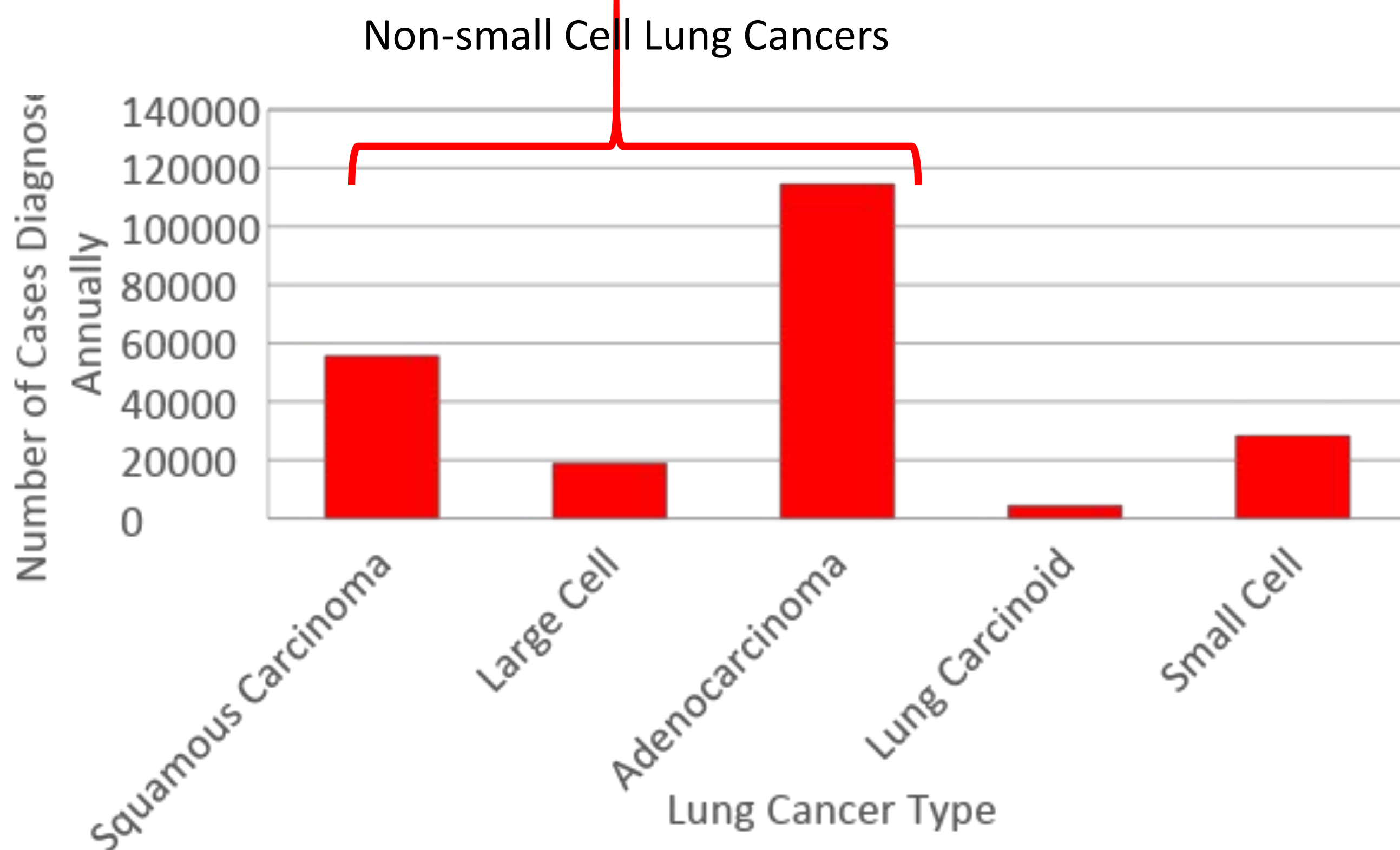


Purpose

Develop a system that can detect and classify tumors in chest CT scans

Background

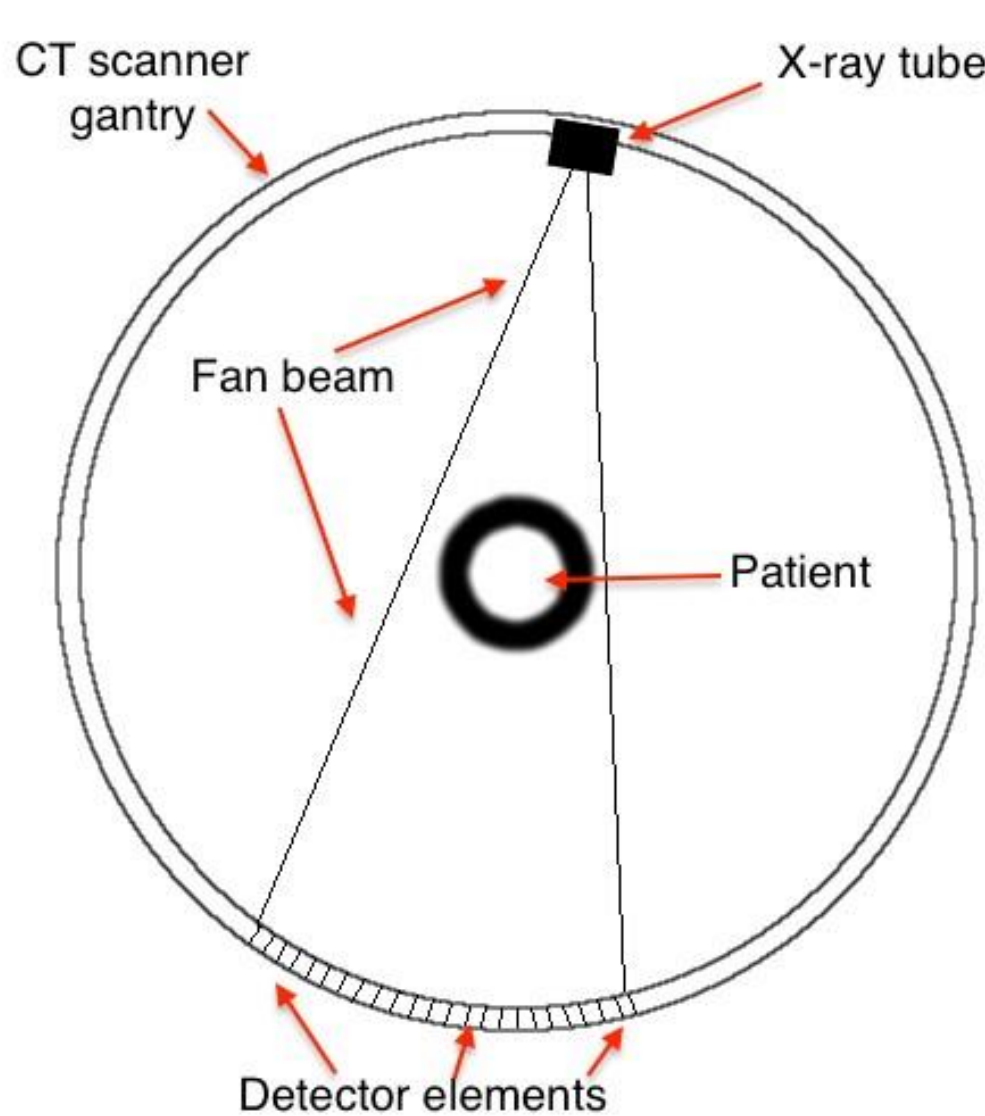
Lung Cancer and Non-small Cell Lung Cancer



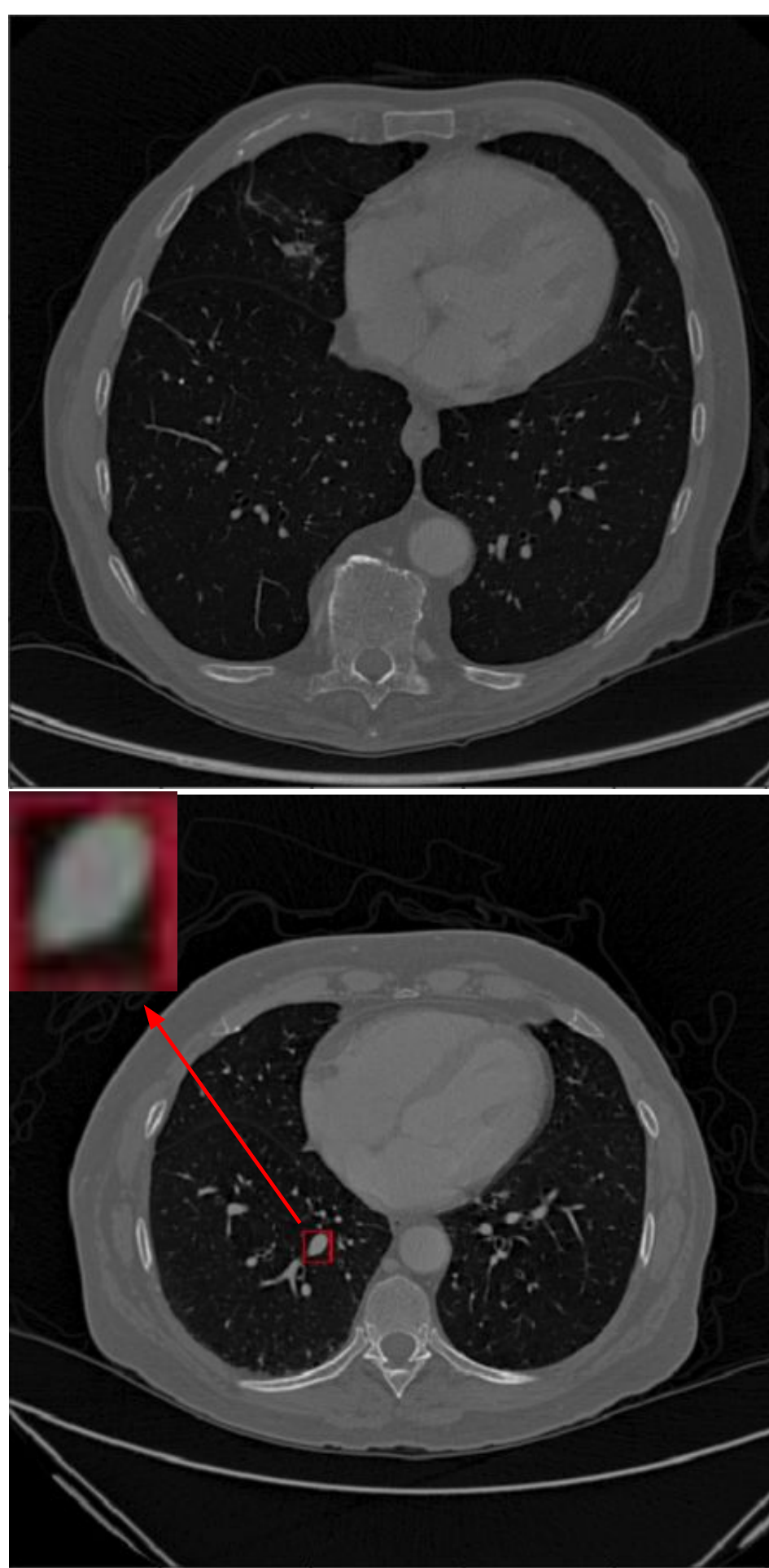
- Lung cancer responsible for 1.69 million (1 in 6) deaths worldwide (in 2015) [8]
- Misdiagnosis results in approximately 40,000 of those deaths [13]
- Most common form of lung cancer, non-small cell lung cancer (NSCLC), constitutes 155,870 of lung cancer deaths annually in the US [1]

