Medical Image Diagnostic Analysis Laidel Presentation

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THE TEAM

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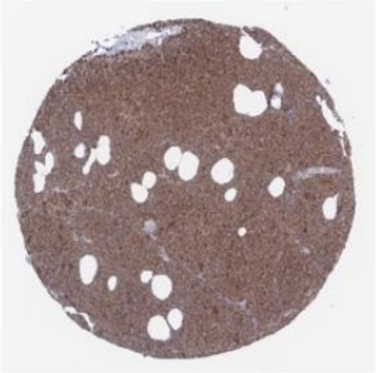
MOTIVATION AND OBJECTIVE

- Reducing clinicians, accelerate patient enrollment and recruitment process to better diagnose ailments of the human body.
- Building a classification model for images related to diseases like lung cancer, Alzheimer, etc. to help in better diagnosis.
- To automate the process for lab experts who individually analyze sliced images to classify or segment them.
- To build state-of-the-art deep learning models to classify electron microscope sliced cell images from different parts of human body.

ORGAN CELL CLASSIFICATION

- The classification dataset is acquired from the CNS lab at IU and contains electron microscope sliced cell images from different parts of human body such as colon, liver, kidney, liver etc.
- It consists of 1200 training and 600 test images of size 4000 x 3000
- The total size of the dataset is 45.1 GB

