COVID-19 Detection from Chest X-Ray Images Using Deep Convolutional Neural Networks with Weights Imprinting Approach

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Abstract

COVID-19 pandemic has drastically changed our lives. Chest radiography has been used to detect COVID-19. However, the number of publicly available COVID-19 x-ray images is extremely limited, resulting in a highly imbalanced dataset. This is a challenge when using deep learning for classification and detection. In this work, we propose the use of pre-trained deep Convolutional Neural Networks (CNN) and integrate them with a few-shot learning approach named imprinted weights. The integrated model is fine tuned to enhance the capability of detecting COVID-19. The proposed solution then combines the fine-tuned models using a weighted average ensemble for achieving an optimal 82% sensitivity to COVID-19. To the best of authors' knowledge, the proposed solution is one of the first to utilize imprinted weights model with weighted average ensemble for enhancing the model sensitivity to COVID-19.

1 Introduction

COVID-19 pandemic has damaged people's health and livelihood. The fight against COVID-19 is ongoing. To save lives and focus resources, accurate screening methods are needed, including chest radiographic examination. Based on recent studies, chest x-ray images for COVID-19 patients show unique abnormalities [1]. Artificial Intelligence (AI) provides great tools for the detection of COVID-19. However, due to the newness of the illness, the number of publicly available COVID-19 images is limited. This is considered a challenge when using deep learning techniques, e.g., deep Convolutional Neural Network (CNN).

To solve this problem, we propose the use of a few-shot learning approach [2] named imprinted weights [3] to enhance the capability of detecting the COVID-19. We use a publicly available dataset named COVIDx [4], which is a highly imbalanced dataset with normal and pneumonia images as majority and a very limited number of COVID-19 images. Our approach starts from training a CNN classifier to classify the dominant classes (normal and pneumonia). It then integrates the imprinted weights technique for enhancing its capability on the classification of a novel class by initializing the final layer weights from novel training examples. The weights imprinting approach provides a good initialization for fine-tuning to achieve a good performance on classifying the novel class (COVID-19).

The proposed model is one of the first in utilizing the imprinted weights approach for enhancing the detectability of COVID-19 from chest x-ray images. It utilizes existing models including pre-trained ResNet-50 [5] and AlexNet models [6] and integrates them with the imprinted weights approach. Combining the different models using a weighted average ensemble with a greedy search algorithm leads to the highest sensitivity in detecting COVID-19 from chest x-ray images. The proposed models are fine-tuned using different learning policies such as random over sampling, manually generated balanced batches, and early stopping techniques.

The proposed solution will serve as a great tool to improve the detection of COVID-19 using chest x-ray images. It will open the door to solve different medical classification problems using few shot learning. Imbalanced dataset is natural in the world of new diseases and utilizing the proposed approach will improve the detection of new diseases using medical images.

2 Proposed Models

In this work, the publicly available COVIDx dataset [4] is used for training and testing. This dataset has 14,198 chest x-ray images measured across 14,002 patient cases. Each image has been labelled as one of the three classes: normal, pneumonia, or COVID-19. It is a highly imbalanced dataset, where approximately 3.5 % of the data are labelled as COVID-19.

In order to deal with the imbalanced dataset, we apply the imprinted weights approach with fine-tuning. The imprinted weights approach is achieved by training a base classifier to classify the two dominant and balanced classes using the available normal and pneumonia x-ray images in COVIDx dataset. The SoftMax layer, which is the classification layer in the used model, is removed and a normalization layer is added. A proxy of chest x-ray images from the COVID-19 class is inputted to the deep CNN. An embedding vector of the novel COVID-19 class is computed from the output of the normalization layer and imprinted to the weight matrix to serve as a good initialization weight for the novel class in the extended classifier.

In this work, a pre-trained ResNet-50 as well as an untrained AlexNet are used as the basis classifiers.The pre-trained ResNet-50 is fine-tuned to classify normal and pneumonia cases by removing the last prediction layer and replacing it with a dense layer followed by a two-node prediction layer for classifying normal and pneumonia cases. The weights of the pre-trained ResNet-50 model are frozen except for the last convolutional layer and the added layers. Similarly, the untrained AlexNet is fine-tuned to classify normal and pneumonia cases by removing the last prediction layer and replacing it with a two-node predication layer. Adam optimizer is used in training using a learning rate of 0.0002.

After training the base classifiers to classify normal and pneumonia cases, imprinted weights are added, and fine-tuning using COVID-19 images is conducted. Fig. 1 illustrates our approach where two fine-tuning approaches are used. The first approach ("Fine Tuning 1") is based on k-fold cross validation where each fold has a balanced data set of 279 images from each class. The second fine-tuning approach ("Fine Tuning 2") is based on a random oversampling approach, where 2,000 images from normal and pneumonia classes are used and 279 images from COVID-19 are used. Each fine-tuning approach shows different performance. Finally, a weighted average ensemble based on a greedy search algorithm is used to combine the four models. The greedy search algorithm is designed to achieve the highest sensitivity to COVID-19 since it is considered as the most important metric in evaluating our proposed models.