Figure 1. Commonality of the different lung cancer forms (figure created by student researchers) [1]

Computed Tomography (CT) Scans



- 3-Dimensional reconstruction of a series of cross sections [18]
- Generally accepted for screening purposes



Lung-RADS Categories for Diagnosis in CT Screening [2]:

- 0: Incomplete
- 1: Negative
- 2: Benign Appearance
- 3: Probably Benign
- 4A: Low Suspicion of Malignancy
- 4B: Intermediate Suspicion of Malignancy
- 4X: Moderate Suspicion of Malignancy
- S: Clinically Significant Findings (Non-Lung Cancer)
- C: Prior Diagnosis of Malignancy

Figure 2. Process of a CT-scan (Source of image: URL: <http://www.neighborhoodradiologist.com>)

- Critical first step in cancer diagnosis [18]
- Radiologists search for suspicious regions in slices and analyze those regions of interest (ROIs) for classification

Figure 3. Juxtaposition between a negative slice of a CT-scan and one that hosts a malignant tumor (images taken from The Cancer Imaging Archive)

Deep Learning

- Advances various fields, especially in medicine
- Convolutional Neural Networks (CNNs), a type of neural network gaining popularity, self-determines relevant features to achieve the desired output [15]
- Artificial Neural Networks (ANNs) require manual feature extraction for a classification task

Convolutional Neural Network (CNN) Overview

Functionality:

- Biological Connection: certain neurons fire when specific features (e.g. edges) are detected
- Classification: ability to output a class label from an input image
- Low-level, basic features detected first and features become more abstract as tensor propagates

Network Structure:

- Input Layer: original image (tensor) for classification
- Convolution Layer: transforms tensor
- Pooling Layer: down-sampling
- Dense Layer: computes class scores
- Output Layer: shows probability of each class
- ReLU: non-linear activation function
- Backpropagation: process of adjusting parameters of the network

