# Johns Hopkins Engineering

EN.525.670.81.SP23 - Machine Learning for Signal Processing

### **Chest X-Ray Image Classification**

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# Overview

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### Introduction

- Classify Images of Chest X-Rays between normal healthy lungs and pneumonia infected lungs
- A study has been done using a pre-trained deep learning Convolutional Neural Network (CNN) on chest x-rays achieved 92% accuracy
- Significance: Increase the efficiency of medical professionals examining X-Rays to fast track infected patients, extend to other diseases if successful
- Results:
  - Support Vector Machine found to perform with the best overall accuracy out our models, but not as good as pre-trained CNN (Kermany)
  - Our CNN performed the best on images of Pneumonia to a high accuracy while mis-classifying normal images with a much worse accuracy



# Objective

- Our goal is compare performance against Support Vector Machine (SVM),
   K Nearest Neighbors, and our own trained CNN image classifiers.
- Maximize overall accuracy and minimize the number of misdiagnosed Pneumonia cases (False Negatives)



Bacterial Pneumonia



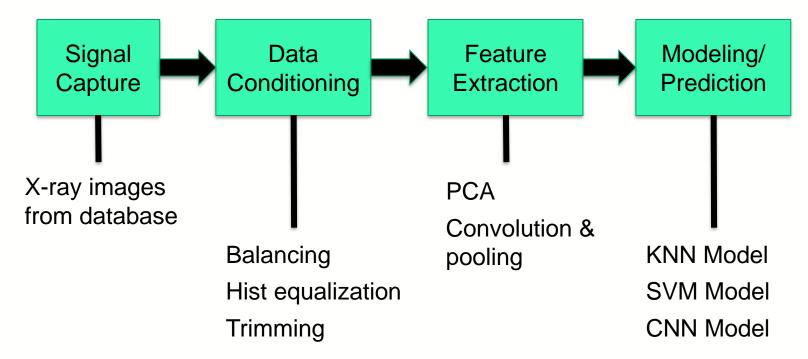
Viral Pneumonia



Normal



## Tasks





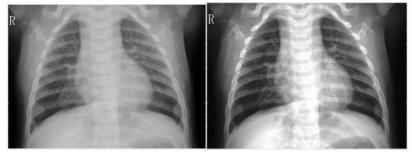
# Results - Sensor / Signal Capture

- X-Ray radiation passes through the body to a detector. Converted to image [2].
- ~5,850 X-rays from pediatric patients. Labeled by three experts and separated into training and test sets [3] [4].
- Downloaded from Kaggle [5].



## Results - Data Conditioning

- Balanced number of "normal" images and "pneumonia" images.
- Eliminated small file sizes [7].
- Tried histogram equalization to improve contrast [10].
- Tried trimming to improve signal-to-noise ratio.



Histogram Equalization (before and after)



Trimming (before and after)

### Results - Feature Extraction

- Principal Component Analysis
  - A dimensionality reduction method by linearly transforming the data into a new coordinate system where the highest variation of the data can be represented [9].
- CNN Feature Extraction
  - Addressed in the Convolution and Pooling Layers of the TensorFlow model
  - These hidden layers of the CNN extract features and combine weights to make output predictions from input values

# Results - Modeling / Prediction

#### K Nearest Neighbor (KNN)

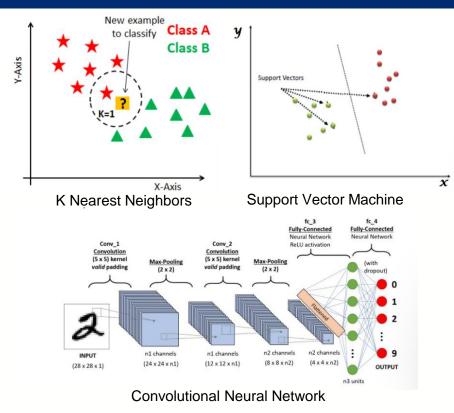
 Unsupervised machine learning classifier that uses the distance between feature vector to predict the most common class

#### Support Vector Machine (SVM)

 Supervised machine learning classifier that uses a linear boundary to make predictions

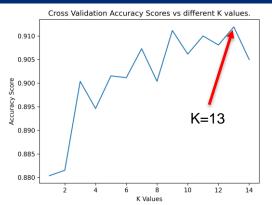
#### Convolutional Neural Network (CNN)

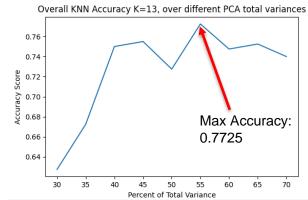
 Unsupervised machine learning classifier using neurons, hidden layers, and convolution to make predictions



### Results - KNN

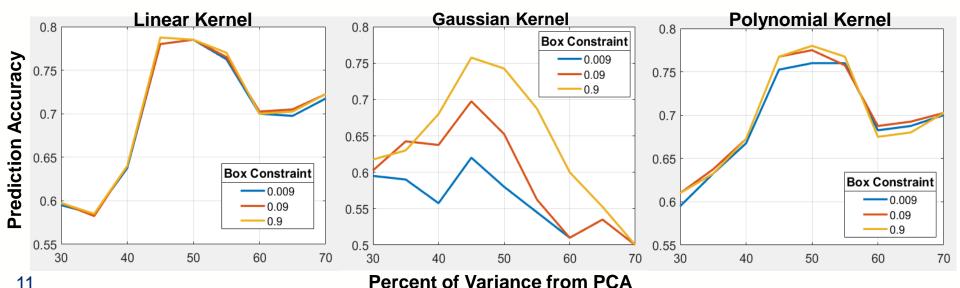
- Used PCA for feature extraction
- Run Cross Validation to find best K-Value to use
- Created K Nearest Neighbors classifier using sklearn python library with best K value (k=13) and populated with training data. [8]
- Predicted each of the test data points and computed confusion matrix & overall accuracy for each total variance