3 Experimental Results and Discussions

In order to evaluate the performance of the proposed model, we compare it with a pre-trained ResNet-50 model, in which the last layers are fine-tuned to classify the three classes using the imbalanced dataset without applying the imprinted weights approach. In the following comparison, we refer to this approach as "All Classes Joint". In addition, we compare the performance of our proposed model with a pre-trained ResNet-50 model after retraining the last layers using a subset of the dataset that has balanced classes, e.g., 279 chest x-ray images in normal, pneumonia and COVID-19 classes. We refer to this approach as "All Classes Joint-Balanced".

The column charts in Fig. 2 and Fig. 3 compare the performance of the proposed model with the "All Classes Joint" and "All Classes Joint-Balanced" in terms of sensitivity and precision, respectively (blue for normal cases, orange for pneumonia cases, and green for COVID-19 cases). Fig. 2 shows that the proposed model significantly outperforms the other models in terms of sensitivity to COVID-19. The proposed model provides 82% sensitivity to COVID-19 comparing to just 1% for "All Classes Joint" and 34% for "All Classes Joint-Balanced". Fig. 3 shows that the proposed model

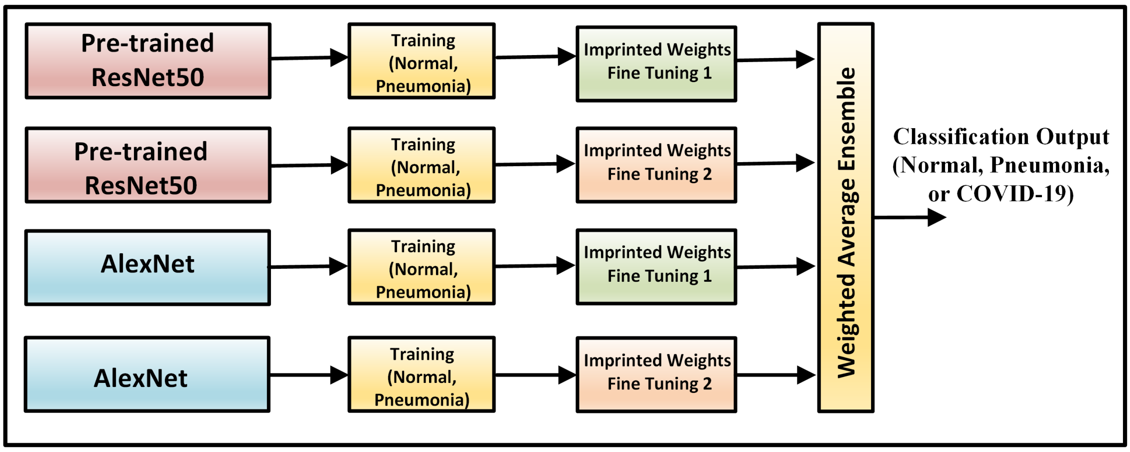

Fig. 1: The proposed ensemble approach integrating pre-trained deep CNNs with imprinted weights.

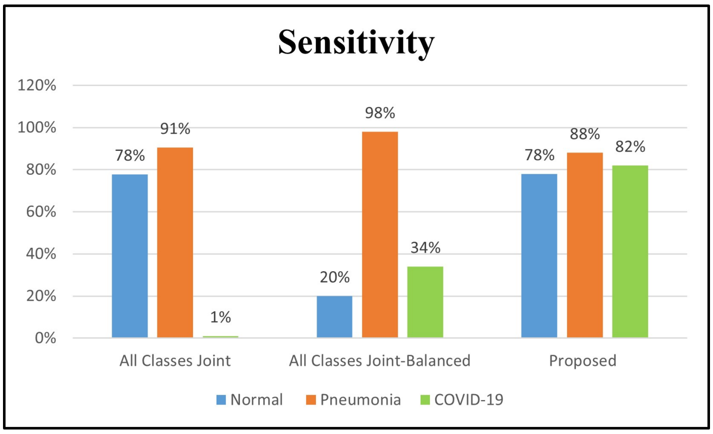

Fig. 2: The resulting performance in terms of sensitivity.

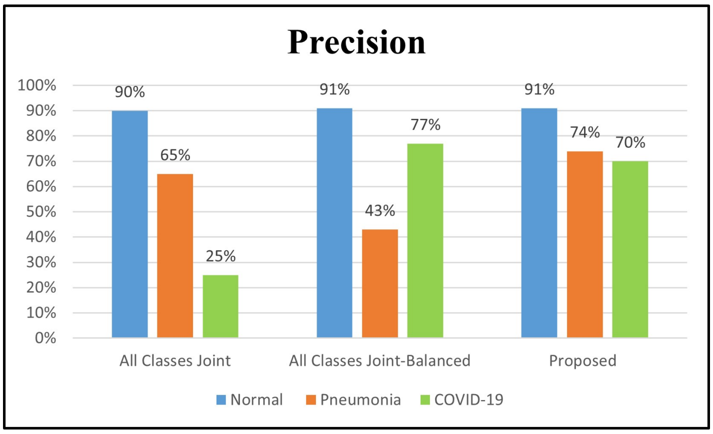

Fig. 3: The resulting performance in terms of precision.

significantly outperforms the "All Classes Joint" in terms of COVID-19 precision and shows comparable precision with "All Classes Joint-Balanced". However, the latter approach has less precision to pneumonia cases. In addition, we compute the overall combined accuracy for the three models in comparison as shown in Fig. 4. In general, Fig. 2 to Fig. 4 indicate that our proposed model shows the best trade-off between sensitivity and precision for COVID-19 cases as well as for normal and pneumonia cases, with the highest accuracy reaching 85%.