CNN Goals

1. Detect Nodules
2. Discern between malignant and benign lung cell tumors

Deep Learning for Classification of Non-small Cell Lung Tumors in CT Scans

Methods

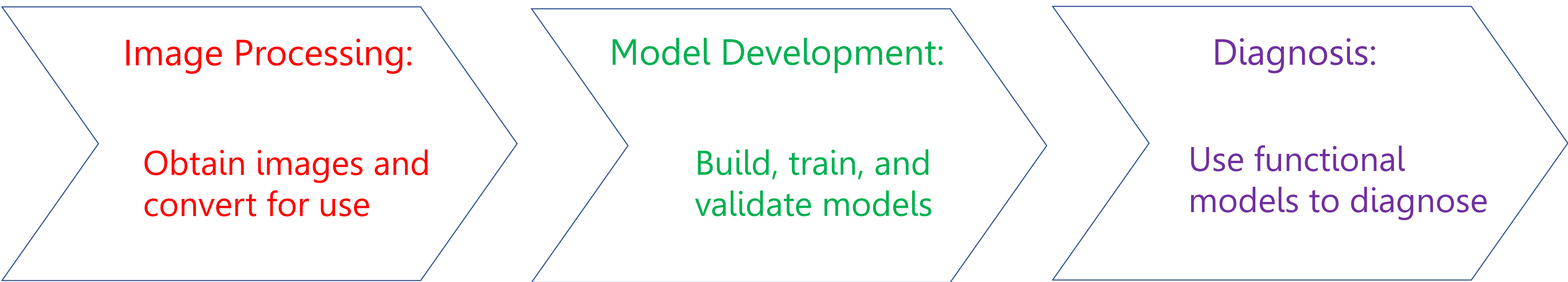


Image Processing

- Obtain CT-scan images and patient diagnosis information from The Cancer Imaging Archive (TCIA)
- Convert Dicom files to “png” for easier use in Python and compatibility with Tensorflow
- Image manipulation with flip and rotations

Model Development

- Define the model
- Train the model using backpropagation
- Validate model to tune network

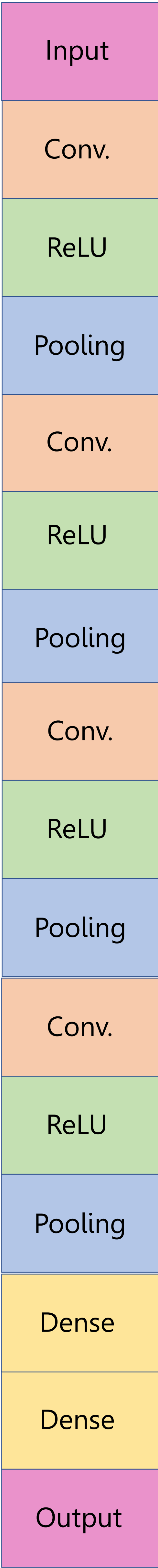


Table 1. Convolution Layer Properties: the filter size and number of filters chosen were based on earlier work [4] (table created by student researchers)

	Filter size:	Number of Filters:
Conv.1	8x8	32
Conv.2	8x8	32
Conv.3	4x4	64
Conv.4	4x4	64

Table 2. Split of the dataset for model development (table created by student researchers)

Dataset	% Split	Detection	Classification
Training	75	5875	414
Validation	15	1036	72
Testing	10	857	49
Total	100	7768	535

- Conv.: Stride- 1x1
- Activation function: ReLU
- Pooling: Type- Max-pooling
- Pooling: Size- 2x2
- Pooling: Stride- 1x1
- Use of Padding
- Training: Batch Size- 32
- Training: AdamOptimizer with a learning rate of 1.0×10^{-4}
- Classification: softmax regression