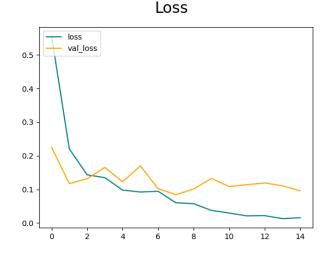
## Results - SVM

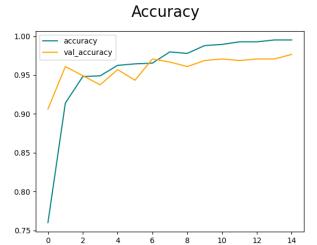
- Ran PCA on training images. Compared different total variances.
- Compared linear, gaussian, and polynomial kernels.
- Compared different box constraints for SVM.
- Compared with and without data conditioning.

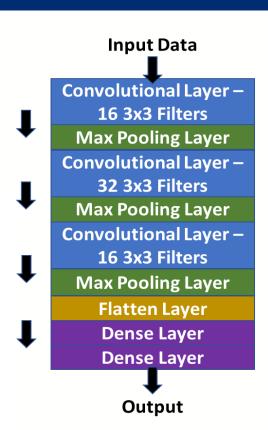


### Results - CNN

- Built a CNN in Python using TensorFlow keras [6] [7].
- Layers: 3 convolutional, 3 pooling, 1 flatten, 2 dense.
- 15 epochs completed during training.
- CNN did not perform as well as expected 66% accuracy on the test data.







### Results - Conclusions

- Demonstrated that machine learning can be used for classifying medical images.
- Different methods can be used for the same classification problem
- SVM performed well overall. Kermany's CNN far outperformed our CNN.
- Future work improve classification of "normal" images – many false positives.
- Future work apply lessons learned from this project to classify other medical images (MRI, CT scans, etc)

K-Nearest Neighbor Model					
		Actual Condition			
		Normal	Pneumonia		
Predicted	Normal	138	29		
Condition	Pneumonia	62	171		
		69%	86%		
		Overall Accuracy: 77.3%			

SVM Model					
		Actual Condition			
		Normal	Pneumonia		
Predicted	Normal	164	49		
Condition	Pneumonia	36	151		
		82%	75.5%		
		Overall Accuracy: 78.8%			

CNN Model					
		Actual Condition			
		Normal	Pneumonia		
Predicted	Normal	66	2		
Condition	Pneumonia	134	198		
		33%	99%		
		Overall Accuracy: 66%			



# Summary

- Demonstrated ability to apply learned MLSP techniques to real world applications through use of multiple image classifiers (KNN, SVM, and CNN) and the MLSP paradigm (sensor, data conditioning, feature extraction, and prediction)
- SVM performed the best (highest overall accuracy), expected as SVM is particularly suited to make binary decisions
- Our CNN performed the best on images of Pneumonia to a high accuracy while mis-classifying Normal images with a much worse accuracy



### References

Our Code can be found: <a href="https://github.com/theRealNoah/mlsp-image-classification">https://github.com/theRealNoah/mlsp-image-classification</a>

- [1] <a href="https://towardsdatascience.com/convolution-neural-network-for-image-processing-using-keras-dc3429056306">https://towardsdatascience.com/convolution-neural-network-for-image-processing-using-keras-dc3429056306</a>
- [2] https://iq.opengenus.org/basics-of-machine-learning-image-classification-techniques/
- [3] Kermany, Daniel; Zhang, Kang; Goldbaum, Michael (2018), "Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification", Mendeley Data, V2, doi: 10.17632/rscbjbr9sj.2
- [4] D. S. Kermany, M. Goldbaum, W. Cai, C. C. S. Valentim, H. Liang, S. L. Baxter, A. McKeown, G. Yang, X. Wu, F. Yan, J. Dong, M. K. Prasadha, J. Pei, M. Y. L. Ting, J. Zhu, C. Li, S. Hewett, J. Dong, I. Ziyar, A. Shi, R. Zhang, L. Zheng, R. Hou, W. Shi, X. Fu, Y. Duan, V. A. N. Huu, C. Wen, E. D. Zhang, C. L. Zhang, O. Li, X. Wang, M. A. Singer, X. Sun, J. Xu, A. Tafreshi, M. A. Lewis, H. Xia, and K. Zhang, "Identifying medical diagnoses and treatable diseases by image-based Deep Learning," Cell, vol. 172, no. 5, 2018.
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- [10] <a href="https://iq.opengenus.org/contrast-enhancement-algorithms/#:~:text=Machine%20Learning%20(ML),-">https://iq.opengenus.org/contrast-enhancement-algorithms/#:~:text=Machine%20Learning%20(ML),-</a>
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