Classification of COVID-19 chest X-Rays using explainable machine and deep learning methods

CSC2515 Project Proposal
November 15, 2021

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1. Background

1.1 Motivation

It was in the last months of the year 2019 that we witnessed a disease quite unknown to mankind. In the following months, the world was forced to a halt as one of the worst diseases spread throughout the continents. As a result, all of the world's focus shifted towards providing the best healthcare for anyone that was affected. Our Machine Learning project is based on one such major goal—to distinguish between X-ray images of normal, pneumonia-ridden, and COVID-19 affected lungs.

1.2 Problem

The importance of this classification problem lies in the fact that in less than a year, hundreds of thousands of deaths have been recorded due to improper and untimely diagnosis of COVID-19 in patients. Through the ML algorithms that we propose and the pipelines that we build in this project, we aim to show how Machine Learning can be an effective tool in performing accurate diagnosis of chest X-rays of diseased lungs into these three categories.

We work using a dataset [1] from Kaggle containing 6939 JPEG image samples of chest X-ray posteroanterior (PA) images divided into three categories—Covid, Pneumonia, and Normal. We are taking an application-focused approach for this project and aim to build different models based on algorithms described in the following section to classify the X-rays. The results will be discussed in terms of accuracy, precision and recall, F1 score, and AUROC to compare the methods. Based on these findings, we will then conclude the best and worst-performing models with a rationale given.

2. Related Work

Several studies have reported the use of machine and deep learning approaches for investigation of COVID-19 chest X-rays.

2.1 Model Architecture

Machine learning

Using a dataset of 225 confirmed COVID-19 X-ray scans, Sekeroglu et al. performed 38 experiments using 4 ConvNet architectures differing in input dimension, and dense layer number and dimension, 10 experiments using five ML models such as Support Vector Machine (SVM), Logistic Regression (LR), Naïve Bayes (NB), Decision Trees (DT) and k-Nearest Neighbor (k-NN), and 14 transfer learning experiments using pre-trained networks. They achieved a mean sensitivity of 93.84%, mean specificity of 99.18%, and mean accuracy of 98.50% [2].

CNN-based architectures

Using a dataset of 1341 normal, 1345 viral pneumonia and 219 COVID-19 patients' chest X-ray images, Satu et al. proposed the use of an enhanced convolutional neural network (CNN) that achieved a 94.03% accuracy, 95.52% AUC and 94.03% F1-measure in detecting COVID-19 from chest X-ray images [3]. However, high accuracy on a heavily imbalanced and small dataset cannot guarantee the effectiveness of COVID-19 detection. Ozturk et al. proposed a deep learning method, DarkCovidNet, that achieved 98.08% test accuracy in binary classification and 87.02% test accuracy in three-category classification (COVID-19, pneumonia and normal cases) [4].

Transfer learning

Minaee et al. trained four popular CNN models, ResNet18, ResNet50, SqueezeNet, and DenseNet-121, on a dataset containing 5000 chest X-ray images with binary labels [5]. Both ResNet18 [6] and ResNet50 [7] were pre-trained on the ImageNet dataset and differed in their number of layers. SqueezeNet employed model compression techniques that alternated between having 1x1 layers to squeeze incoming data, and two parallel 1x1 and 3x3 layers to expand the data [8]. In DenseNet, each layer received feature maps from preceding layers with fewer channels [9]. DenseNet is also known to have higher computational and memory efficiency. In this study's dataset, since the number of scans in the COVID-19 class were limited, the last layer of their CNN was fine-tuned and the pre-trained models were used as a feature extractor. Their best model achieved a sensitivity of 98% while having a specificity of 92% [9]. They included the receiver operating characteristic (ROC) curve, precision-recall curve, average prediction and confusion matrices for each model. They also created saliency maps for explainability by sliding a NxN region inside the scans and making predictions on the occluded image [9].

Sethy et al. also performed transfer learning using pre-trained networks including AlexNet, VGG16, VGG19, GoogleNet, ResNet101, InceptionV3, MobileNetV2 and ShuffleNet. They extracted features from the fully connected layers of pre-trained networks and fed them to an SVM classifier for multi-class classification. They achieved an accuracy of 98.66% using ResNet50 and SVM [10].

Stubblefield et al. used a deep CNN, CheXNet, for extracting image features and XGBoost for performing classification [11]. By using the output vector from CheXNet as input for the XGBoost model, they transferred high-level latent representations of the chest X-ray image's features. This decreased the amount of time needed to train the XGBoost model. For comparison, they computed the average performance for a logistic regression and k-NN model. They also used SHAP's "TreeExplainer" to determine the most significant features in the imaging modalities [11].

Rajagopal et al. performed a similar comparative study on four different models: transfer learning model (VGGNet), CNN, SVM using features extracted from a CNN, and XGBoost with features extracted from a CNN, achieving an accuracy of 95.27%, 95.52%, 94.94% and 95.71%, respectively [12].

2.2 Feature Extraction

Although deep learning techniques enable image classification without manual feature engineering, Khuazni et al. showed that dimensionality reduction techniques, such as kernel-PCA, can generate a set of optimal features and considerably decrease their model's training time due to lower redundancy [13]. They also showed that their model had ~10,000 parameters, which is considerably smaller than typical classification models like AlexNet with 60M parameters, and ResNet50 with 25M parameters [13].

3. Hypothesis and Technical Details

The proposed contributions of this work are summarized as follows:

- Perform experiments on a Kaggle dataset composed of chest X-rays from nine different data sources [1], such that all three classes contain ~2300 samples each
- Understand the impact of different image processing and dimensionality reduction techniques on subsequent model performance and training time
- Perform a comparative study of machine learning algorithms such as SVM, Decision Trees, LT and Random Forests, deep learning algorithms like 2D-CNNs, pre-trained CNN architectures including ResNet, DenseNet, MobileNet, and SqueezeNet and transfer learning methods like XGBoost-CNN and SVM-CNN. We aim to compare these models based on predictive performance metrics such as accuracy, precision, recall, F1-score, and AUROC, on binary (COVID-19 and non-COVID-19 scans) and multiclass classification (COVID-19, pneumonia and normal scans) tasks.
- Model explainability has often been overlooked in this application area. Knowing which feature or image region carries more context in predicting a class can help us construct more robust and reliable models for potential clinical use. We aim to explain the classification models' predictions using class activation mapping [14], and SHAP Kernel, Deep and Tree Explainers [15].

In our work, we hypothesize that CNN-based architectures will outperform traditional machine-learning-based classifiers, confirming the trend observed in previous studies.

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