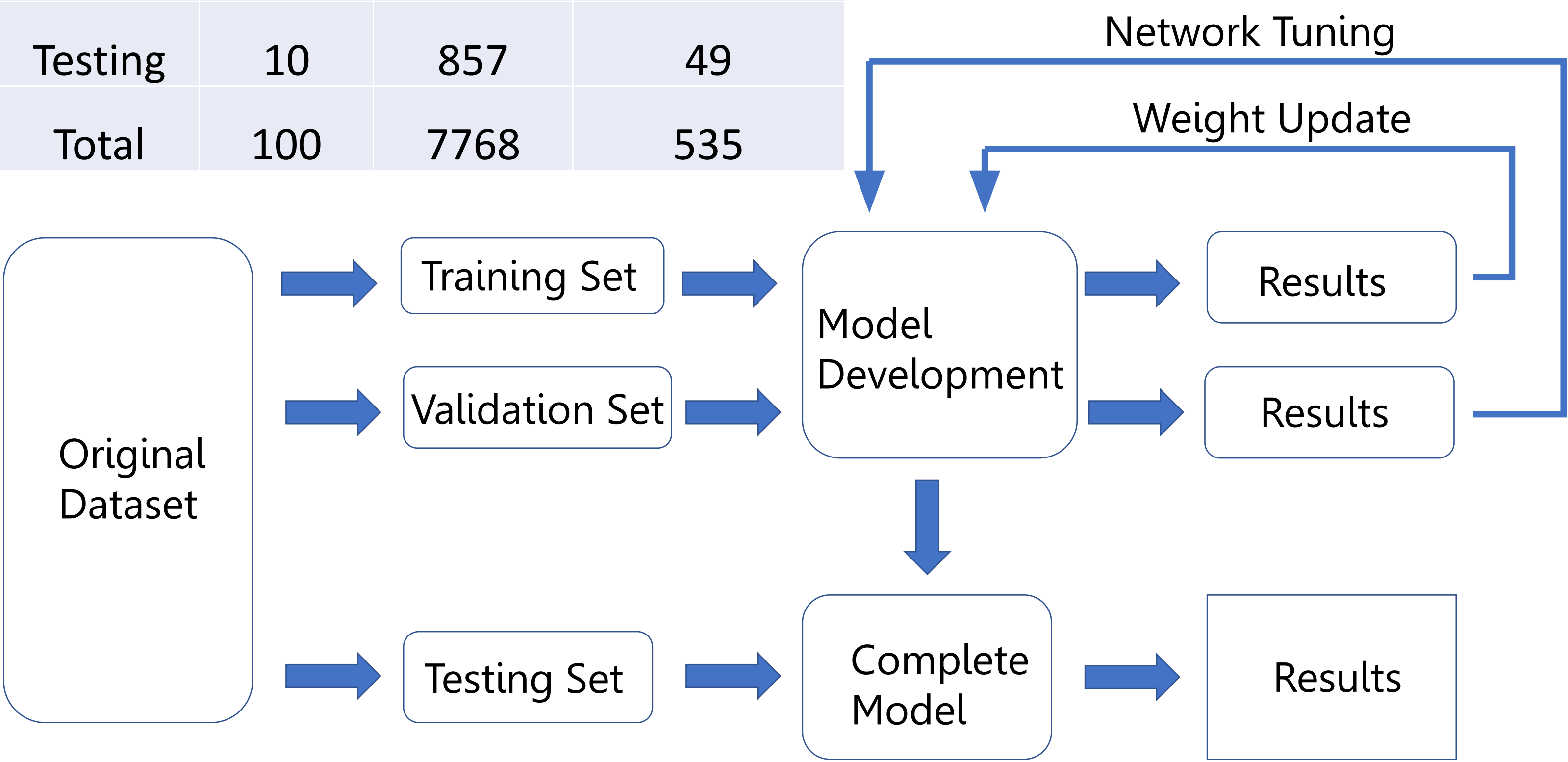
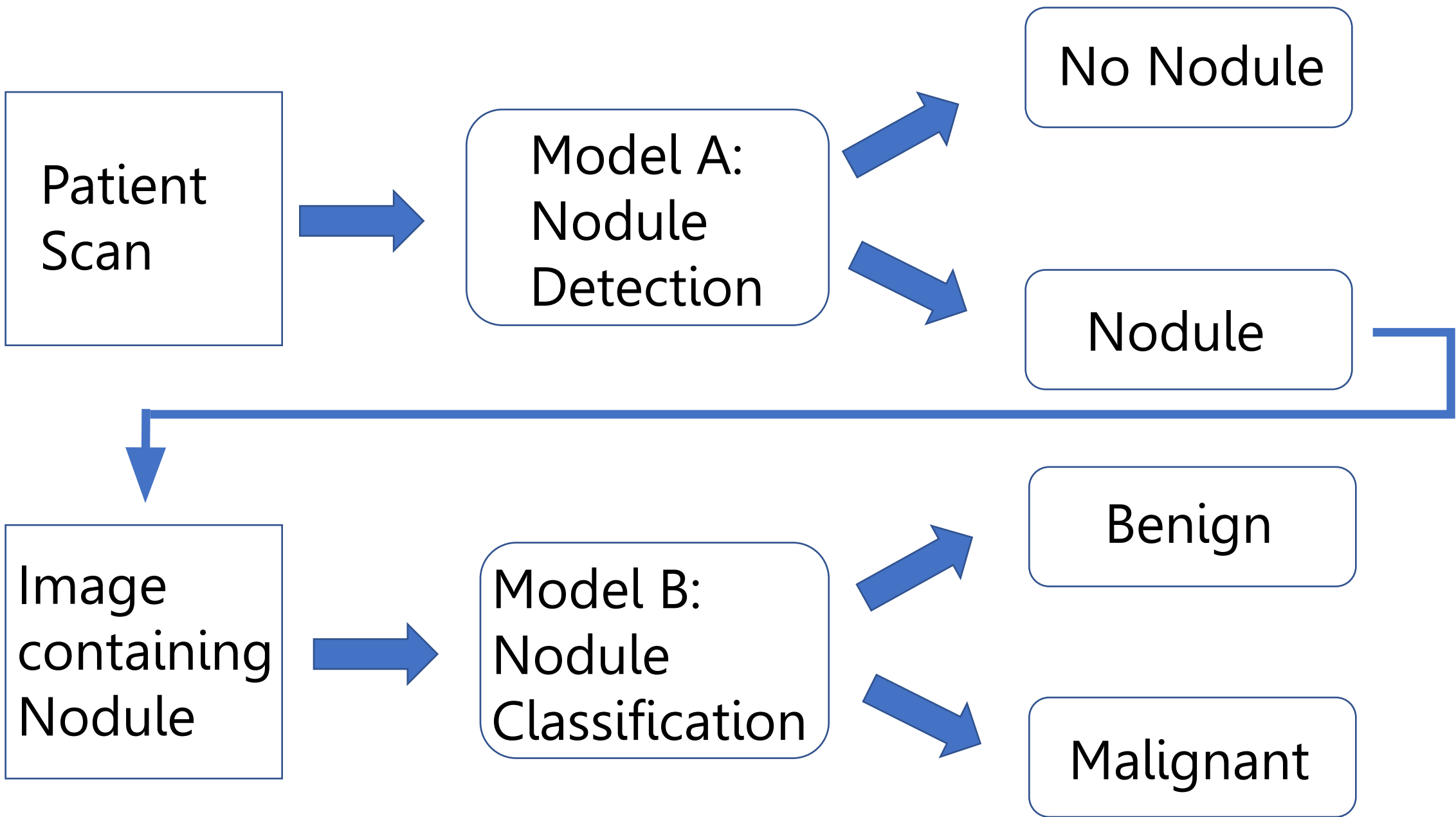