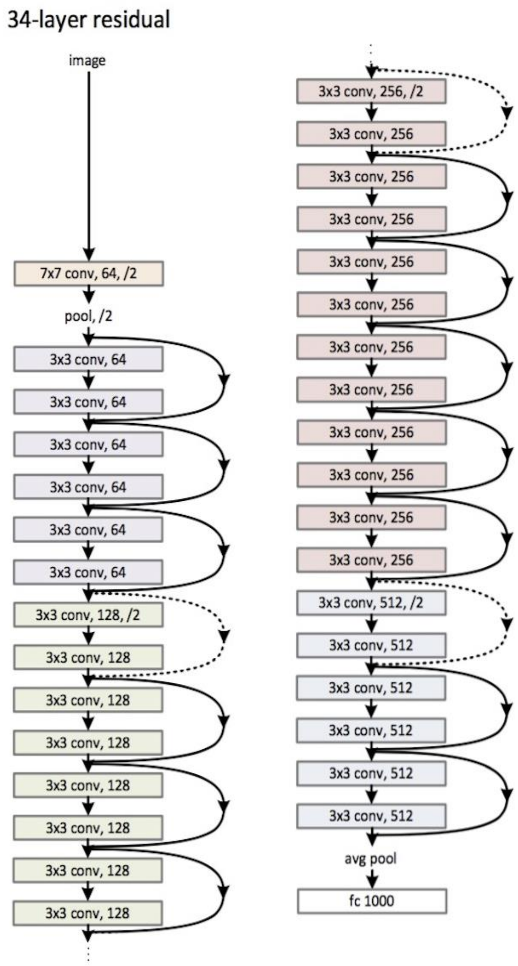
Liver



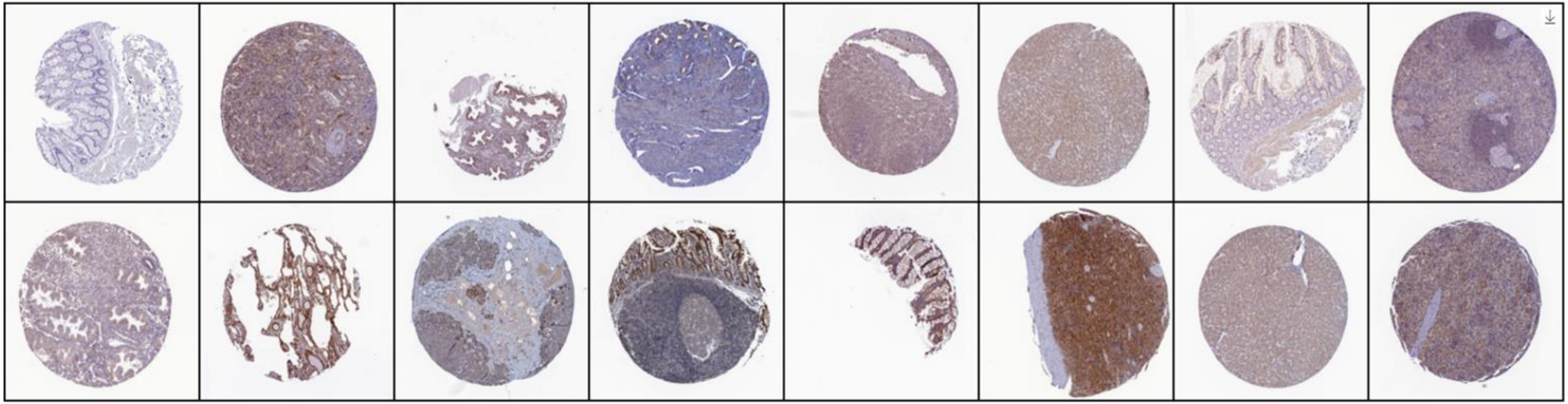
Pancreas

ResNet-34 Architecture

- The experimentation includes a basic CNN model which feeds input images of two sizes, 224 X 224 and 128 X 128.
- In order to boost performance, we then moved to pretrained ResNet models namely three ResNet models - ResNet 18, ResNet 34 and Resnet 50.
- For all the images we converted them to 224 X 224 before feeding it to the model along with data augmentation techniques like flipping, rotation, contrast normalization, etc.



Visualization of Predictions at Epoch 1

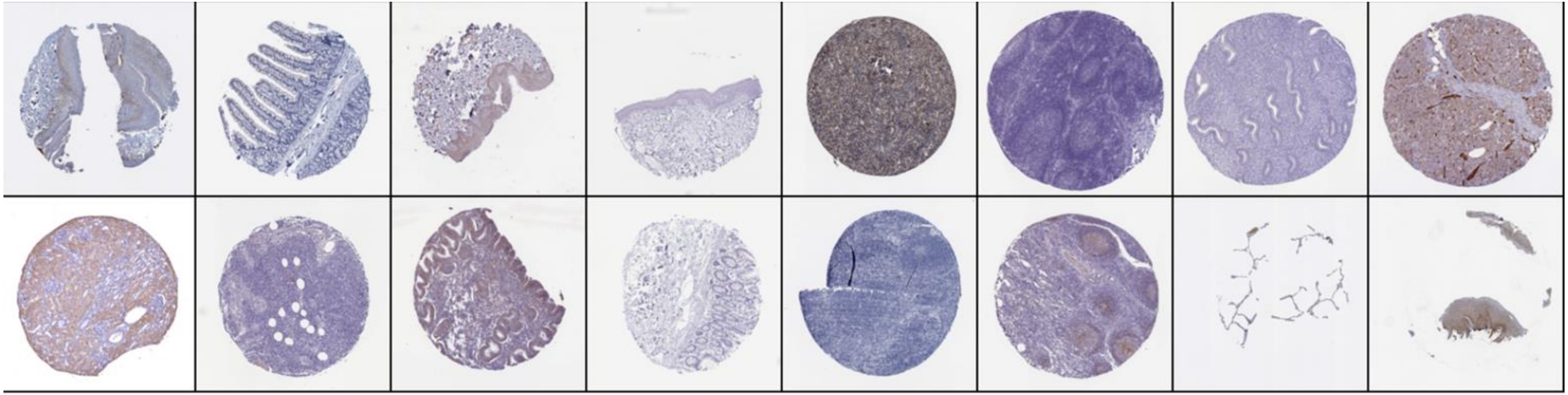


Pred: ['lung', 'liver', 'pancreas', 'liver', 'liver', 'liver', 'liver', 'pancreas', 'liver', 'pancreas', 'liver', 'liver', 'pancreas', 'liver', 'liver', 'liver'] Truth: ['colon', 'small_intestine', 'spleen', 'endometrium_1', 'small_intestine', 'spleen', 'pancreas', 'small_intestine', 'endometrium_1', 'liver', 'spleen', 'pancreas', 'colon', 'small_intestine', 'spleen', 'small_intestine']

