Pneumonia Detection using Convolutional Neural Network

NCSU CSC-522

P-21

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Contents

Objective

To build a deep convolutional neural network to determine pneumonia (bacterial or viral) using chest x-ray scans

Motivation

- According to the WHO[1], Pneumonia accounts for 15 percent of all deaths of children under five years old, killing 808,694 children in 2017
- Proposed method would help in the early detection of the disease
- Will help in bringing low cost diagnostic services to under - privileged people

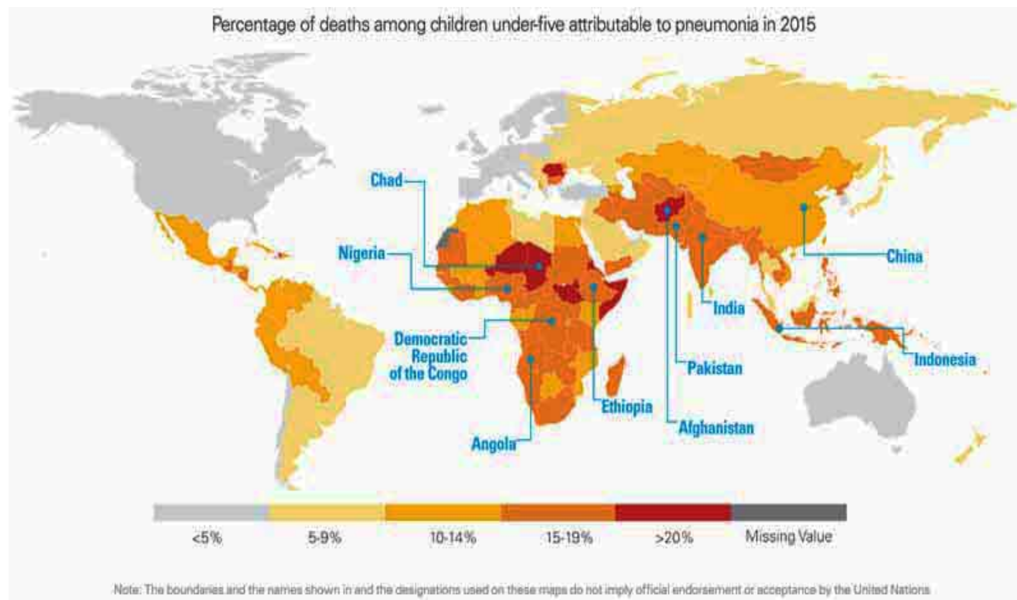


Figure 1: Percentage of deaths among children (less then 5) due to Pneumonia

CNN

- CNN's are proved to be exceptional when it comes to image classification
- 3 Layers: Convolutional Layers, Pooling Layers, Fully Connected Layers
- Faster training, needs fewer samples, reduces the chance of overfitting as compared to ANN
- Extensively used for medical image analysis

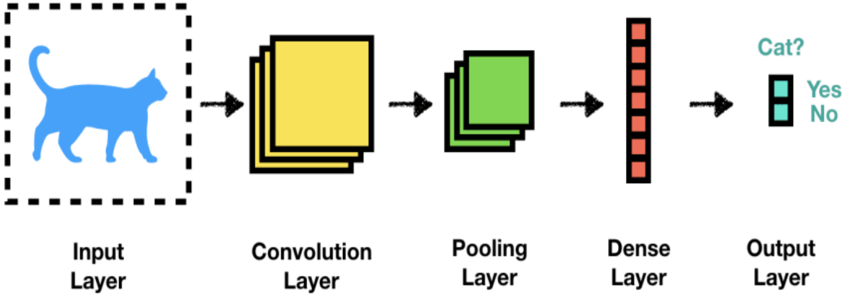


Figure 2: Basic CNN architecture

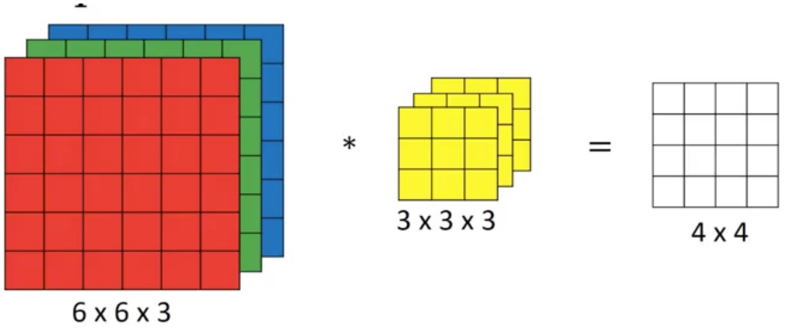


Figure 3: Convolutional operation

Proposed CNN architecture:

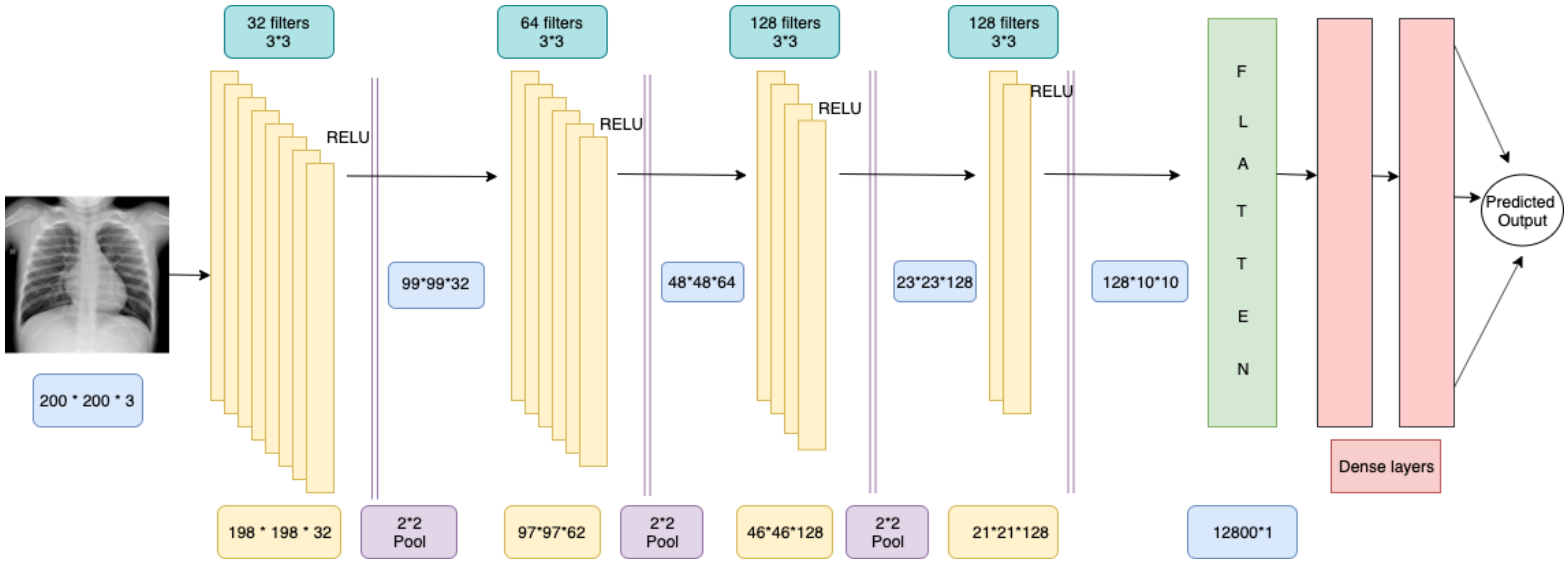


Figure 4: CNN model architecture

- 4 feature extractors, 1 flatten layer and 2 dense layers.
- A single feature extractor consists of one 2-D convolutional layer, a 2x2 max-pooling layer and ReLu activation.
- Architecture inspired from existing open source medical image classification models [2][3]

Initial CNN Results

- 50 epochs
- Test Data:
    - Accuracy: 0.75
    - Precision: 0.81
    - Recall: 0.71
    - F1 score: 0.72
    - Loss: 1.08
- Train Data:
    - Accuracy: 0.94
    - Loss: 0.16
- **Model is overfit !**

