results of the study show promise for developing improved algorithms for pneumonia detection in the future.

[4]

This paper, Automated Methods for Detection and Classification Pneumonia based on X-Ray Images Using Deep Learning presents a comparison of various Deep Convolutional Neural Network (DCNN) architectures for the automatic binary classification of pneumonia images, specifically focusing on SARS, COVID-19, and similar diseases. The goal is to aid in the diagnosis and containment of these diseases by rapidly processing X-ray and CT images using deep learning and image processing techniques.

The researchers evaluated several DCNN architectures, including VGG16, VGG19, DenseNet201, Inception_ResNet_V2, Inception_V3, ResNet50, MobileNet_V2, and Xception. The evaluation was performed using a dataset consisting of 5856 chest X-ray and CT images, with 4273 images showing pneumonia and 1583 images labeled as normal.

The results indicate that the fine-tuned versions of ResNet50, MobileNet_V2, and Inception_ResNet_V2 achieved highly satisfactory performance. These architectures demonstrated a significant increase in training and validation accuracy, exceeding 96% accuracy. On the other hand, CNN, Xception, VGG16, VGG19, Inception_V3, and DenseNet201 displayed lower performance, with accuracy levels below 84%.

The introduction highlights the potential of deep learning (DL) methods in image processing and computer vision, particularly in the field of medical imaging. DL techniques have shown success in various medical imaging applications such as skin cancer detection, breast cancer detection, lung cancer detection, etc. However, one challenge is the lack of available medical imaging datasets for training these models.

To address the limited dataset availability, the proposed work aims to fine-tune the top layer of several DL architectures, including CNN, VGG16, VGG19, DenseNet201, Inception_ResNet_V2, Inception_V3, Xception, Resnet50, and MobileNet_V2. The performances of these architectures will be compared to determine their effectiveness.

The baseline CNN architecture for the experiment is described, consisting of an input layer for X-ray images with dimensions of 244x244. It includes three convolutional layers with a filter size of 3x3 and zero padding, followed by max pooling layers with a 2x2 size and stride of 2. ReLU layers are used for each convolutional layer, and there is one inner-product layer. The model ends with a fully connected output layer using sigmoid activation.

The selected DL architectures (VGG16, VGG19, Inception_V3, DenseNet201, Xception, Resnet50, Inception_ResnetV_2, and MobileNet_V2) have been extensively investigated for pneumonia diagnosis since 2016. These architectures have shown high accuracy and promising results in previous studies, justifying their inclusion in the comparison.

Overall, the paper aims to evaluate the performance of these DL architectures for pneumonia diagnosis, taking into account the limited availability of medical imaging datasets.

The present work introduces a publicly available dataset called the chest X-Ray & CT dataset, which includes 5856 images in JPEG format. The dataset consists of two categories: 4273 images representing pneumonia cases and 1583 images representing normal cases. The paper provides a link to access this dataset.

The data pre-processing stage involves enhancing the quality of the input images using different techniques. Intensity normalization and Contrast Limited Adaptive Histogram Equalization (CLAHE) are applied in this study. Intensity normalization, achieved through min-max normalization (Equation 1), ensures that the input images follow a standard normal distribution. Additionally, CLAHE is used to improve image contrast. Figure 5 provides an example of the application of these techniques.

To perform the binary classification task, the dataset is split into training and validation sets. In this experiment, 60% of the images are used for training, while 40% are used for validation. To address the issue of class imbalance, as 75% of the images represent the pneumonia class, data augmentation is employed. Each original image is used to generate two new images with different augmentation techniques. As a result, the number of images in the normal class is doubled to balance the dataset.

After the data pre-processing, splitting, and data augmentation steps, the training dataset is ready for the feature extraction process using the proposed models. The features extracted from each model are flattened and combined to create a vectorized feature map. This feature vector is then passed to a multilayer perceptron for classification, which assigns each image to its corresponding class. The performance of the method is evaluated on test images using the trained model. The experiments are repeated three times, and the average results are reported.

