2021-2022 M.Sc. in Data Science and Analytics

Pneumonia Detection in Chest X-ray Images Using Deep Convolutional Neural Network

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Objective

The main objective of this project is to utilize the power of deep convolutional neural network (DCNN) to diagnose pneumonia using chest x-ray images. In addition, the effect of data augmentation and sampling techniques on the performance will be discussed and readers will better understand DCNN by visualizing intermediate feature maps and class activation maps of the proposed model.

Background

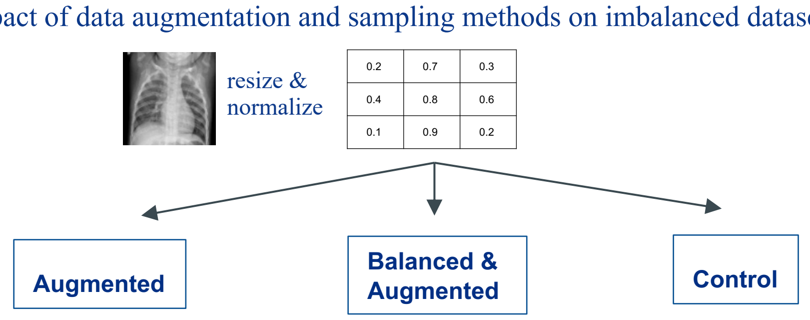
Pneumonia is a life-threatening disease that leads to the death of individuals within a short period due to the flow of fluid in the lungs. Almost a third of all victims were children and it is the leading cause of death for children under 5. Early diagnosis and treatments are very important to avoid the progress of pneumonia and chest x-ray is the most conventional method to diagnose the disease.

However, differentiating pneumonia in x-ray images, particularly in the early stage is very difficult and human-assisted approaches have drawbacks such as availability of experts and diagnostic tools. Either of false positive and false negative diagnosis has substantial impacts on patients. Hence, we need more reliable and consistent computational methods in the diagnosis steps.

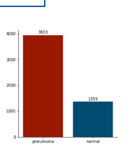
Methodology

Dataset: 5932 chest x-ray images of one to five years old pediatric patients, categorized into Pneumonia and Normal classes.

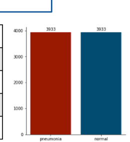
I. Image pre-processing: Three different data groups are generated to test the impact of data augmentation and sampling methods on imbalanced dataset.

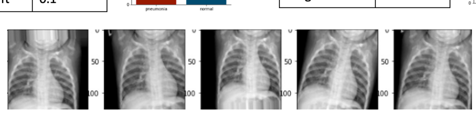


Augmentation	Parameter
Rotation	10°
Zoom range	0.1
Width Shift	0.1
Height Shift	0.1

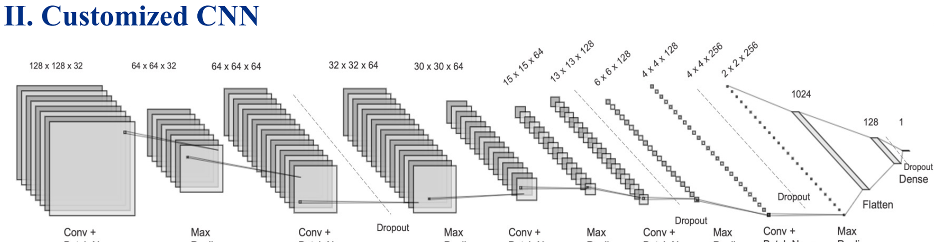


Augmentation	Parameter
Rotation	10°
Zoom range	0.1
Width Shift	0.1
Height Shift	0.1