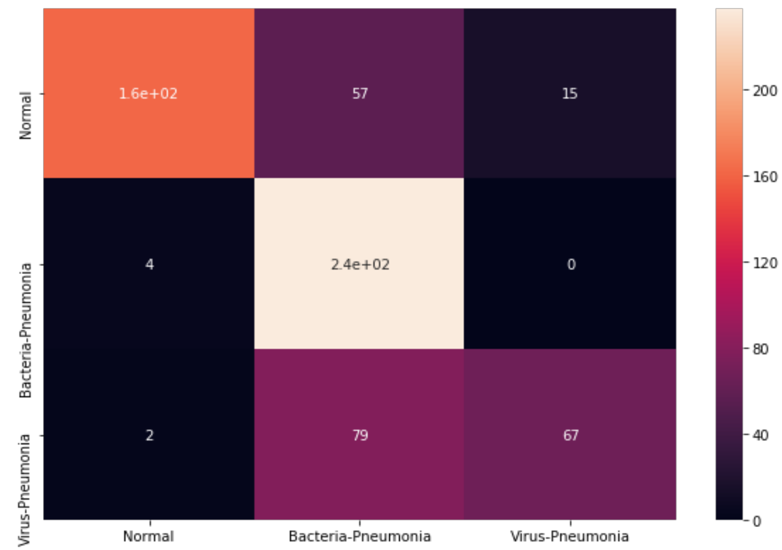


Figure 5: Confusion Matrix

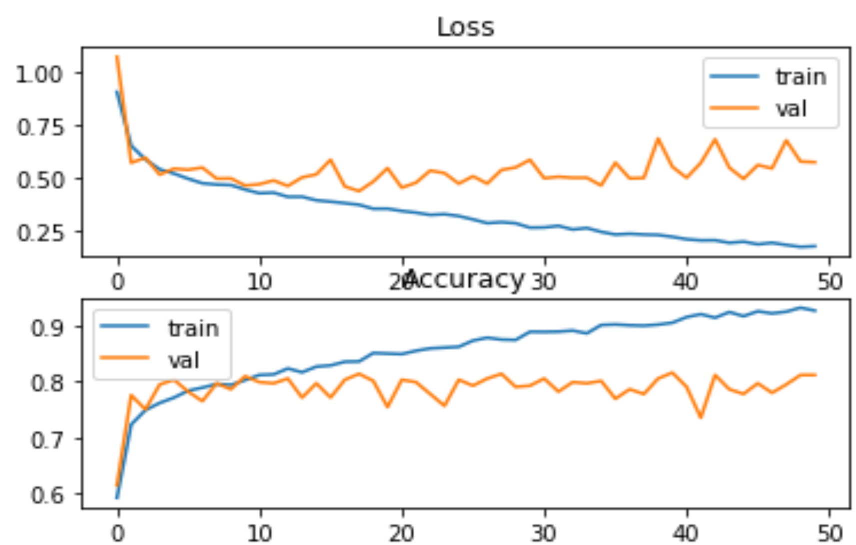


Figure 6: Loss and accuracy plots

Experiments

A) Data Augmentation

- A wide array of domain-specific transformations to synthetically expand a training set
- Significantly increase the diversity of data available for training models
- Common techniques involves cropping, padding, and horizontal flipping[4]