The experimental setup includes the following parameters: the images in the dataset are resized to 224x224 pixels, except for the Inception_V3 model which uses a size of 299x299 pixels. The batch size is set to 32, and the number of epochs is set to 300. The training and validation samples consist of 159 and 109 images, respectively. The Adam optimizer with $\beta1=0.9$ and $\beta2=0.999$ is used, with a learning rate initially set to 0.00001 and decreased to 0.000001. Weight decay is applied to reduce overfitting, using L2 regularization provided by Keras. The implementation is done on a computer with an Intel Core i7-7700 CPU @ 3.60 GHz, 8 GB RAM, running on Windows 10 Professional (64-bit). The simulation is performed in Python 3, using Keras/TensorFlow as the deep learning backend. The training and validation steps utilize an NVIDIA Tesla P40 with 24 GB RAM.

The evaluation criteria for classification include accuracy, sensitivity, specificity, precision, and F1 score. These metrics are used to assess the performance of the classification task. In the case of balanced data, the metrics are defined as follows:

- Accuracy: (TP+TN)/(TP+TN+FP+FN)
- Sensitivity: TP/(TP+FN)
- Specificity: TN/(TN+FP)
- Precision: TP/(TP+FP)
- F1 Score: 2 * (Precision * Sensitivity) / (Precision + Sensitivity)

Here, TP represents True Positive, FP represents False Positive, TN represents True Negative, and FN represents False Negative.

In this study, we proposed automated methods for classifying chest X-rays into pneumonia and normal classes using nine different Deep Learning architectures. The main objective was to determine if any of these techniques outperformed the others. We conducted experiments using the chest X-Ray & CT dataset, which consists of 5856 images, with 4273 pneumonia cases and 1583 normal cases. The performance of the models was evaluated using various metrics.

The results demonstrated that the Resnet50, MobileNet_V2, and Inception_Resnet_V2 architectures achieved high performance, with an accuracy of over 96%. On the other hand, the remaining architectures mentioned in the study achieved lower accuracy, around 84%.

Future work aims to develop a comprehensive system for pneumonia detection, segmentation, and classification using deep learning techniques. Additionally, performance can be further improved by incorporating more datasets and employing advanced feature extraction techniques based on deep learning, such as You-Only-Look-Once (YOLO) and U-Net, which have been specifically designed for biomedical image segmentation.

[5]

In this paper Deep Learning for Automatic Pneumonia Detection, Deep Learning for Automatic Pneumonia Detection, Tatiana Gabruseva identified Pneumonia is a significant cause of mortality globally, particularly among young children. Traditionally, the detection of pneumonia involves examining chest X-ray radiographs by highly-trained specialists. However, this process can be time-consuming and prone to disagreements among radiologists. Computer-aided diagnosis systems have shown promise in improving diagnostic accuracy.

In this work, we have developed a computational approach for detecting pneumonia regions in chest X-rays. Our approach utilizes single-shot detectors, squeeze-and-extinction deep convolutional neural networks, augmentations, and multi-task learning techniques. We applied and evaluated our approach in the context of the Radiological Society of North

America Pneumonia Detection Challenge, where we achieved one of the best results among the participants.

By leveraging advanced deep learning techniques and incorporating multi-task learning, our approach aims to enhance the accuracy and efficiency of pneumonia detection in chest X-rays. The results obtained in the challenge highlight the effectiveness of our proposed method in identifying pneumonia regions, thereby demonstrating its potential for improving pneumonia diagnosis and ultimately reducing mortality rates associated with this condition. For the challenge, the US National Institutes of Health Clinical Center provided a labeled dataset of chest X-ray images and patients' metadata. The database consists of frontal-view X-ray images from 26,684 unique patients. Each image is assigned one of three different classes based on the associated radiological reports: "Normal," "No Lung Opacity / Not Normal," and "Lung Opacity."