Figure 5. The developmental process of a neural network: figure based on earlier work [10] (figure adapted by student researchers)



Diagnosis:

- Complete model is usable with a certain trusted accuracy derived from the results of the testing set

Figure 4. Architecture of the constructed model (figure created by student researchers)

Figure 6. Dual-network Layout (figure created by student researchers)

Results and Discussion

Table 3. Model B's training progress
(table created by student researchers)

Epoch	Validation Accuracy (%)	Loss
1	65.6	0.664
2	59.4	0.664
3	65.6	0.642
4	59.4	0.636
5	65.6	0.630
6	62.5	0.625
7	68.8	0.613
8	71.9	0.610
9	71.9	0.606
10	71.9	0.603
11	78.1	0.598
12	75.0	0.597
13	71.9	0.594
14	75.0	0.587
15	75.0	0.585

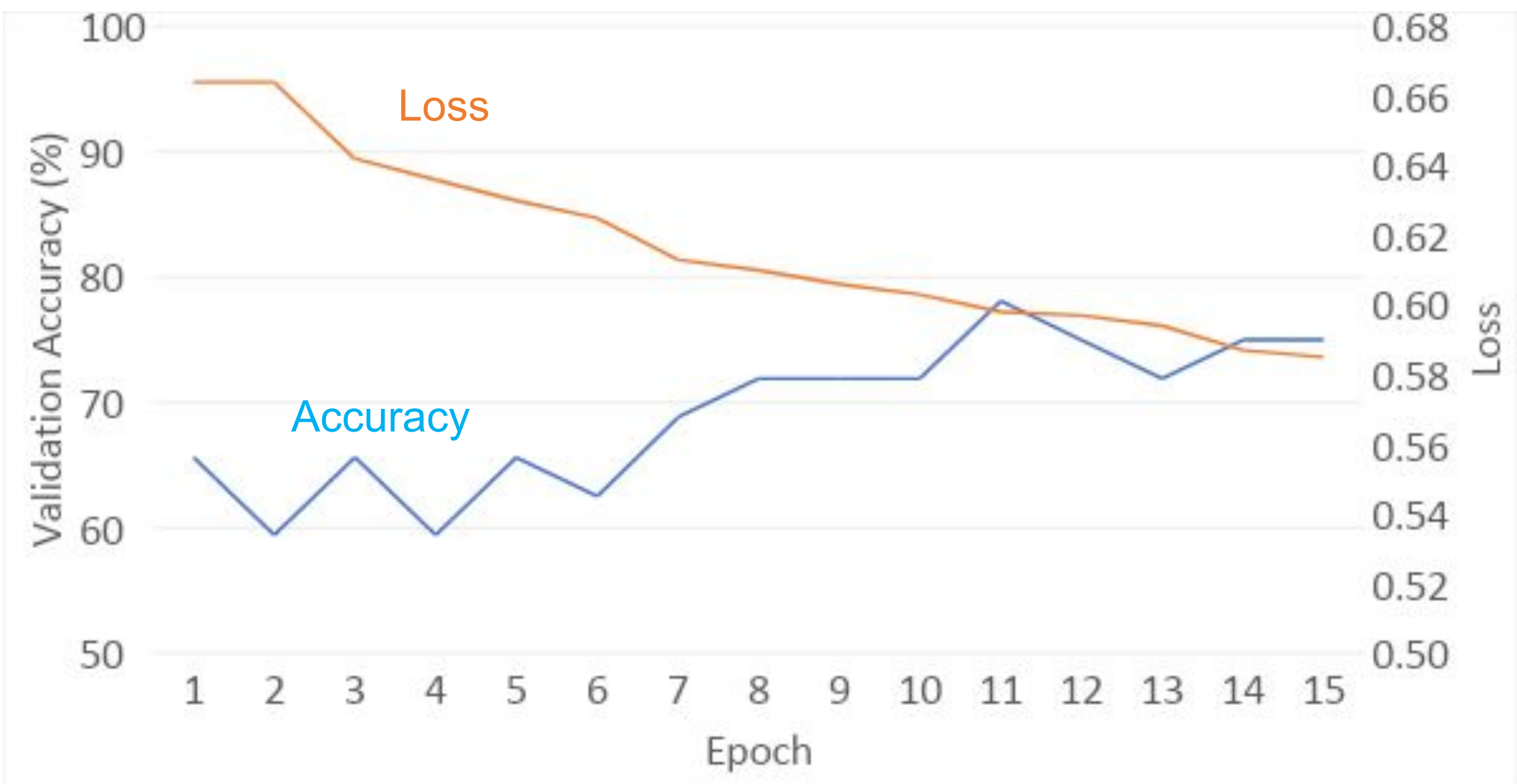


Figure 7. Model B's training progress indicating improvement
(figure created by student researchers)

