FINAL PROJECT CDSS

Clinical Decision Support System (SBE 3030)

Team 6

Omar Abdulnasser

Mahmoud Magdy

Ahmed Kamal

Abdullah Mohamed

Submitted to: Dr. Eman Ayman

Eng. Samar Alaa

Problem Definition

The problem at hand is the classification of chest X-ray images into two distinct categories: normal and pneumonia. This task holds significant importance in the field of medical diagnostics as it aims to assist healthcare professionals in the accurate and timely identification of pneumonia cases. By analysing chest X-ray images, the goal is to develop robust algorithms that can differentiate between normal lung conditions and those affected by pneumonia. Accurate classification can aid doctors in making informed decisions regarding patient treatment plans and interventions. The successful development of such classification models can contribute to the improvement of pneumonia detection, enabling early intervention and potentially saving lives.

Related Papers

Pneumonia detection in chest X-ray images using an ensemble of deep learning models.

Source: [Click Here]

Objective:

- The primary objective of the study was to develop a reliable and accurate deep learning model for automatically detecting pneumonia in chest X-ray images.
- Additionally, the researchers aimed to compare the performance of an ensemble model (combining multiple deep learning models) with individual models.

Methodology:

- The study used a large dataset of chest X-ray images, labelled as either normal or pneumonia-infected.
- Four different deep learning models were trained on the dataset: ResNet50, VGG16, InceptionV3, and DenseNet201.
- An ensemble model was created by combining the predictions of these individual models.
- The performance of all models was evaluated using various metrics, including accuracy, precision, recall, and F1-score.

Results:

- The ensemble model achieved the highest accuracy (92.4%), precision (93.1%), recall (91.7%), and F1-score (92.4%) compared to the individual models.
- This suggests that combining the predictions of different deep learning models can lead to better performance than relying on a single model.
- The study also found that the ensemble model was able to generalize well to unseen data, indicating its potential for clinical applications.

Deep neural network ensemble for pneumonia localization from a large-scale chest x-ray database

Source: Click Here

Objective:

- The main objective of this paper is to develop and evaluate a deep learning approach for localizing pneumonia in chest X-ray images, not just detecting its presence.
- This means identifying the specific region of the lung affected by pneumonia.

Methodology:

- The researchers used a massive dataset of over 380,000 chest X-ray images with bounding boxes marking the pneumonia regions.
- They created an ensemble model consisting of multiple deep learning networks: DenseNet-121, ResNet-50, and InceptionV3.
- Each network was trained to predict the probability of pneumonia at each pixel in the image.
- The ensemble model combined these predictions to refine the localization accuracy.

Results:

- The ensemble model achieved state-of-the-art performance in pneumonia localization, surpassing previous methods.
- It scored high on various metrics, including area under the ROC curve (AUC) and average precision.
- The study also demonstrated the model's ability to localize different types of pneumonia, not just common ones.

Dataset Description

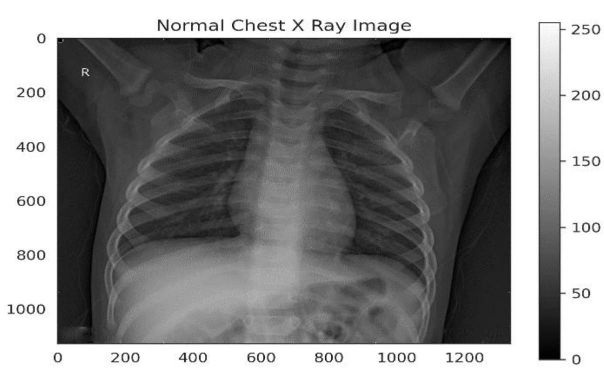
The dataset available at the provided Kaggle link (*https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia*) is known as the "Chest X-Ray Images (Pneumonia)" dataset. It is a comprehensive collection of chest X-ray images that have been labeled for the presence of pneumonia. The dataset is divided into three main folders: "train," "test," and "val" (short for validation), which represent the training, testing, and validation subsets, respectively.