In a healthy individual, the lungs are filled with air. However, in cases of pneumonia, the air in the lungs is replaced by other substances such as fluids, bacteria, and immune system cells. Lung opacities refer to areas in the X-ray images that appear more opaque than they should, indicating possible unhealthy lung tissue.

The "Normal" class includes data from patients who are deemed healthy without any identified pathologies, including pneumonia, pneumothorax, atelectasis, and others. The "Lung Opacity" class contains images showing fuzzy clouds of white in the lungs, which are associated with pneumonia. Regions of lung opacities are labeled with bounding boxes. It's worth noting that lung opacities can be related to pneumonia or other conditions. The "No Lung Opacity / Not Normal" class represents patients with visible lung opacity regions on the X-ray images but without a diagnosis of pneumonia.

The dataset provided in this challenge allows researchers to develop computational methods and algorithms for pneumonia detection based on the labeled X-ray images and associated metadata, fostering advancements in computer-aided diagnosis systems for pneumonia detection.

In this work, the training dataset consisted of data from 25,684 patients, while the test set contained data from 1,000 patients. To build the models, a variety of base models pre-trained on the ImageNet dataset were utilized. It was observed that models without pre-training on ImageNet performed well on the classification task but performed worse on the regression task.

For all training experiments, the following hyperparameters were used, as outlined in Table 2:

1. The training dataset was reasonably balanced, as indicated in Table 1, so no additional balancing techniques were necessary.

2. A learning rate scheduler was employed using the ReduceLROnPlateau function available in PyTorch. The patience parameter was set to 4, and the learning rate was decreased by a factor of 0.2.

3. The losses for whole image classification, individual boxes classification, and anchors regression were combined using weights and used as the total loss during training.

In this paper, the authors present a straightforward yet effective algorithm for localizing lung opacity regions. Their model is based on the RetinaNet single-shot detector, with Se-ResNext101 encoders that were pre-trained on the ImageNet dataset. To enhance the model's accuracy, several improvements were implemented.

Firstly, a global classification output was added to the model. Additionally, heavy augmentations were applied to the data during training. The ensemble of four folds and multiple checkpoints were utilized to improve the model's generalization capabilities. Ablation studies were conducted to demonstrate the effectiveness of these proposed approaches in enhancing the model's accuracy.

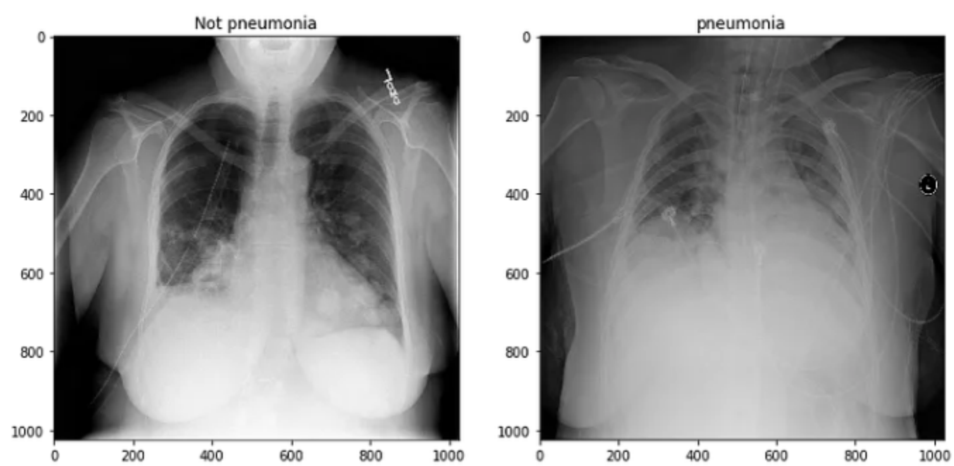
Importantly, the method intentionally does not involve test-time augmentation, providing a good balance between accuracy and resource requirements. The reported results indicate that the proposed method achieved one of the best performances in the challenge.

