Ensemble of Convolution Neural Networks for Automatic Tuberculosis Classification

Mustapha Oloko-Oba and Serestina Viriri

School of Mathematics, Statistics & Computer Science, University of KwaZulu-Natal, Durban.
mustaphasmo@yahoo.com.

1. Introduction

- Tuberculosis has ranked among the highest causes of mortality as reported by World Health Organization. Tuberculosis mostly attacks the lungs (pulmonary) but sometimes attacks other body parts (extra-pulmonary) [1].
- Tuberculosis is curable, and most of the causalities could be averted if only the disease is detected early for appropriate treatment [2].
- Diverse procedures can be used to screen Tuberculosis but Chest X-Ray is recommended from screening the lungs [3]

2. Problems and Motivation

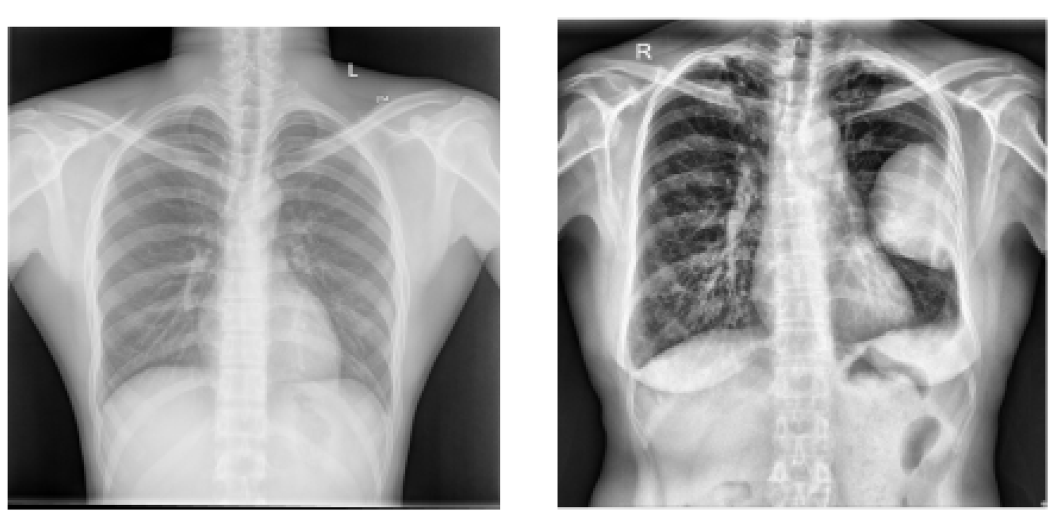
- As much as Tuberculosis can be detected on CXR, Tuberculosis prevalent regions usually lack expert radiologists to adequately diagnose and or interpret the screening results [1].
- Manually diagnosing large number of patients is a tedious and time consuming task which could result in misdiagnosis. In most developing regions where the resources required to undertake accurate diagnosis is lacking, curbing the Tuberculosis epidemic becomes a major challenge.
- Consequently, to tackle this problem, we proposed an Ensemble model that takes advantage of the strength of different pre-trained Convolutional Neural Networks to increase detection rate and achieve early diagnosis with high sensitivity.

3. Datasets

The proposed model was trained on the SHENZHEN dataset and validated on the MONTGOMERY dataset. These datasets contains Tuberculosis specific CXR images provided by the National Library of Medicine (NLM) and publicly made available for research purposes.

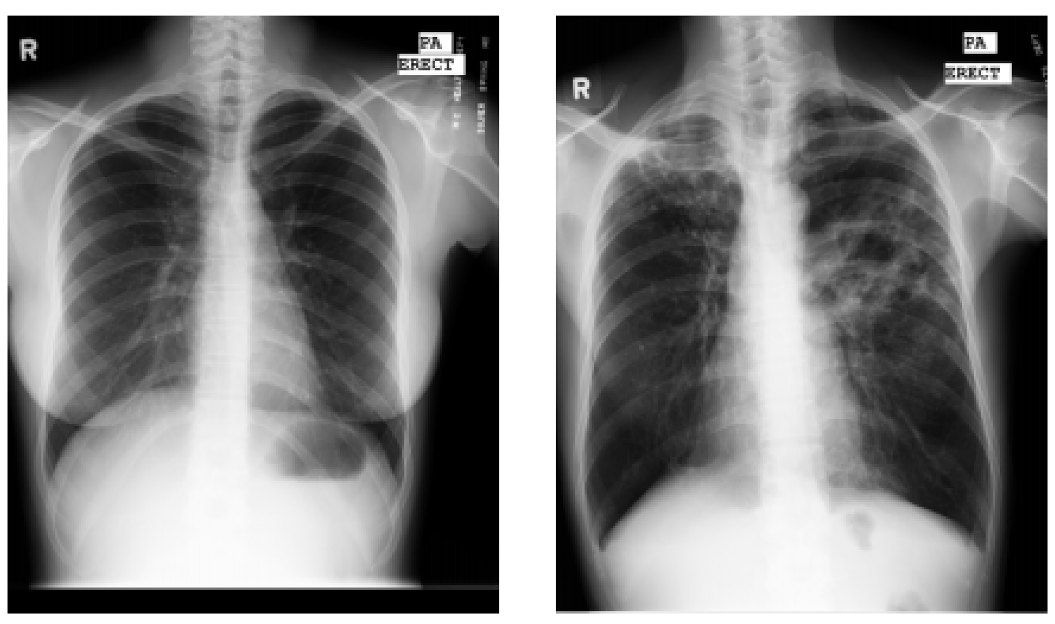
More details on the datasets can be found at: https://lhncbc.nlm.nih.gov/publication/pub9931