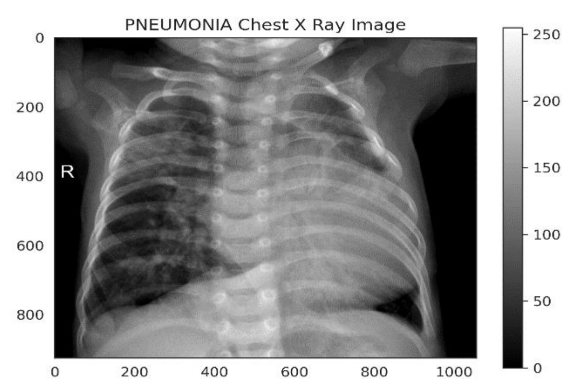
Within each subset, the images are further categorized into two classes: "normal" and "pneumonia." The "normal" class includes chest X-ray images of individuals with no signs of pneumonia, while the "pneumonia" class comprises images of patients diagnosed with pneumonia. This labeling allows for the classification of chest X-ray images based on the presence or absence of pneumonia.

The dataset contains a total of 5,856 chest X-ray images, with approximately 3,600 images in the training set, 600 images in the validation set, and 600 images in the testing set. The images are provided in JPEG format and vary in size and resolution.

This dataset serves as a valuable resource for researchers, data scientists, and machine learning practitioners interested in developing and evaluating algorithms for pneumonia detection using chest X-ray images.

Samples From The Dataset

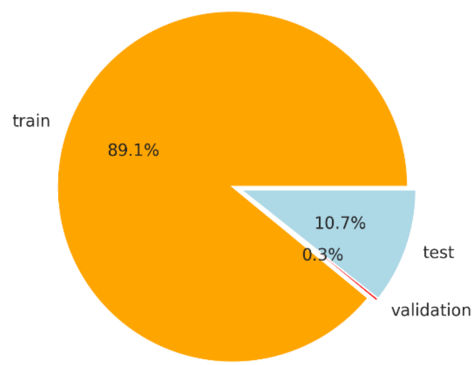




Splitting the Data

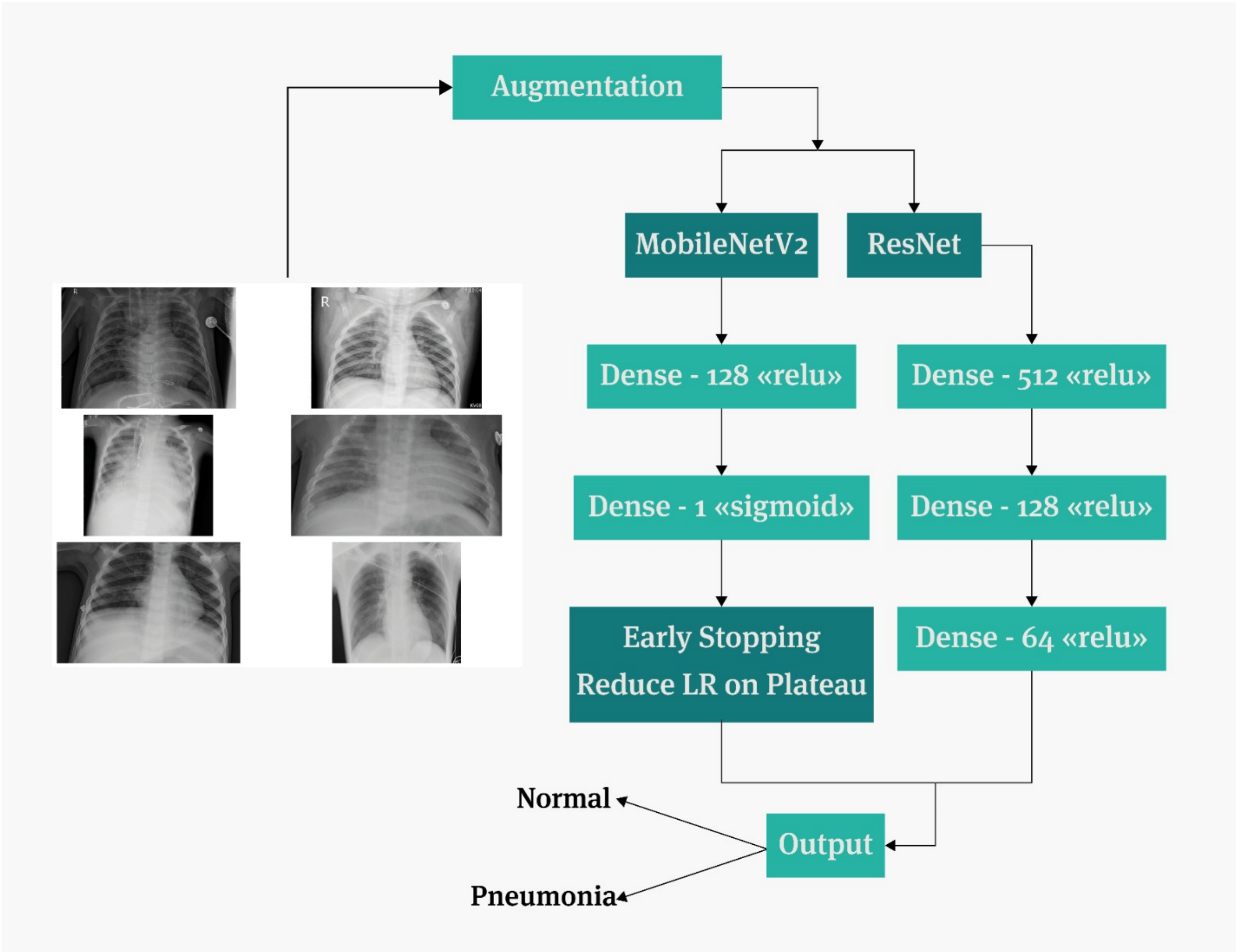
Pie chart that shows the percentage of data used for training, testing, and validation in the deep learning model. The pie chart is divided into three slices:

- The largest slice, labeled "train," is 89.1% of the data. This data is used to train the machine learning model.
- The middle slice, labeled "test," is 10.7% of the data. This data is used to test the accuracy of the trained model.
- The smallest slice, labeled "validation," is 0.3% of the data. This data is used to fine-tune the hyperparameters of the deep learning model.



Outline of Methodology

Our methodology is summarized in Figure below. It includes the following steps: chest X-ray image preprocessing, data augmentation, MobileNetV2, ResNet neural networks, feature extraction and ensemble classification. Then steps are explained in more detail in the subsequent subsections.



Data Augmentation

In order to enhance the performance and generalization abilities of our deep learning model, we implemented a data augmentation technique to expand our existing dataset. Data augmentation involves applying various transformations and modifications to our original data samples, effectively creating new instances that retain the same underlying information. By introducing these artificially generated examples, we aimed to provide our model with a more diverse and robust training set. Our augmentation pipeline consisted of a range of operations, such as random rotations, translations, scaling, flipping, and noise injection. These transformations helped introduce variations in the data, capturing different perspectives and scenarios that might occur in real-world situations. By incorporating data augmentation into our deep learning model, we successfully increased the dataset size, leading to improved model performance, enhanced accuracy, and enhanced ability to handle novel and unseen instances.

To demonstrate the impact of data augmentation, let's consider two images: Image A and Image B. Image A represents an original sample from our dataset, while Image B is a transformed version generated through augmentation techniques. By comparing these two images, we can observe the tangible differences introduced by data augmentation, such as rotations, translations, scaling, flipping, and potentially even noise injection. These variations help our model become more robust and adaptable, as it learns to recognize and understand different manifestations of the underlying patterns in the data. Ultimately, the integration of data augmentation has significantly enriched our training set, leading to improved model performance and a higher capacity to handle diverse and novel instances.

