Multilabel Thoracic Disease Classification through a Lightweight Convolutional Neural Network

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Abstract

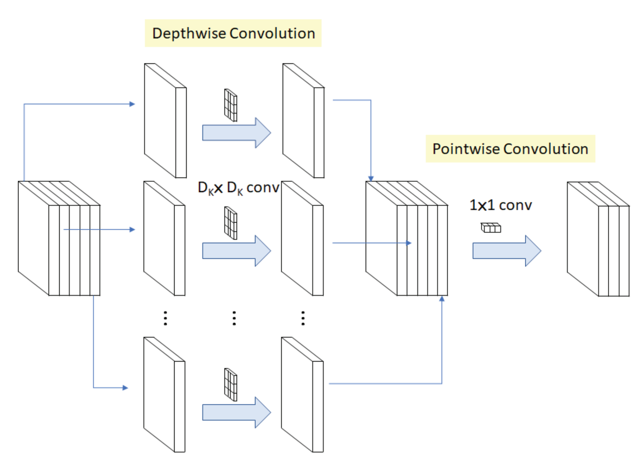
Medical diagnosis through artificial intelligence has presented enormous potential, however many hospitals and clinical settings have yet to implement any deep learning methods. There are several reasons for this divide including lack of transparency, difficulty with reproducibility, among many others. This project will address these two specific issues, using explainability techniques and by presenting a comprehensive overview of how to build and test a simple convolutional neural network (CNN) model.

MobileNet

The simplified CNN model used here is the MobileNetV1 from Keras, due to the size of the NIH Chest X-Ray dataset. Its computational speed and reduced dimensions are superior to normal methods, though its accuracy may be slightly impacted.

Key differences: Depthwise Separable Convolutions, Width Multiplier, Resolution Multiplier

Layer (type)	Output Shape	Param #
mobilenet_1.00_128 (Functional)	(None, 4, 4, 1024)	3228288
conv_pw_13 (DepthwiseConv2D)	(None, 4, 4, 1024)	10240
conv_pw_13_relu (Activation)	(None, 4, 4, 1024)	0
global_average_pooling2d_3 (GlobalAveragePooling2D)	(None, 1024)	0
dropout_6 (Dropout)	(None, 1024)	0
dense_6 (Dense)	(None, 512)	524800
dropout_7 (Dropout)	(None, 512)	0
dense_7 (Dense)	(None, 13)	6669



References

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Background

Physicians are *overburdened* with the increasing number of patients requiring care for thoracic diseases, which easily exceed two hundred distinct types.