Truth Values: colon, small intestine, spleen, endometrium, small intestine, spleen, pancreas, endometrium

Predicted Values: lung, liver, pancreas, liver, liver, liver, pancreas, liver

Visualization of Predictions at Epoch 30

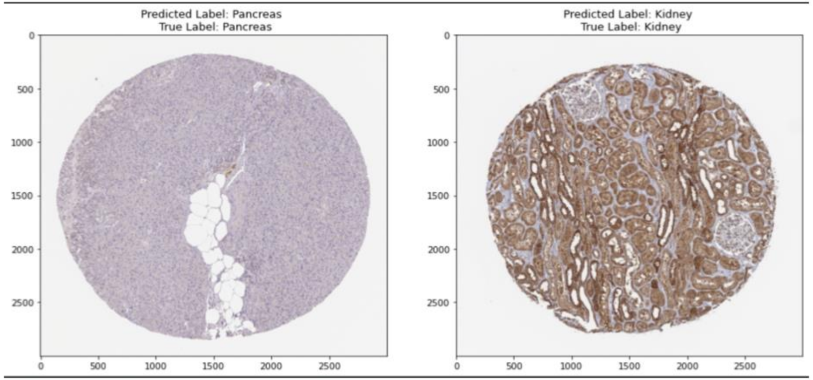


Pred: ['lymph_node', 'endometrium_1', 'lymph_node', 'kidney', 'colon', 'endometrium_1', 'small_intestine', 'pancreas', 'skin_1', 'endometrium_1', 'small_intestine', 'skin_2', 'endometrium_1', 'endometrium_1', 'lymph_node', 'lymph_node'] Truth: ['lymph_node', 'endometrium_1', 'kidney', 'kidney', 'colon', 'endometrium_1', 'small_intestine', 'pancreas', 'skin_1', 'endometrium_1', 'small_intestine', 'skin_2', 'endometrium_1', 'endometrium_1', 'lymph_node', 'lymph_node']

Truth Values: lymph node, endometrium, kidney, kidney, colon, endometrium, small intestine, pancreas

Predicted Values: lymph node, endometrium, lymph node, kidney, colon, endometrium, small intestine, pancreas

Results



Above figure shows the result of image classification model using ResNet34 which achieves an accuracy of 97.33%

Name	Runtime	batch_size	epochs	lr	test_batch_size	Test Accuracy	Test Loss	Train Accuracy	Train Loss
resnet-50	14372	32	30	0.001	32	78.5	11.37189287	95.08333333	7.026275456
basic_cnn_small	14770	64	30	0.001	64	50.66666667	15.5384897	76.75	11.43894145
basic_cnn	15129	16	30	0.001	16	49.5	97.77161705	92.5	16.4266745
resnet-34	5799	32	30	0.001	1000	97.33333333	0.156270385	93.74478732	9.096587978
resnet-18	7779	128	30	0.001	1000	92.5	0.341986388	92.41034195	3.759079576

Results for image-classification task: above table shows the comparative analysis on different models tried on the same dataset

National Institutes of Health Chest X-Ray

- 112,120 X-ray images with disease labels from 30,805 unique patients.
- Natural Language Processing is used to text-mine disease classifications from the associated radiological reports.
- Labels are expected to be >90% accurate and suitable for weakly-supervised learning.

There are 15 classes (14 diseases, and one for "No findings"). Images can be classified as "No findings" or o[illegible]asses.