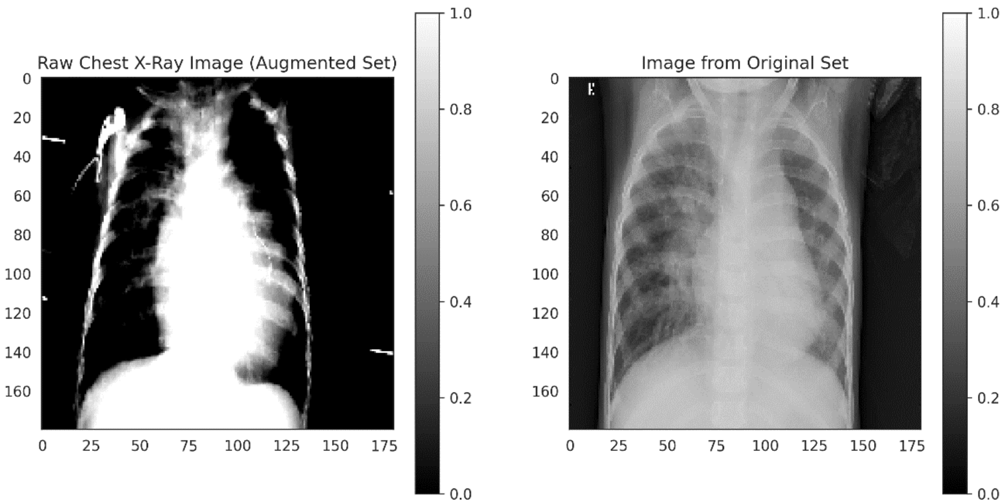


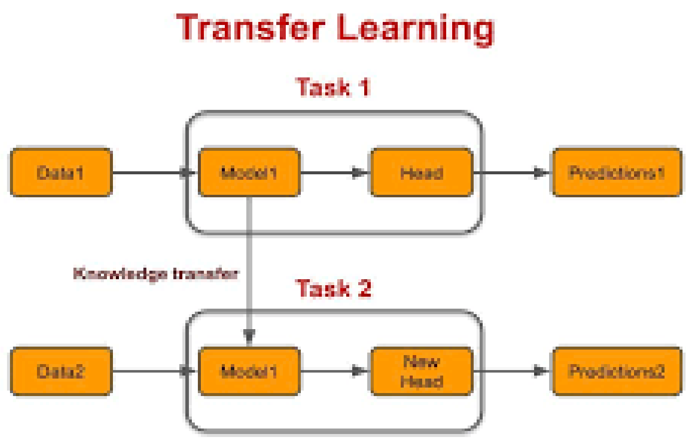
Figure 2: shows the original image (A) and the image (B) in the augmented set.

Transfer Learning

Transfer learning is a powerful technique widely used in machine learning and deep learning, including in the analysis of medical images such as chest X-rays. It involves leveraging pre-trained models that have been trained on large-scale datasets, typically on a different but related task, and then adapting them to a new task or domain with limited labeled data.

In the context of pneumonia detection from chest X-ray images, transfer learning allows us to benefit from the knowledge and representations learned by models trained on massive datasets, such as ImageNet. These pre-trained models, often based on deep convolutional neural networks (CNNs), have learned to recognize and extract meaningful features from a wide range of images.

By using transfer learning, we can take advantage of these learned features and adapt them to our specific task of pneumonia classification. Instead of training a model from scratch, which can require a large amount of labeled data, transfer learning enables us to initialize our model with pre-trained weights and fine-tune it on our smaller dataset of chest X-ray images. This approach significantly reduces the training time and can lead to better generalization and performance, especially when the new dataset is limited.



Transfer Learning Models

MobileNetV2 Model

MobileNetV2 is a deep convolutional neural network architecture that is specifically designed for mobile and resource-constrained environments. It is known for its efficiency and lightweight nature, making it suitable for applications on devices with limited computational resources.

In the transfer learning approach mentioned earlier, MobileNetV2 serves as the pre-trained model that provides the initial weights and learned representations. These pre-trained weights are obtained by training MobileNetV2 on a large-scale dataset, such as ImageNet, which consists of various images from different categories.

To utilize MobileNetV2 in the model for pneumonia detection, the pre-trained MobileNetV2 model is typically used as a feature extractor. The early layers of the MobileNetV2 capture low-level features like edges and textures, while the deeper layers capture more complex and abstract features. These learned features are highly transferable and can be used as a foundation for the pneumonia classification task.

In the transfer learning process, the pre-trained MobileNetV2 model is loaded and the last fully connected layer, which is responsible for the original ImageNet classification, is removed. The remaining layers of the MobileNetV2 are frozen, meaning their weights are not updated during training. This freezing step helps to preserve the learned representations in the earlier layers.

A new set of fully connected layers is added on top of the MobileNetV2 architecture, which will be specifically trained for the pneumonia classification task. These additional layers learn to map the extracted features from the MobileNetV2 to the target classes (normal and pneumonia).

During the training process, the weights of the newly added layers are updated while keeping the pre-trained MobileNetV2 layers frozen. This approach allows the model to benefit from the pre-trained MobileNetV2's learned representations while fine-tuning the classification layers specifically for the pneumonia detection task using the available labeled data.

By using MobileNetV2 in the transfer learning process, we can take advantage of its efficiency, portability, and strong feature extraction capabilities, enabling us to build accurate and lightweight models for pneumonia detection from chest X-ray images.

ResNet Model

ResNet (Residual Neural Network) is a deep convolutional neural network architecture known for its ability to effectively train very deep neural networks. It introduces the concept of residual connections, which help address the degradation problem encountered in deep networks.