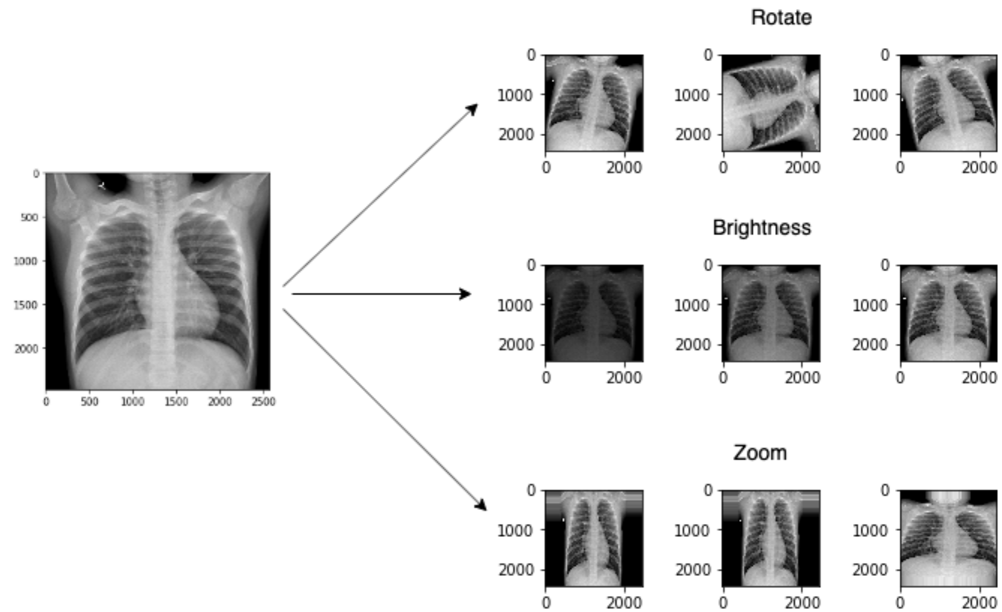


Figure 7: Data Augmentation

Experiments

B) Dropout

- Prevents all neurons in a layer from synchronously optimizing their weights
- Prevents all the neurons from converging to the same goal, thus decorrelating the weights[5]
- The activations of the hidden units become sparse

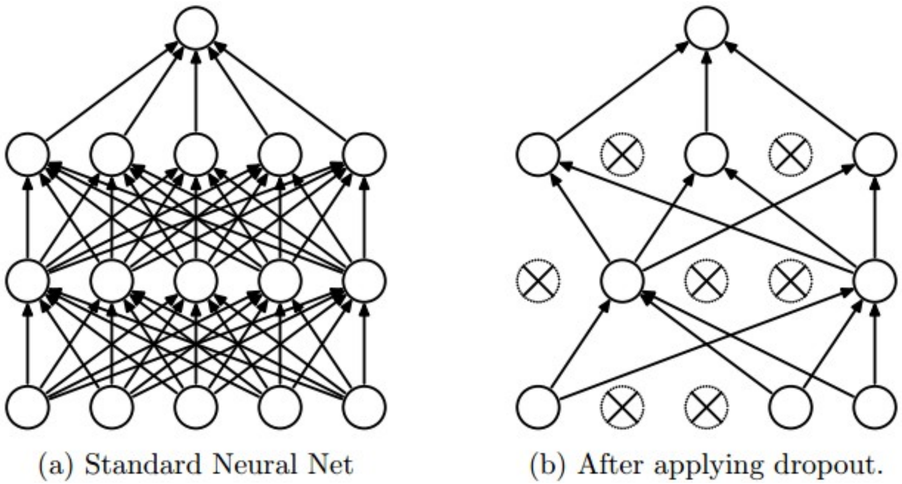


Figure 8: Dropout

Experiments

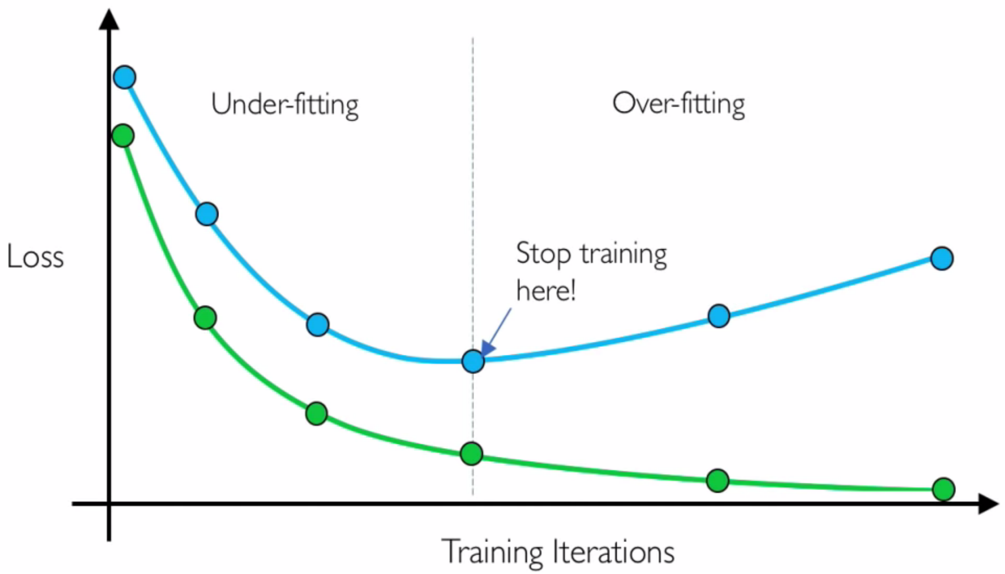


Figure 9: Early Stopping during training

C) Early-Stopping

- Sometimes, during training, the generalization gap starts to increase, instead of decreasing[6]
- Generalization gap is the difference between training and validation error
- Model is overfitting
- Stop training when the generalization gap is getting worse