Table 4. Progress of loss value in both models
(table created by student researchers)

Epoch	N.D. Loss	N.C. Loss
1	0.692	0.664
2	0.239	0.664
3	0.279	0.642
4	0.018	0.636
5	0.025	0.630
6	0.014	0.625
7	0.015	0.613
8	0.013	0.610
9	0.136	0.606
10	0.013	0.603
11	0.012	0.598
12	0.012	0.597
13	0.009	0.594
14	0.043	0.587
15	0.006	0.585

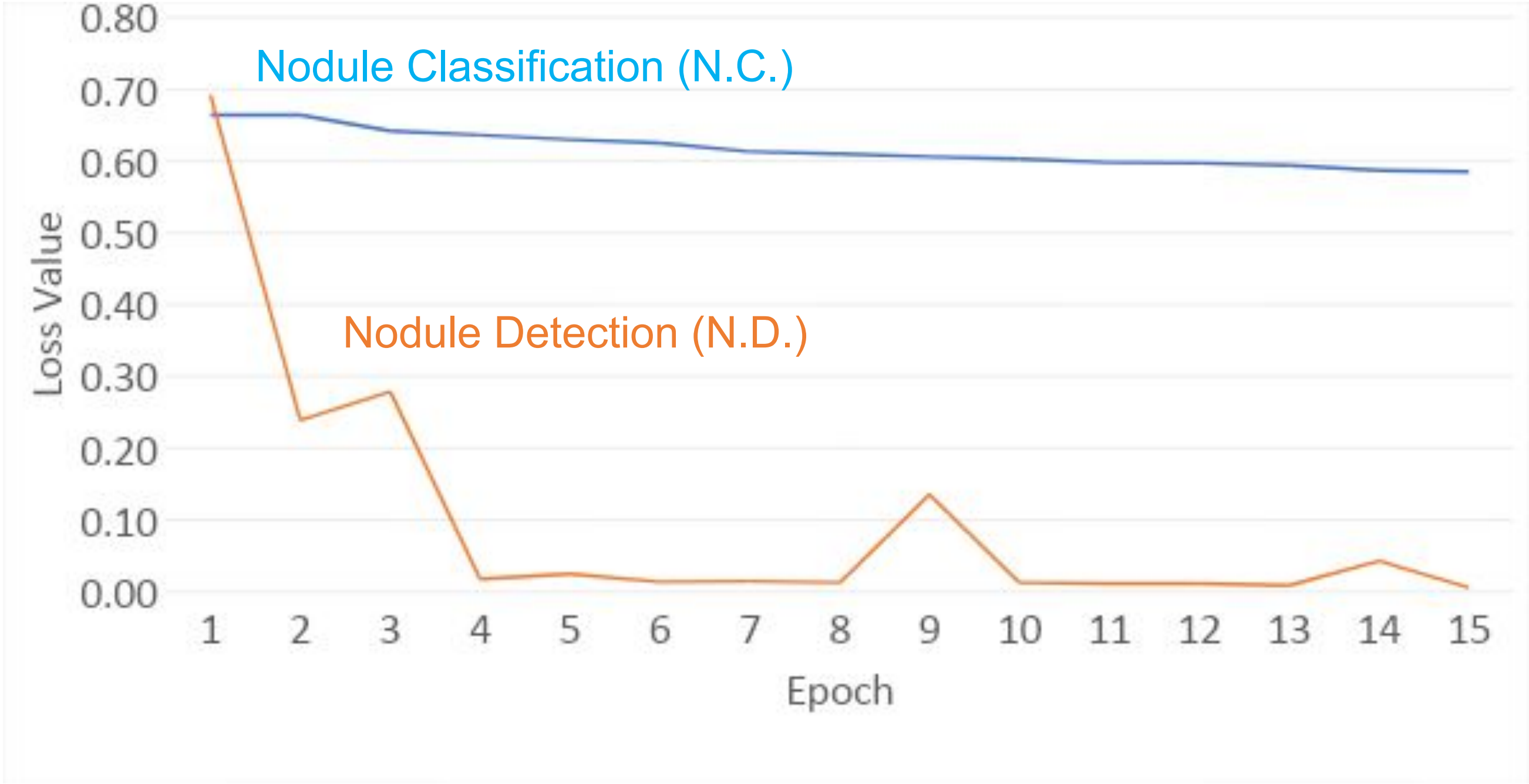


Figure 8. Progress of reducing the loss value in the classification and detection tasks (figure created by student researchers)