DATASET DETAILS

The dataset we considered was from Pneumonia Dataset. It consists of 5863 samples with 90000 columns(300*300) each indicating pixel values and two categories(Pneumonia/Normal). The images obtained from each row are of dimension (300,300,3).

Chest X-ray images (anterior-posterior) were selected from retrospective cohorts of pediatric patients of one to five years old from Guangzhou Women and Children's Medical Center, Guangzhou. All chest X-ray imaging was performed as part of patients' routine clinical care.For the analysis of chest x-ray images, all chest radiographs were initially screened for quality control by removing all low quality or unreadable scans. The diagnoses for the images were then graded by two expert physicians before being cleared for training the AI system. In order to account for any grading errors, the evaluation set was also checked by a third expert.

Sample image:



Dataset size:

- Training data: 5216 samples.
- Validation data :16 samples.
- Testing data: 626 samples

IMPLEMENTATION DETAILS

Model 1– Convolutional neural network

In our implementation we've built a convolutional neural network to detect pneumonia. The model architecture is as follows:

Conv2D : convolutes the 2-D image by reducing the number of features using a specified filter.

Filter: are pre-chosen m*n(Here 3*3) matrices that scan the incoming image matrix and via matrix multiplication produce some results which give ideas about various image features

Stride: is how far the filter moves in every step along one direction.(Here 1)

Padding: refers to the amount of pixels added to an image when it is being processed which allows more accurate analysis.(Here we've used 'SAME' padding which adds zeros to borders)

We've also used **BatchNormalization** and **Dropout** layers to avoid overfitting.

Model 2- AlexNet Architecture

In our implementation we used AlexNet architecture convolutional layers .

Conv2D : convolutes the 2-D image by reducing the number of features using a specified filter.

Filter: are pre-chosen m*n(Here 3*3 along with 11*11) matrices that scan the incoming image matrix and via matrix multiplication produce some results which give ideas about various image features

Stride: is how far the filter moves in every step along one direction.(Here 1) with size of 1,2,3,4.

Padding: refers to the amount of pixels added to an image when it is being processed which allows more accurate analysis.(Here we've used 'SAME' padding which adds zeros to borders and 'valid' padding) .

Model 3–ResNet50 Architecture

Architecture: ResNet50 has four stages, and each stage has a convolution block and an identity blockThe convolution block has three convolution layers, and the identity block has three convolutional layersThe input image size is 224 x 224 x 3, and the network can take an image with height and width as multiples of 32 and 3 as channel width.

Model 4–VGG16 architecture

We used existing vgg-16 model freezing all the layers for training and implementing GlobalAveragePooling2D and using Ann layer with ‘relu’ activation and output layer with ‘softmax layer’

Libraries/Tools used:

- Tensorflow+Keras to implement CNN model
- Numpy, Pandas to handle dataset
- OpenCV to handle/preprocess images
- Matplotlib, Seaborn,IPython for visualizations
- Sklearn for classification reports
- Base64 to decode image captured via webcam

MODEL SUMMARY

Model 1

```
Model: "model_8"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_9 (InputLayer)        [(None, 300, 300, 3)]     0

 block1_conv1 (Conv2D)       (None, 300, 300, 64)      1792

 block1_conv2 (Conv2D)       (None, 300, 300, 64)      36928

 block1_pool (MaxPooling2D)  (None, 150, 150, 64)      0

 block2_conv1 (Conv2D)       (None, 150, 150, 128)     73856

 block2_conv2 (Conv2D)       (None, 150, 150, 128)     147584

 block2_pool (MaxPooling2D)  (None, 75, 75, 128)       0

 block3_conv1 (Conv2D)       (None, 75, 75, 256)       295168

 block3_conv2 (Conv2D)       (None, 75, 75, 256)       590080

 block3_conv3 (Conv2D)       (None, 75, 75, 256)       590080

 block3_pool (MaxPooling2D)  (None, 37, 37, 256)       0
...
Total params: 15,241,025
Trainable params: 526,337
Non-trainable params: 14,714,688
_________________________________________________________________
```