Experiments

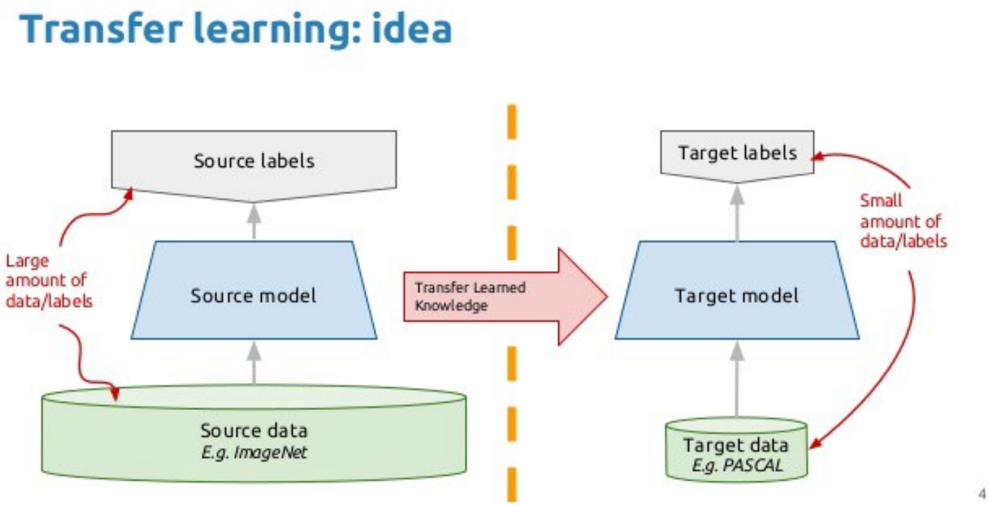


Figure 10: Transfer Learning

D) Transfer learning

- A model trained on one task is re-purposed on a second related task[7]
- Less layers to train and thus quicker training of model and better generalization.
- Used pre-trained ImageNet model

Results(cnn + experiments)

- 50 epochs
- Test Data:
  - Accuracy: 0.854
  - Precision: 0.851
  - Recall: 0.835
  - F1 score: 0.839
  - Loss: 0.455
- Train Data:
  - Accuracy: 0.807
  - Loss: 0.442
- **Model not overfit !**

