Multi-Task learning for Pneumonia Detection on Chest X-Ray Images*

Sushil Deore
Data Science
University of Colorado Boulder
Boulder, Colorado, USA
sude8287@colorado.edu

Vishadh Vilas Sawant
Data Science
University of Colorado Boulder
Boulder, Colorado, USA
visa4353@colorado.edu

Charan Kanwal Preet Singh
Data Science
University of Colorado Boulder
Boulder, Colorado, USA
chch4792@colorado.edu

ABSTRACT

Pneumonia is a severe lung infection resulting from several different viral infections. Pneumonia's similarity to other pulmonary diseases makes the task of identification and treatment difficult and complex. Multi Task Learning, which works on leveraging knowledge gained in a certain task to improve the generalized performance of all the tasks, has shown much better results than single task learning. One reason for this improved performance is the utilization of more data from several learning tasks when compared to single task learning. With additional data, MTL can develop more robust and universal representations for numerous tasks as well as more potent models, improving knowledge transfer between tasks, each task's performance, and each task's risk of overfitting.

For our problem, detection of the lesion boundary of the X ray image serves as the auxiliary task. Auxiliary tasks are tasks which are of minor relevance for the application but as a kind of additional regularization, they are expected to boost the performance of the ultimately desired main task, which in our case is detection of pneumonia.

Pneumonia is a life-threatening lung infection resulting from several different viral infections. Identifying and treating pneumonia on chest X-ray images can be difficult due to its similarity

to other pulmonary diseases. Thus, the existing methods for predicting pneumonia cannot attain substantial levels of accuracy

INTRODUCTION

Throughout history, virus infection has posed one of the most serious risks to human health. Pneumonia is among the viruses that are most often spread . The lungs are harmed by bacterial and viral infections. Pain, coughing, shortness of breath, and other symptoms of pneumonia are frequent.(Veronika Cheplygina b, 2019) Every year, 7.7% of people worldwide are affected with pneumonia.As a result, early detection is critical for such illnesses.

This can be solved by using Multi-task Learning.In the multi-task learning paradigm (M. Togaçara, 2019), machine learning models are trained utilizing data from several tasks at once, employing shared representations to discover the commonalities among a group of related tasks.

Also one of the most popular and commonly utilized approaches for creating medical picture classification jobs is deep learning (DL) (Ramzi Mahmoudi). Furthermore, employing chest X-ray pictures from pneumonia patients, DL models outperformed conventional techniques in terms of performance.

The idea of learning several outputs from a single input simultaneously, or multi-task learning, has been applied to many tasks and methodologies over the past few decades, including artificial neural network topologies with rigid parameter sharing. Convolutional neural network (CNN) architectures for multi-task learning have shown to be effective, particularly when object detection and semantic segmentation are combined (Vikash Chouhan, 2020).

RELATED WORK

Deep learning has been used over the past decade to detect lung diseases and infections. A deep CNN was used to detect pneumonia in chest x-rays and achieved an accuracy of almost 93.8%. Instead of training CNNs from scratch (Gaobo Liang, 2019), they used three well-known CNNs (DenseNet169, MobileNetV2 and Vision Transformer) that were pre-trained using the ImageNet database. An ensemble of neural networks helped deal with over configuration and improve performance. Similarly, CheXNet, a 121-layer CNN trained using 100,000 chest X-ray images of different diseases (Okeke Stephen, 2019). This approach was also applied to 20 chest X-rays, and the CNN results exceeded the average performance for radiological pneumonia detection. A method based on adaptive mean CNN filtering and random forest to predict pneumonia using chest radiographs(Alhassan Mabrouk, 2022). Adaptive filtering was used to remove noise from the chest X-ray image, improving accuracy and facilitating detection. Dropout is then used to create a two-layer CNN model for feature extraction.(Ansh Mittal, 2020). However, more preprocessing with an adaptive filter is needed to improve the classification accuracy of CNN.

METHODOLOGY

Multiple atomic tasks from the computer vision domain must be solved for a variety of applications using just one input image. Single-image depth estimation (SIDE), semantic segmentation, and image classification are examples of such fundamental tasks. Even though each work is often completed separately, there are many links between them. Utilizing them by resolving them together can improve each task's performance and save time during training and inference. The idea of learning several outputs from a single input simultaneously, or multi-task learning, has been applied to many tasks and methodologies over the past few decades, including artificial neural network topologies with rigid parameter sharing. Convolutional neural network (CNN) architectures for multi-task learning have shown to be effective, particularly when object detection and semantic segmentation are combined.

In light of the fact that integrating knowledge from several areas is a fundamental component of human intelligence, we think MTL more truly captures the learning process of humans than single task learning.

EVALUATION

In scholarly discourse, the performance of classification models is frequently evaluated using a set of established metrics, including Accuracy, Precision, Recall (or Sensitivity), F1 Score, and Receiver Operating Characteristic (ROC) Curve.

Accuracy is commonly defined as the ratio of the number of correct predictions made by the model to the total number of predictions, expressed as (True Positives + True Negatives) / Total Predictions.

Precision is defined as the number of true positive predictions made by the model divided by the total number of positive predictions. It is a measure of the model's ability to minimize false positive predictions and can be expressed as True Positives / (True Positives + False Positives).

Recall (or Sensitivity) is calculated as the number of true positive predictions made by the model divided by the total number of actual positive cases. It is a metric that quantifies the model's ability to identify all positive cases and can be expressed as True Positives / (True Positives + False Negatives).

The F1 Score, which provides a balance between precision and recall, is computed as the harmonic mean of precision and recall, and is given by 2 * Precision * Recall / (Precision + Recall).

The Receiver Operating Characteristic (ROC) Curve is a graph that depicts the relationship between the true positive rate and the false positive rate for a classification model as the threshold for making predictions is varied. The area under the ROC curve (AUC) is often used as a summary metric to assess the performance of a classification model(Yu Zhang, 2022).

It should be noted that in these equations, True Positives (TP) represent the number of positive cases that were correctly identified by the model, False Positives (FP) are the number of negative cases that were incorrectly identified as positive, True Negatives (TN) are the number of negative cases that were correctly identified, and False Negatives (FN) are the number of positive cases that were incorrectly identified as negative.

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