Figures 1 and 2 below show samples of the training and testing datasets.



(a) Healthy CXR from train-set (b) Unhealthy CXR from train-set

Figure 1. Sample of the Shenzhen dataset.



(c) Healthy CXR from test-set (d) Unhealthy CXR from test-set

Figure 2. Sample of the Montgomery dataset.

4. Methodology

The type of Ensemble implemented in this study is the "Bagging" method because of its strength to achieve low variance, thereby controlling model overfitting. Bagging yield stability and achieve better performance by combining multiple models.

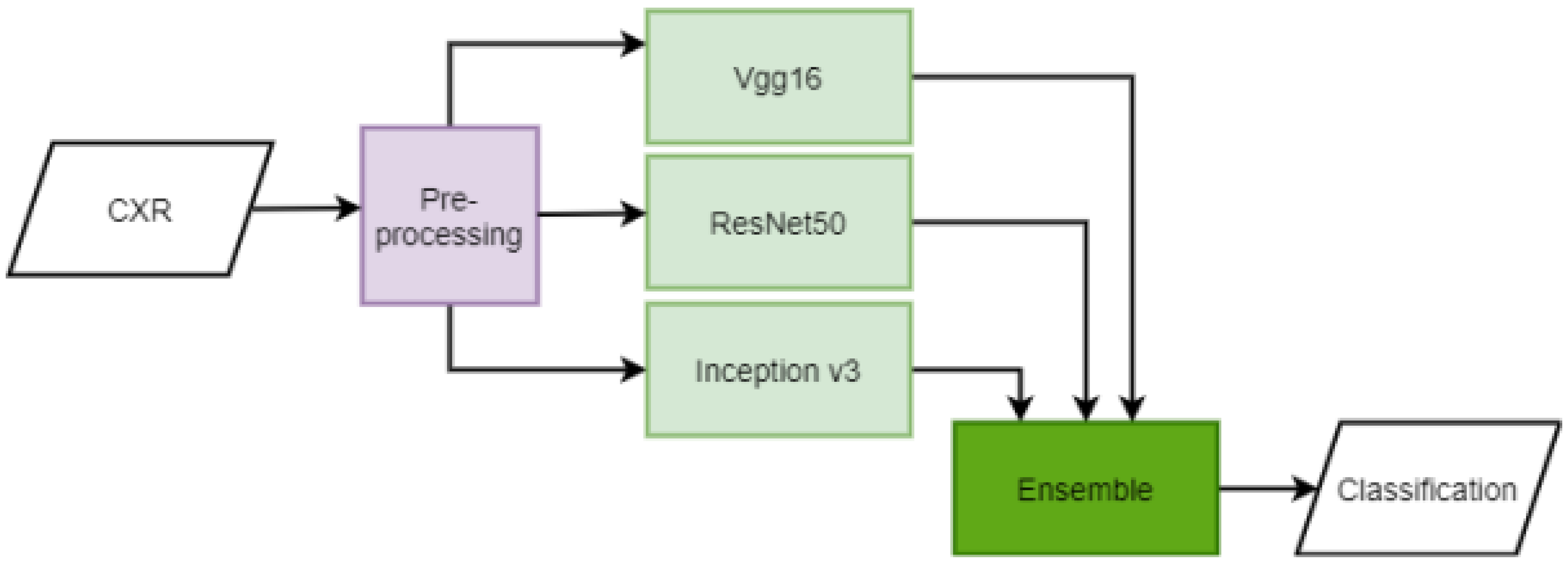


Figure 3: Process diagram of the proposed model

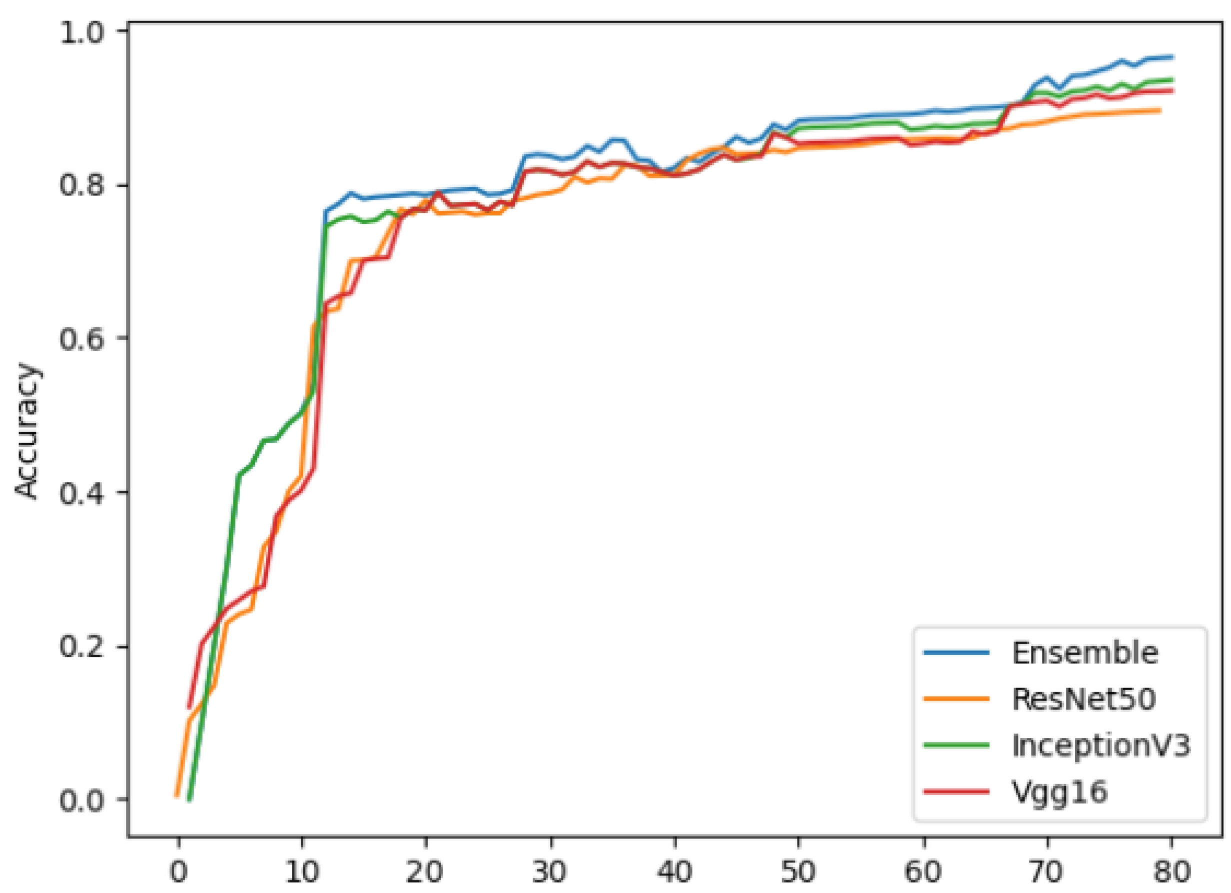
Each of the pre-trained CNN models is trained independently using different hyper-parameters that is found to perform best in terms of the optimizer, learning rate, and activation function.

The models were trained each for 80 iterations (epochs) with a batch size of 32 to obtain the probability of each CXR sample belonging to either a positive or negative class representing TB and non-TB classes. The output from the individual model is then combined to obtain the final prediction through the Ensemble classifier.

5. Results

Table 1: Experimental results

	Ensemble	ResNet50	Vgg16	Inception
Accuracy (%)	96.14	89.51	92.10	93.50
Sensitivity (%)	90.03	89.09	88.25	79.31
Specificity (%)	92.41	90.08	91.00	83.36



6. References

[1] World Health organization. Global tuberculosis report, 2017.

[2] World Health Organization. Global tuberculosis report: executive summary., 2021.

[3] World Health Organization et al. Chest radiography in tuberculosis detection: summary of current who recommendations and guidance on programmatic approaches. Technical report, World Health Organization, 2016.