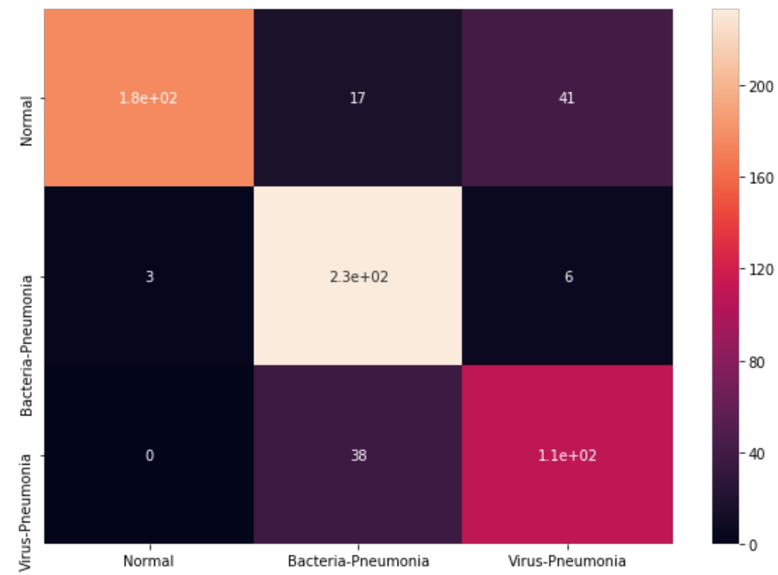


Figure 11: Confusion Matrix

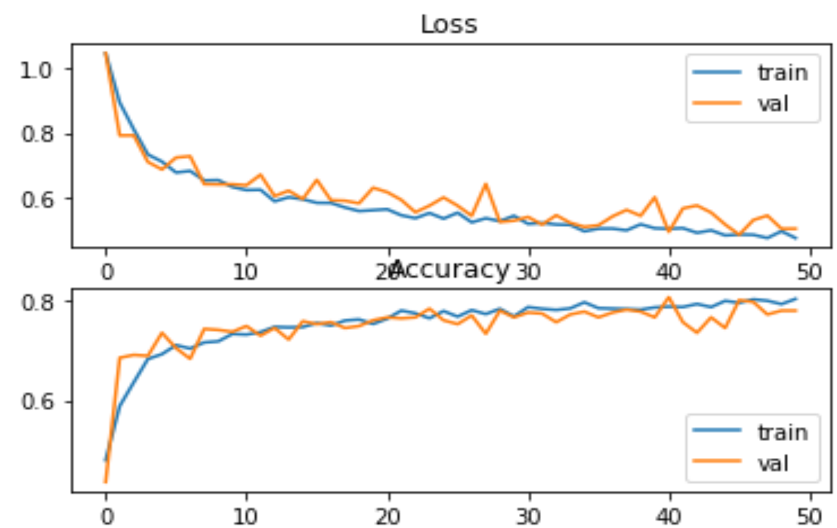
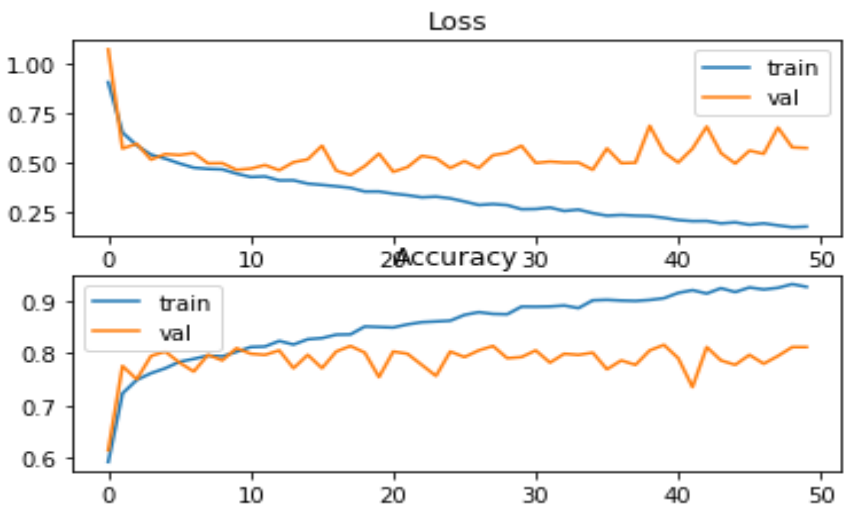


Figure 12: Loss and accuracy plots

Results(Comparisons)

CNN Model

- 50 epochs
- Test Data:
  - Accuracy: 0.75
  - Loss: 1.08
- Train Data:
  - Accuracy: 0.94
  - Loss: 0.16



CNN Model (with experiments)

- 50 epochs
- Test Data:
  - Accuracy: 0.89
  - Loss: 0.45
- Train Data:
  - Accuracy: 0.81
  - Loss: 0.442

References

[1]: https://www.who.int/news-room/fact-sheets/detail/pneumonia

[2] : Bar, Y., Diamant, I., Wolf, L., Lieberman, S., Konen, E. and Greenspan, H., 2015, April. Chest pathology detection using deep learning with non-medical training. In *2015 IEEE 12th International Symposium on Biomedical Imaging (ISBI)* (pp. 294-297). IEEE.

[3]: Milletari, F., Ahmadi, S.A., Kroll, C., Plate, A., Rozanski, V., Maiostre, J., Levin, J., Dietrich, O., Ertl-Wagner, B., Bötzel, K. and Navab, N., 2017. Hough-CNN: deep learning for segmentation of deep brain regions in MRI and ultrasound. *Computer Vision and Image Understanding*, *164*, pp.92-102.

[4]:https://towardsdatascience.com/data-augmentation-for-deep-learning-4fe21d1a4eb9

[5]: Wu, H. and Gu, X., 2015. Towards dropout training for convolutional neural networks. *Neural Networks*, *71*, pp.1-10.

[6] : https://keras.io/callbacks/

[7]: Oquab, M., Bottou, L., Laptev, I. and Sivic, J., 2014. Learning and transferring mid-level image representations using convolutional neural networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 1717-1724).

Thank You…