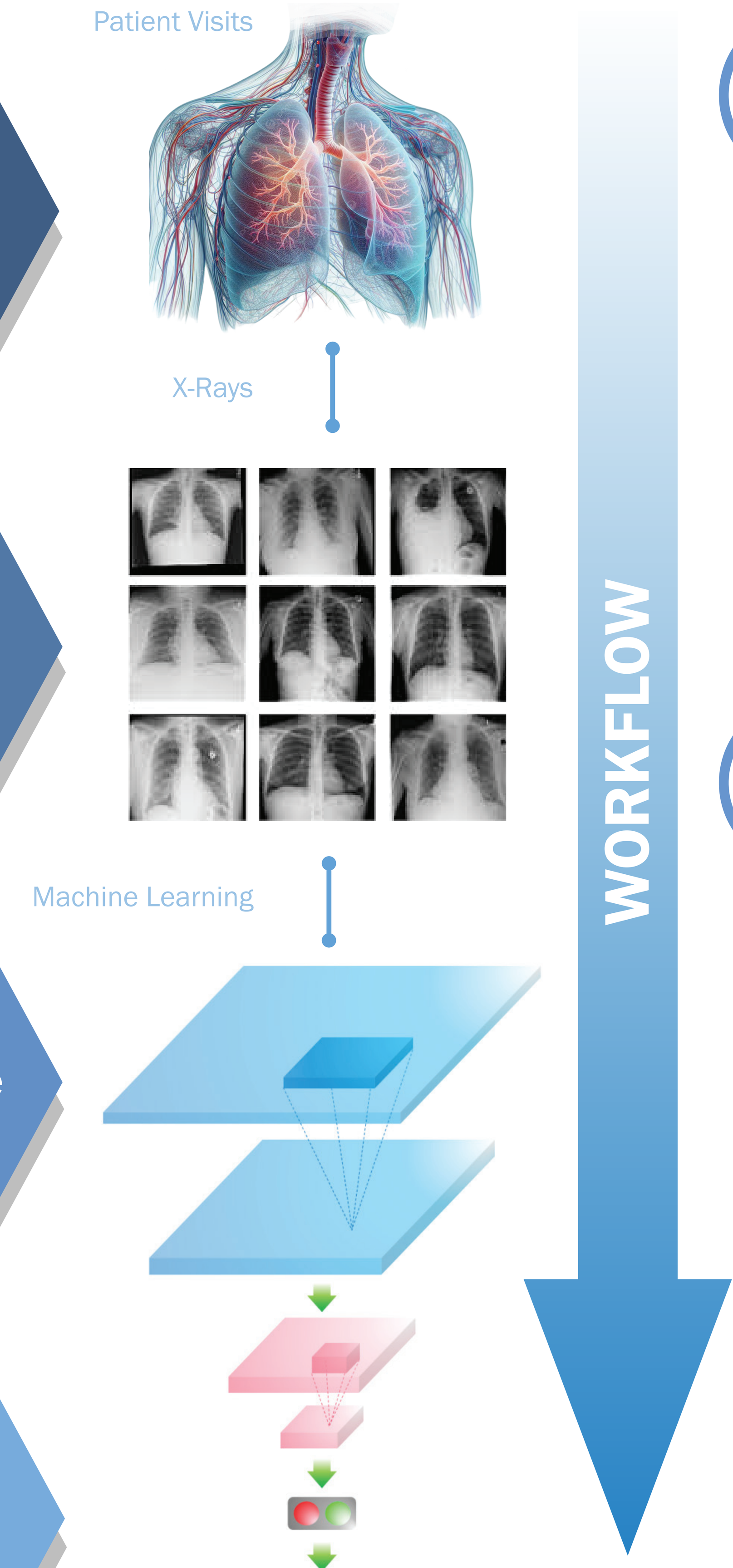
Image classification is one of the most fundamental tasks in the field of computer vision. It is the act of categorizing pictures using assigned labels from datasets of annotated pictures.

Using *pixel-level analysis*, CNNs makes predictions on which group the input belongs to. CNNs are a popular choice for handling large amounts of high-dimensional, spatial data, and are flexible across many datasets.

The *NIH Chest X-Ray dataset* will be used due to its quality and accessability. There are fourteen separate categories of thoracic disoders that will act as the labels for the model.

Many prior studies have leveraged this dataset, however the majority have only explored *binary classification* of specific diseases. Additionally, many lack sufficient interpretability for outsiders.

The project will classify some of the most commonly identified illnesses using a simple CNN to *a high degree of accuracy*, and produce *visualizations* to demonstrate how the model generated its results.



Methods

0 *Set-Up*

1. Download image zip file and CSV spreadsheet.
2. Upload to Google Drive and mount it to Google Collab.
3. Find all image file paths and connect them from the CSV to individual pictures.
4. Select the top 15 percent of individual labels which makes up 84.27 percent of the total dataset.
5. Produce data visualizations for initial analysis.

1 *Preprocessing*

1. Remove "No findings" label. Any other tags not under the 14 labels are classified as no finding.
2. Create one hot encoded columns for each unique disease label.
3. Drop diseases that have <1000 cases.
4. Enter weights for normalization and resize images.
6. Split dataset into train & test/validation data.
7. Create data loaders for training.

2 *Feature Extraction*

Use pretrained MobileNet model as a base for feature extraction:

1. Load the model by calling MobileNet.
2. Input the shape of the x-ray images and keep the rest of the default parameters.
3. Add layers to the base model for feature extraction.

3 *Model Training*

- *Optimizer*: Adam
- *Loss:* Binary cross-entropy
- *Sample Size*: 1k, 10k, 40k
- Using "Early Stopping function", epochs are ended early if they are overfitting.
- *Output Metrics*: Loss, binary accuracy, mean absolute error, AUC curve.