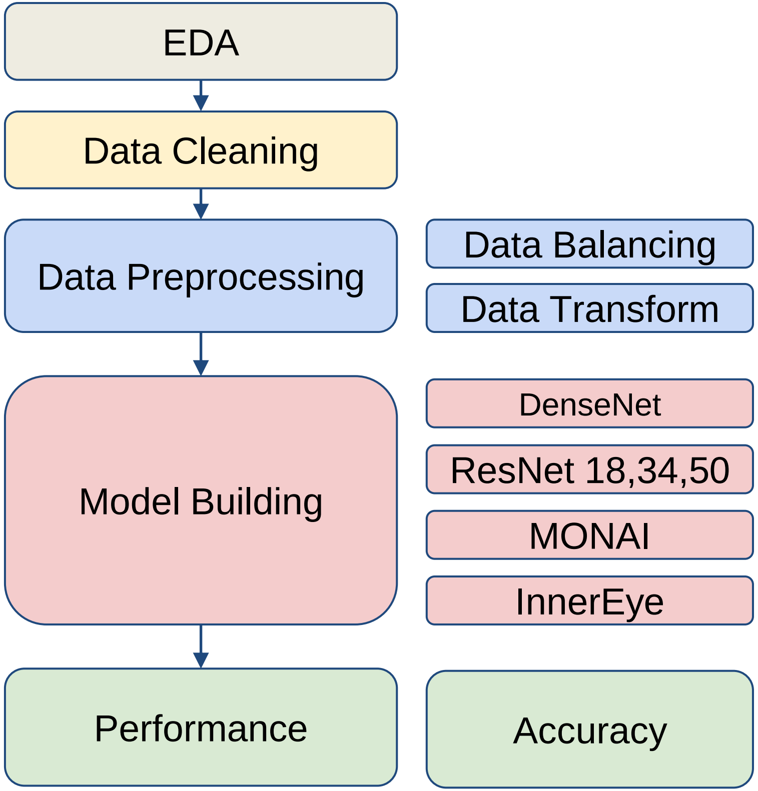
Cardiomegaly|Emphysema

Cardiomegaly|Effusion

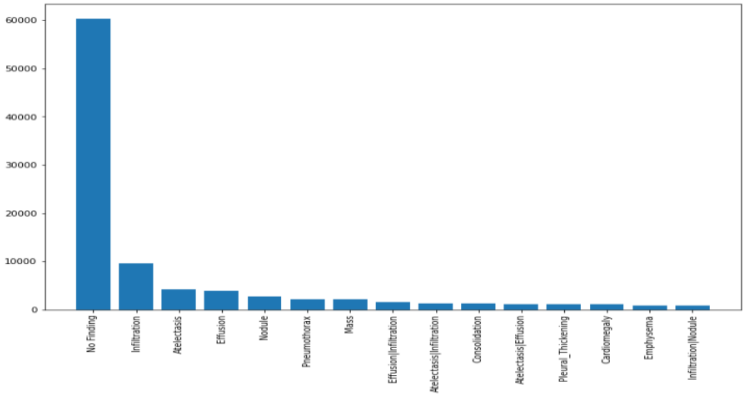
OTHER DATASETS

1. BRATTS
   a. Problems
      i. Segmentation is available but no labels
   b. Positives:
      i. Can be used with MONAI or InnerEye models
2. OASIS-3
   a. Problems:
      i. 3-D dataset which requires slicing and lot of preprocessing
   b. Positives:
      i. Can be used with MONAI or InnerEye models