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Model 2

```
Model: "model_7"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 input_8 (InputLayer)           [(None, 300, 300, 3  0           []
                                )]

 conv1_pad (ZeroPadding2D)      (None, 306, 306, 3)  0           ['input_8[0][0]']

 conv1_conv (Conv2D)            (None, 150, 150, 64  9472        ['conv1_pad[0][0]']
                                )

 conv1_bn (BatchNormalization)  (None, 150, 150, 64  256         ['conv1_conv[0][0]']
                                )

 conv1_relu (Activation)        (None, 150, 150, 64  0           ['conv1_bn[0][0]']
                                )

 pool1_pad (ZeroPadding2D)      (None, 152, 152, 64  0           ['conv1_relu[0][0]']
                                )

 pool1_pool (MaxPooling2D)      (None, 75, 75, 64)   0           ['pool1_pad[0][0]']

 conv2_block1_1_conv (Conv2D)   (None, 75, 75, 64)   4160        ['pool1_pool[0][0]']

...
Total params: 25,686,913
Trainable params: 2,099,201
Non-trainable params: 23,587,712
__________________________________________________________________________________________________
```

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Model 3

```
Model: "sequential_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_33 (Conv2D)          (None, 73, 73, 96)        34944

 max_pooling2d_21 (MaxPoolin  (None, 36, 36, 96)       0
 g2D)

 conv2d_34 (Conv2D)          (None, 36, 36, 256)       614656

 max_pooling2d_22 (MaxPoolin  (None, 17, 17, 256)      0
 g2D)

 conv2d_35 (Conv2D)          (None, 17, 17, 384)       885120

 conv2d_36 (Conv2D)          (None, 17, 17, 384)       1327488

 conv2d_37 (Conv2D)          (None, 17, 17, 256)       884992

 max_pooling2d_23 (MaxPoolin  (None, 8, 8, 256)        0
 g2D)

 flatten_7 (Flatten)         (None, 16384)             0

...
Total params: 87,645,569
Trainable params: 87,645,569
Non-trainable params: 0
_________________________________________________________________
```

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Model 4

```
Metal device set to: Apple M2 Pro

systemMemory: 16.00 GB
maxCacheSize: 5.33 GB

Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d (Conv2D)             (None, 300, 300, 32)      896       
                                                                 
 max_pooling2d (MaxPooling2D  (None, 150, 150, 32)     0         
 )                                                               
                                                                 
 batch_normalization (BatchN  (None, 150, 150, 32)     128       
 ormalization)                                                   
                                                                 
 dropout (Dropout)           (None, 150, 150, 32)      0         
                                                                 
 conv2d_1 (Conv2D)           (None, 150, 150, 32)      9248      
                                                                 
 max_pooling2d_1 (MaxPooling  (None, 75, 75, 32)       0         
 2D)                                                             
                                                                 
 batch_normalization_1 (Batc  (None, 75, 75, 32)       128       
...
Total params: 2,823,617
Trainable params: 2,823,425
Non-trainable params: 192
_________________________________________________________________
```

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CONCLUSION:

This study explored the application of deep learning models for pneumonia detection using chest X-ray images. Different architectures were evaluated, with the Convolution neural network,AlexNet,ResNet50, andVGG16 model performing exceptionally well. The publicly available Chest X-Ray dataset was utilized for training and evaluation. The results demonstrated the potential of deep learning in achieving high accuracy for pneumonia detection. Implementing deep learning-based approaches in clinical settings can improve diagnostic accuracy, reduce radiologists' workload, and enhance patient outcomes. Continued advancements in algorithms and datasets will further enhance pneumonia detection systems.

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