In the transfer learning approach mentioned earlier, a pre-trained ResNet model is utilized as the starting point for the pneumonia detection model. The pre-trained ResNet model has typically been trained on large-scale image datasets, such as ImageNet, and has learned to extract meaningful features from various images.

To incorporate ResNet into the pneumonia detection model, the pre-trained ResNet model is used as a feature extractor. The initial layers of ResNet capture low-level features, while the deeper layers capture more abstract and complex features.

During the transfer learning process, the pre-trained ResNet model is loaded, and the final fully connected layer, which was originally designed for the ImageNet classification task, is removed. The remaining layers of the ResNet model are frozen, meaning their weights are not updated during training. This freezing step helps retain the learned representations in the earlier layers.

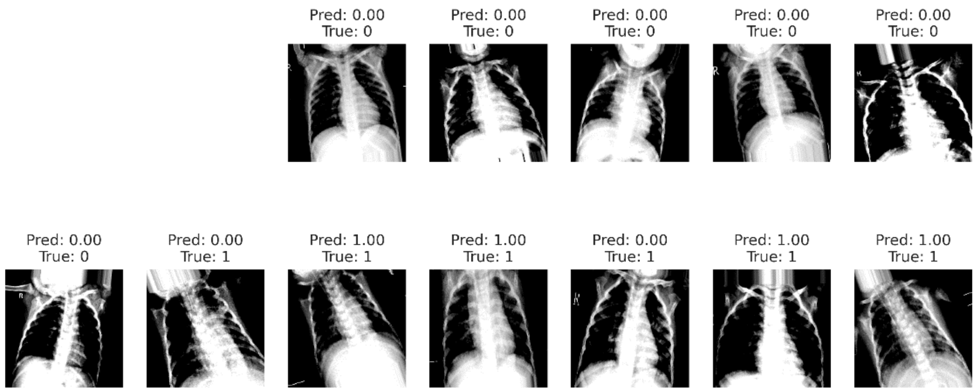
Additional layers, such as fully connected layers, are then added on top of the ResNet architecture. These added layers are specifically trained for the pneumonia classification task. They learn to map the extracted features from the ResNet model to the target classes (normal and pneumonia).

During training, the weights of the newly added layers are updated while keeping the pre-trained ResNet layers frozen. This way, the model can leverage the learned representations and powerful feature extraction capabilities of the pre-trained ResNet while fine-tuning the classification layers for pneumonia detection using the available labeled data.

By utilizing the ResNet model in transfer learning, the pneumonia detection model benefits from the depth and representational power of ResNet while adapting the model specifically for the task of classifying pneumonia in chest X-ray images. This approach reduces the need to train a deep network from scratch and allows for efficient and accurate pneumonia detection.

Evaluation

Sample of the model’s predictions vs the true labels.



Confusion Matrix MobileNetV2		Actual: Positive	Actual: Neagtive	
Predicted	Positive	140	94	Train Accuracy 95.97%
	Neagtive	10	380	Test Accuracy 83.81%
Confusion Matrix ResNet		181	53	Train Accuracy 85.54%
		62	328	Test Accuracy 81.09%

The table that shows the results of two machine learning models, MobileNetV2 and ResNet, on a classification task. The task appears to be binary classification, where the models are trying to predict whether a data point belongs to one of two classes, "Positive" or "Negative."

The table shows the confusion matrices for both models, as well as their train and test accuracies. A confusion matrix is a table that shows how many data points were correctly classified by the model, and how many were incorrectly classified. The diagonal elements of the confusion matrix show the number of correctly classified data points, while the off-diagonal elements show the number of misclassified data points.

For example, the confusion matrix for MobileNetV2 shows that it correctly classified 140 positive data points and 380 negative data points. Also, it shows that it misclassified 10 positive data points and 94 negative data points.

The train and test accuracies are overall measures of how well the model performs on the training and test data, respectively. The train accuracy for MobileNetV2 is 95.97%, and the test accuracy is 83.81%. The train accuracy is usually higher than the test accuracy, because the model is trained on the training data and tends to overfit to it. The test accuracy is a better measure of how well the model will perform on new data that it has not seen before.

In this case, it appears that MobileNetV2 is performing slightly better than ResNet on this task. It has a higher train accuracy and a slightly higher test accuracy. However, the difference in performance is not very large, so it is possible that ResNet would perform better on a different dataset or with different training parameters.