Sensitivity to COVID-19 chest x-ray images is a very important metric in our comparison. Therefore, we have studied the effect of changing the percentage of the COVID-19 chest x-ray images in the training dataset on the sensitivity of our proposed model. The results are plotted in Fig 5, where sensitivity to normal and pneumonia classes joint, which we refer to as "None COVID-19", is measured in blue, and sensitivity to the COVID-19 class is measured in

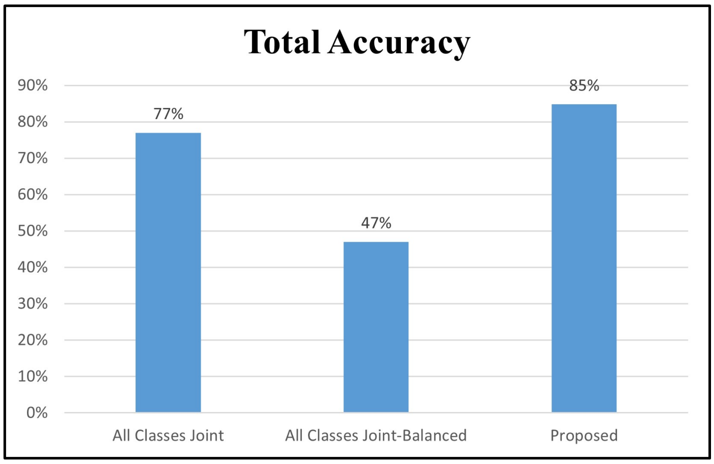

Fig. 4: The resulting performance in terms of accuracy for the three classes.

red. Resulting performance shows that when all COVID-19 chest x-ray images available for training are used, which is around 3%, we achieve the highest sensitivity of 82%. When the percentage of COVID-19 chest x-ray images used for the training is reduced to 2.5% and 2%, sensitivity slightly decreases to around 72%. Finally, when the percentage of COVID-19 chest x-ray images used for the training is reduced to 1.5%-0.5 %, sensitivity decreases further to the range of 54%-59%. However, even for those cases where the sensitivity is in the range of 54%-59%, the proposed model still significantly outperforms "All Classes Joint" and "All Classes Joint-Balanced" as Fig. 2 shows. Changing the percentage of COVID-19

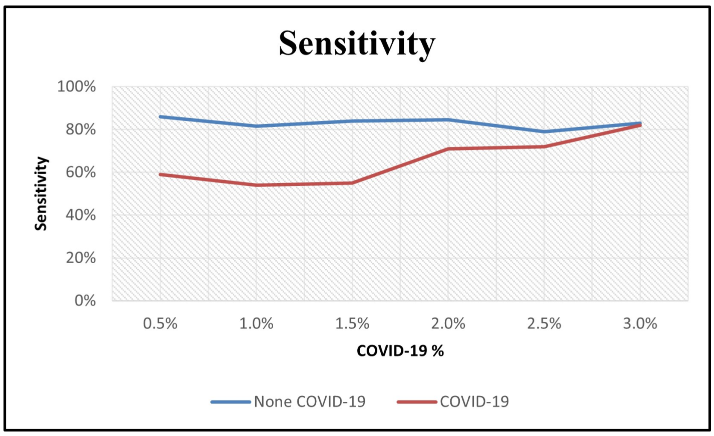

Fig. 5: The effect of changing the percentage of COVID-19 images to the total number of images in the training data set on the sensitivity of our model.

chest x-ray images does not change the sensitivity of our proposed model to "None COVID-19" chest x-ray images which contain normal and pneumonia cases. In this context it is worthwhile to mention that different models using different fine-tuning approaches have been studied, evaluated, and compared. The presented model in Fig. 1 achieves the highest performance.

4 Conclusion and Future work

In this work, the imprinted weights method is integrated with fine-tuned deep CNN models for enhancing the detectability of the COVID-19, using an imbalanced dataset with a very limited number of COVID-19 chest x-ray images. The proposed solution combines different fine-tuned models using a weighted average ensemble. Greedy search algorithm is used to find the best weights that leads to the highest model sensitivity to COVID-19. The ensemble model shows good classification results for the COVID-19 category. The results indicate that the imprinted weights provide a better starting point for fine-tuning the network than the usual random initialization or using the pre-trained weights for some layers. As a future work, the weights imprinted approach should be compared with other few shot learning approaches, for instance, triplet network [7] or prototypical networks [8]. Integrating different pre-trained models such as VGG network might lead to improvement in the performance. Finally, using pre-processed and cropped images with our proposed model can lead to further improvement.

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