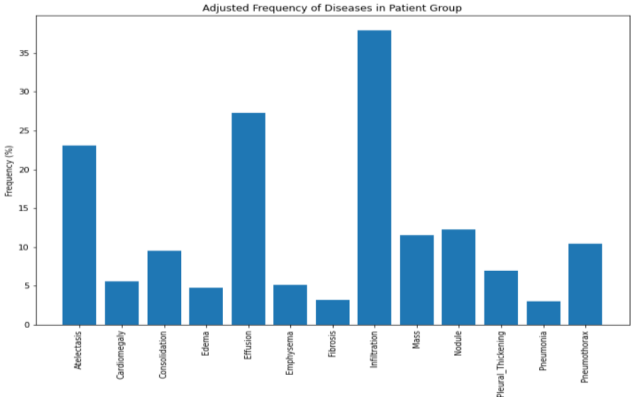
METHODOLOGY

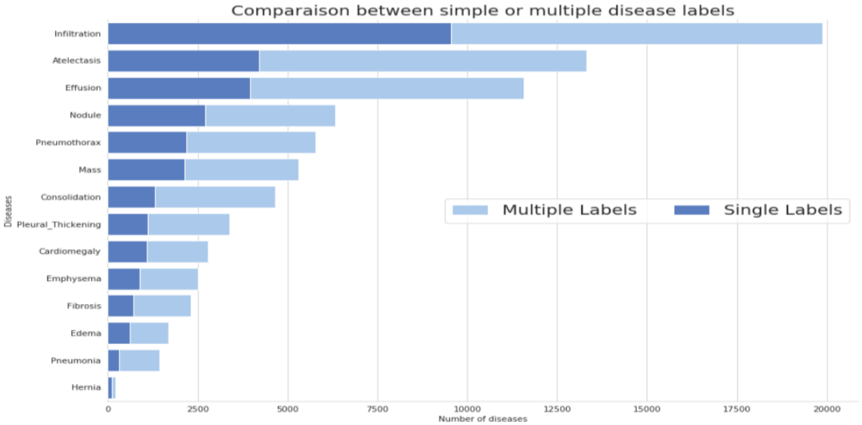


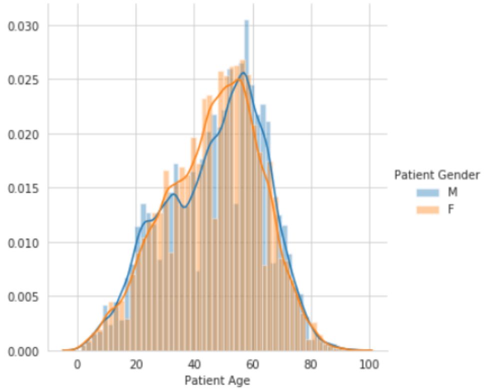
EXPLORATORY DATA ANALYSIS



Balancing







DATA CLEANING

PHOTO: Citation link

1. Imbalanced Data
   a. As mentioned above their are a lot of images with no findings.
2. Null Values
3. Multiple Diseases in one entry
   a. These images are separated to create separate instance for each disease
4. Less number of entries for a particular disease.
   a. Some diseases were found to have entries <1000
   b. These diseases are removed

DATA PREPROCESSING

1. Unlabelled image data
2. Not separated according to diseases

Rectifications:

1. Identified and grouped images related to various diseases
2. Images with multiple diseases were duplicated
3. Created separate folders for training and testing with folder for each disease