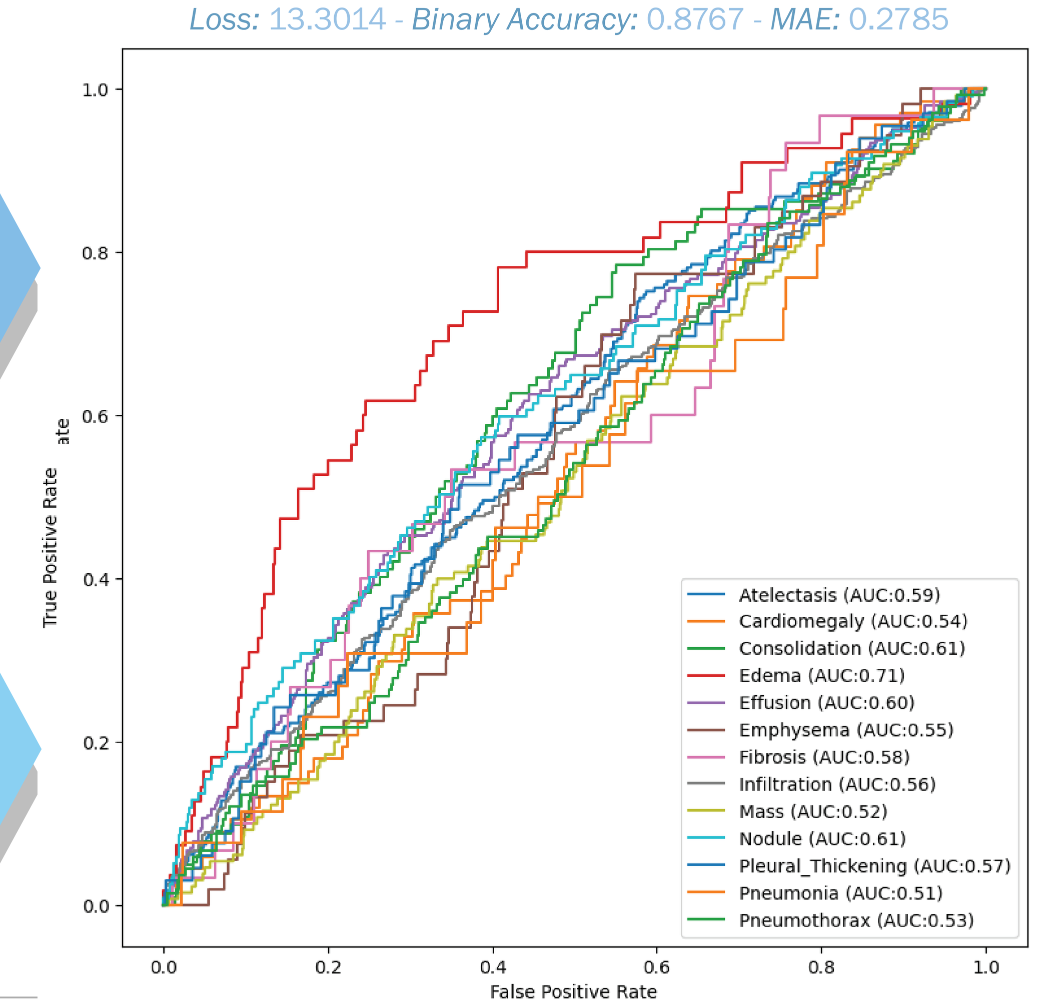
Attempted Explainability Techniques: LIME, Anchors, SHAP Values, GradCAM

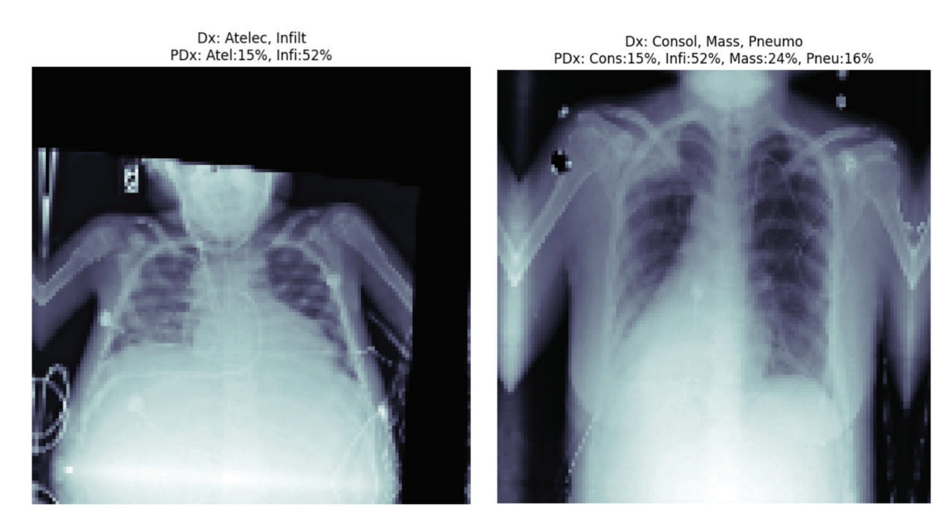
- Most of these appear to work with standard CNN models, however they were completely inoperable on this project. MobileNet structure appears to be incompatible with most popular explainability techniques.
- *Occlusion sensitivity* and *confusion matrixes* were the only two that were able to be executed.