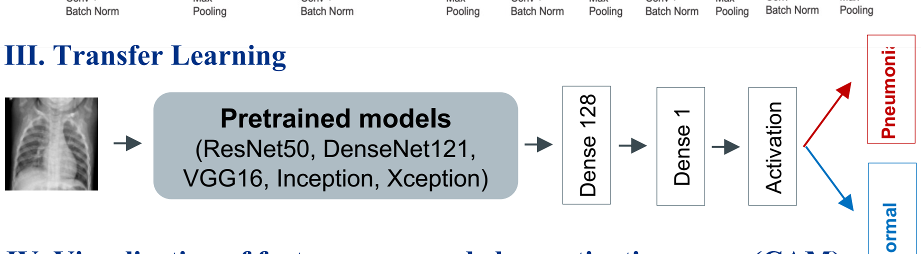




II. Customized CNN



III. Transfer Learning



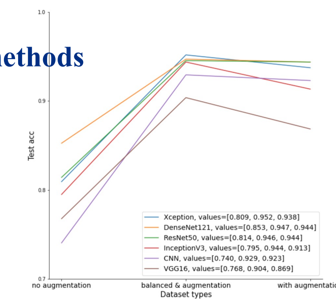
IV. Visualization of feature maps and class activation maps (CAM)

- Feature maps: first nine and last three layers of transfer learning models are observed to see which features are activated by convolutional layers
- CAM: project back the weights onto the last convolution layer's feature map and produce a coarse localization map, highlighting the important regions in the image of the prediction conception

Results

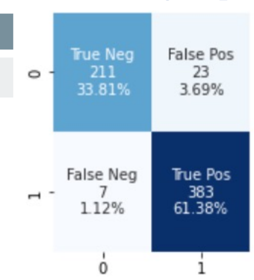
Impact of data augmentation and sampling methods

The chart shows the test accuracy of the six DCNN models that are each trained with three different data groups. It is shown that models trained with 'balanced & augmented' data group show the highest accuracy in classifying categories.



Proposed Xception classifier with 'balanced & augmented' data group

Acc.	Loss	Recall	Prec.	F1	AUC
0.9519	0.2899	0.94	0.955	0.945	0.947

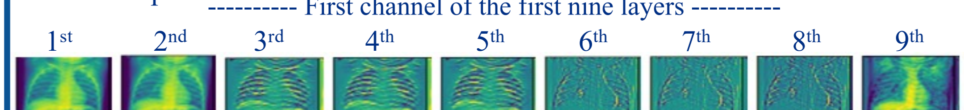


The Xception DCNN model trained with 'balanced and augmented data group resulted in the highest accuracy and the least number of errors in the test set compared to other classifiers in the study.

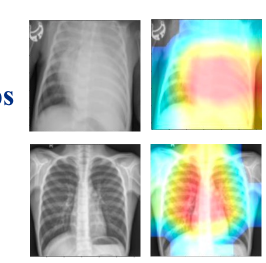
Interpretation of visualization of intermediate layers

Initial layers identify low-level features such as edges and deeper layers learn more abstract features like specific lung regions. The earlier features get combined and are passed onto the next subsequent layer and the last layers of the network become complicated. we lose the ability to interpret the deeper feature maps

---------- First channel of the first nine layers ----------



---------- First channel of the last three layers ----------



Interpretation of visualization of class activation maps

The weights of the last conv. layer inside the 14th conv. block of Xception model are used to produce CAM. There are good localizations, and the layer sees that the lung regions are relevant when classifying the image.

Conclusions

The Xception model demonstrated promising performance compared to customized CNN model and other four DCNN based transfer learning models tested under study. Transfer learning approaches resulted in faster convergence with reduced bias, overfitting, and improved generalization, compared to customizing CNN model from scratch.

There is a significant performance difference between 'augmented data' trained and 'non-augmented data' trained DCNN models. In addition, over-sampling infrequent class to balance out the imbalanced class distribution in the training set result in better accuracy. It is shown that data augmentation and balancing out class distribution are necessary parts of successful application of DCNN models on image data.

For future work, the prosed model can be extended to classify bacterial and viral pneumonia. It is also possible to apply the proposed algorithms to diagnose several other diseases such as cancers, blockages, and fractures which can be diagnosed by x-ray testing.