RESULTS AND PROBLEMS FACED

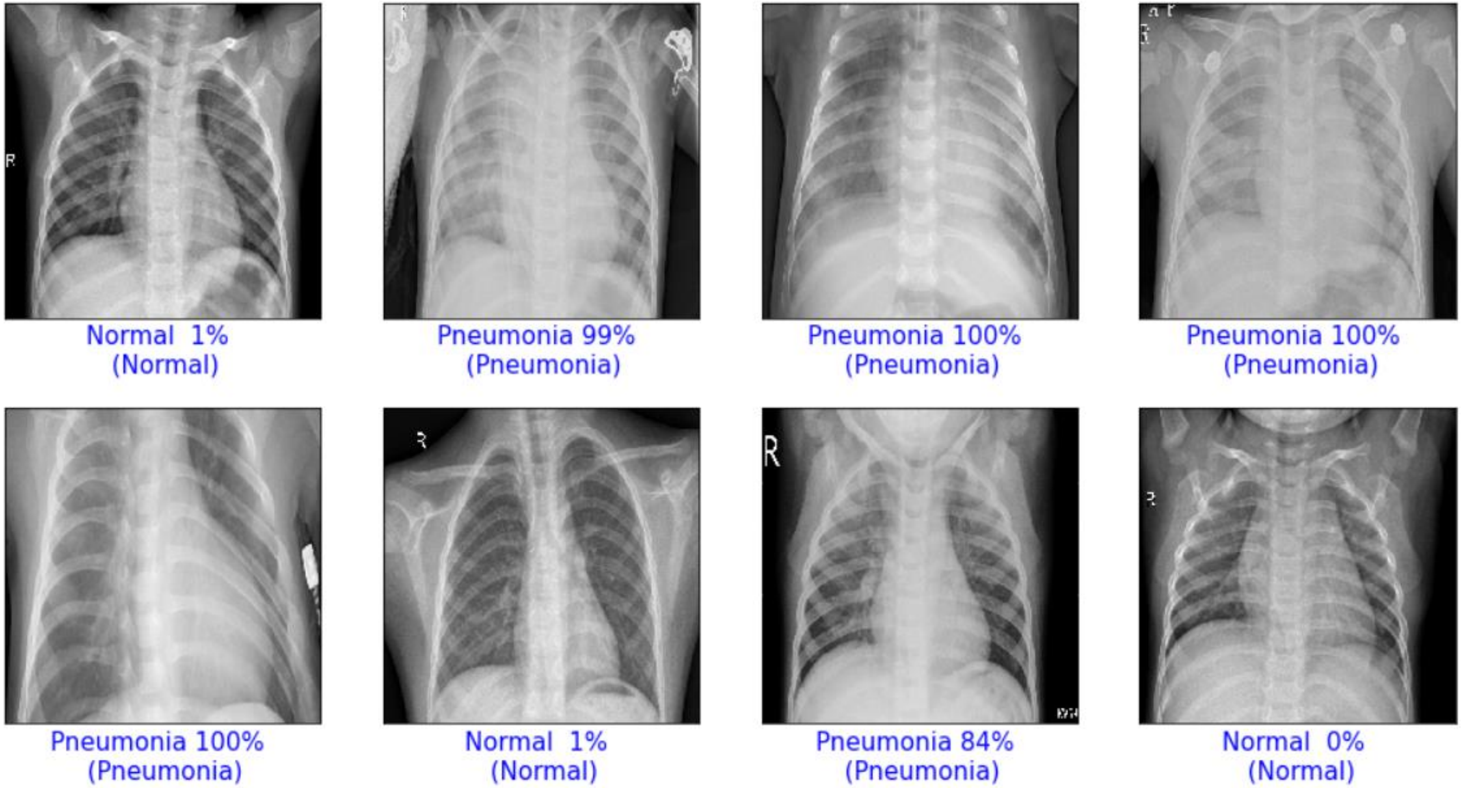
1. Even after extensive cleaning of dataset, building various models, and hyperparameter tuning, the accuracy received was not good. (~30-35%)

1. On top of building good models having an appropriate dataset is of utmost importance

1. The resnet model trained on the organ cell dataset worked really well but it didn’t give results on the NIH dataset as expected

1. NIH dataset requires further manual cleaning by going through all the images which is out of scope for this project

BINARY CLASSIFICATION: Pneumonia Detection



GUIDE FOR FUTURE WORK

- Explore other classification datasets in the medical domain for example: Oasis-3 for brain image classification
- Our models can be extended further for catering various datasets and real-world dataset as well.
- Majorly, the models will be utilized directly, if the data is pre-processed well to be fed into our created architectures.

THANK YOU