- Radiologists have a correct diagnosis rate of 81% [14]
- Accuracy of second model indicates that its performance is exceeded by health professionals in terms of percentage
- Correct nodele detection rate: 93.8%
- Correct nodele classification rate: 75.5%

Conclusions

- Model A is 93.8% effective in detecting tumors
 - Model A exceeded expectations of correctly detecting tumors
- Model B shows promise with a 75.5% success rate despite its severely limited dataset
 - Other possible limitations: sizes of tumor, resolution, and training time

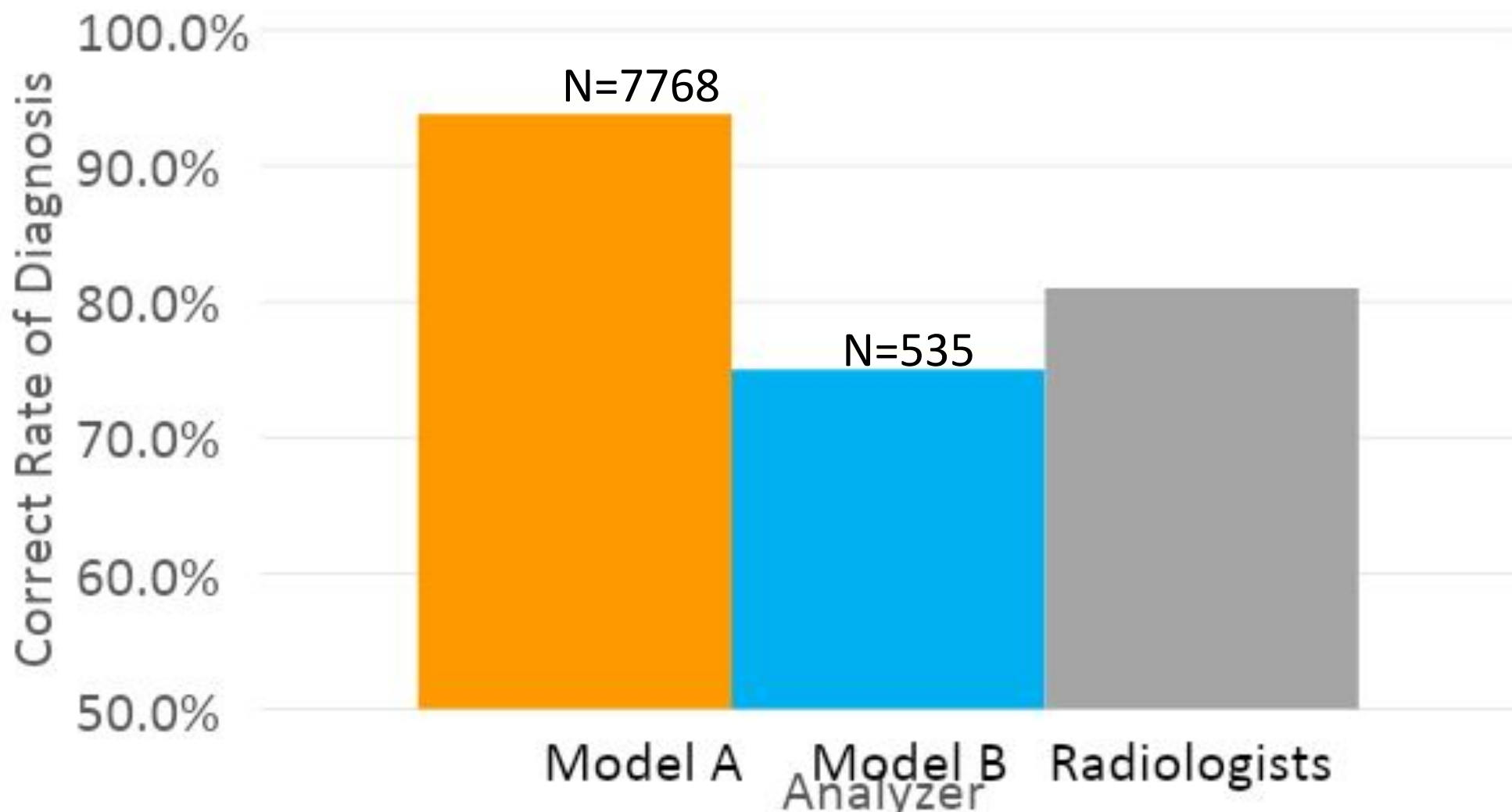


Figure 8. Comparison between the classification accuracy of the developed models and radiologists (figure created by student researchers)

Future Research

- Increase number of images for the classification task
- Further analyze performance with a consideration for recall and precision
- Use different combinations of layers and parameters
- Output: nodes resemble the Lung-RADS categories, provide the location of nodules
- Create a model that incorporates all slices or a reconstruction as an input

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