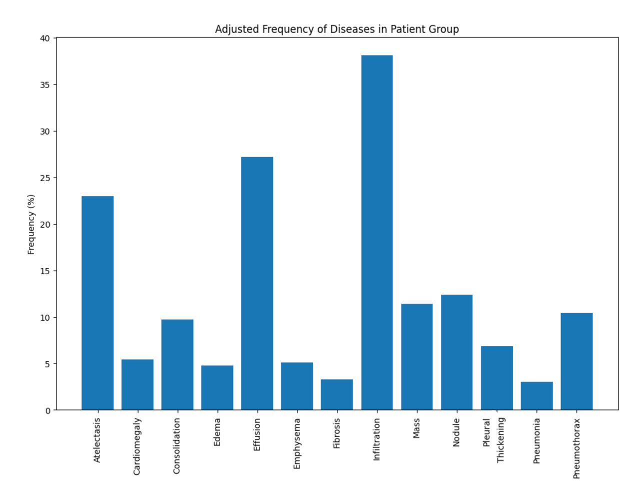
Diseases	Dx	PDx
Atelectasis	23.63%	28.85%
Cardiomegaly	6.54%	17.53%
Consolidation	9.96%	19.79%
Edema	5.37%	15.86%
Effusion	24.80%	32.22%
Emphysema	5.18%	19.82%
Fibrosis	2.93%	18.79%
Infiltration	37.50%	33.13%
Mass	12.70%	24.58%
Nodule	11.43%	24.78%
Pleural Thickening	6.45%	22.51%
Pneumonia	2.54%	16.88%
Pneumothorax	12.99%	25.48%

Results-40k

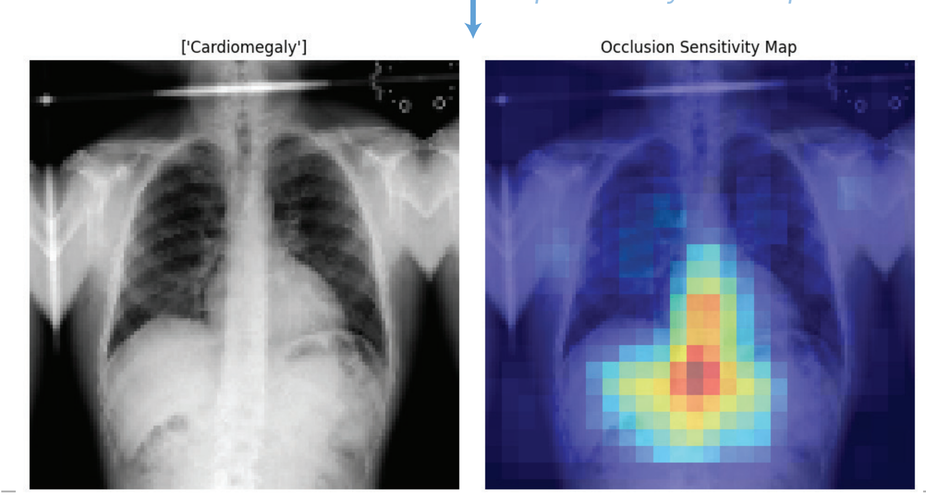
Loss: 13.3014 - *Binary Accuracy:* 0.8767 - *MAE:* 0.2785







Explainability Technique



Conclusion

While much more efficient and computationally easier, MobileNet is very limited in its functions. More layers and samples correlated to higher performance but significant increases in precoessing times and memory usage. *Future work* will involve experimenting with more layers and parameters for a higher accuracy.