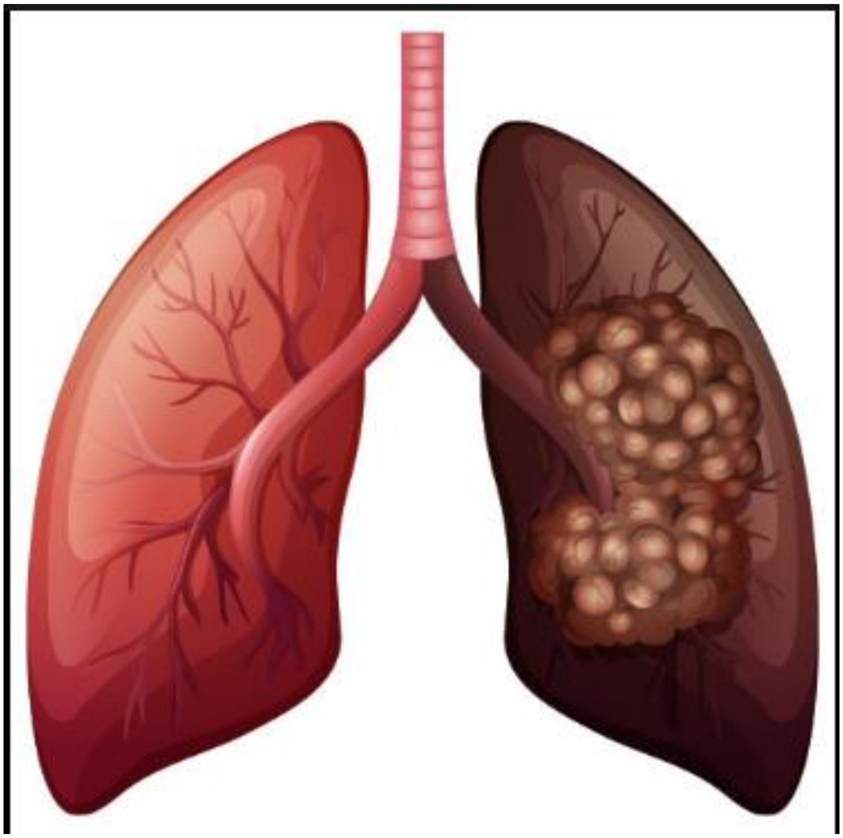

LUNG CANCER DIAGNOSIS

2019 MC 253 |Intelligent Systems | 1/2/2024

Complex Engineering Activity

A Comparative Analysis of Fuzzy Logic and Neural Network-Based Lung Cancer Detection Systems

1. Problem Statement:

Lung cancer remains a leading cause of mortality worldwide, necessitating the development of advanced diagnostic systems for early detection and improved treatment outcomes. Conventional diagnostic methods, though valuable, often face limitations in terms of accuracy and efficiency. To address these challenges, this study explores the implementation and comparison of two distinct methodologies for lung cancer detection – a fuzzy logic-based system and a neural network-based system.

2. Fuzzy Logic Implementation:

The initial phase of our study involved the development of a fuzzy logic system designed to handle 12 inputs and produce two outputs, representing the stage and recommended treatment for lung cancer. While fuzzy logic systems are renowned for their interpretability and ability to incorporate expert knowledge, challenges arose as we expanded the number of inputs. The system, though accurate in some scenarios, exhibited discrepancies and became computationally intensive.

Results:

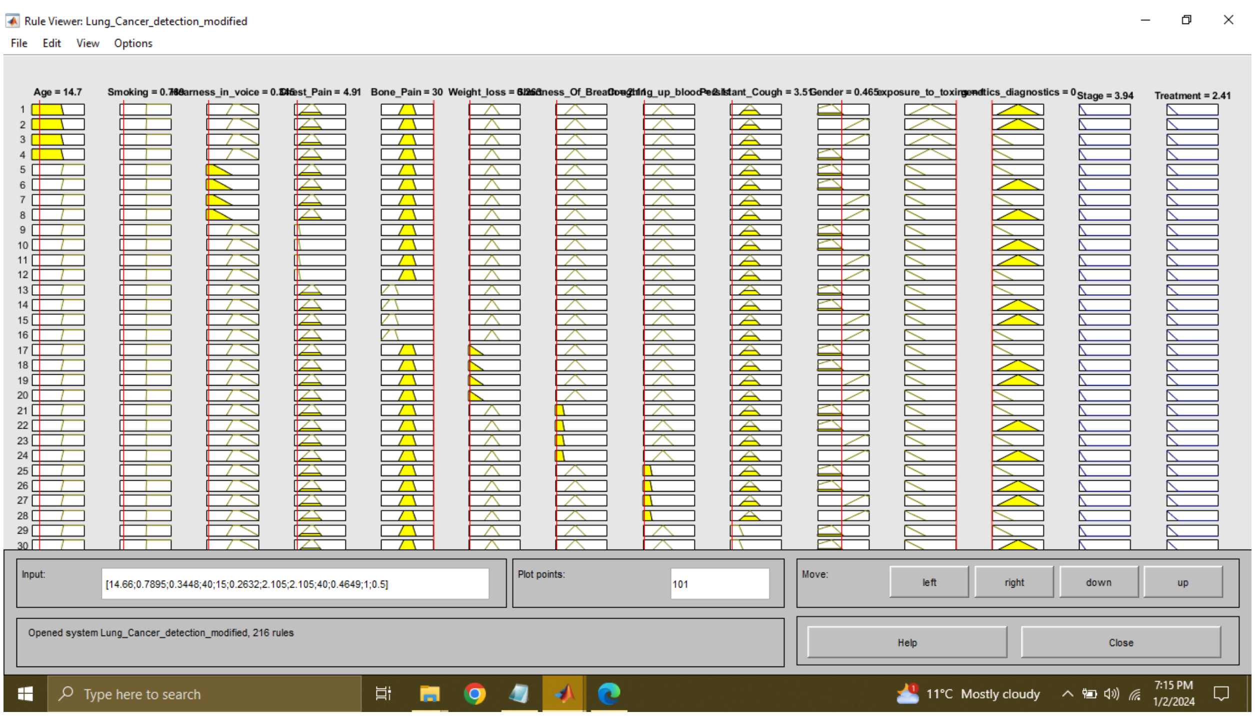

Figure 1(Parent Rule-2 implementation)

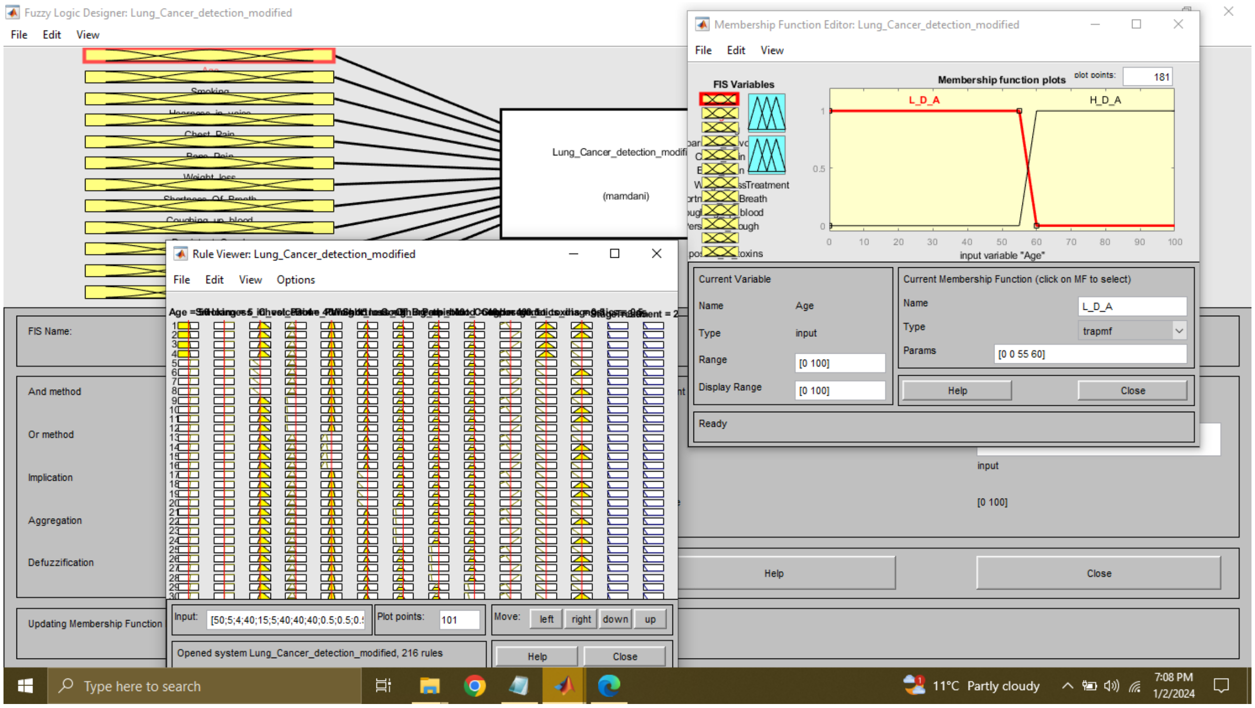

Figure 2(Final Fuzzy system)

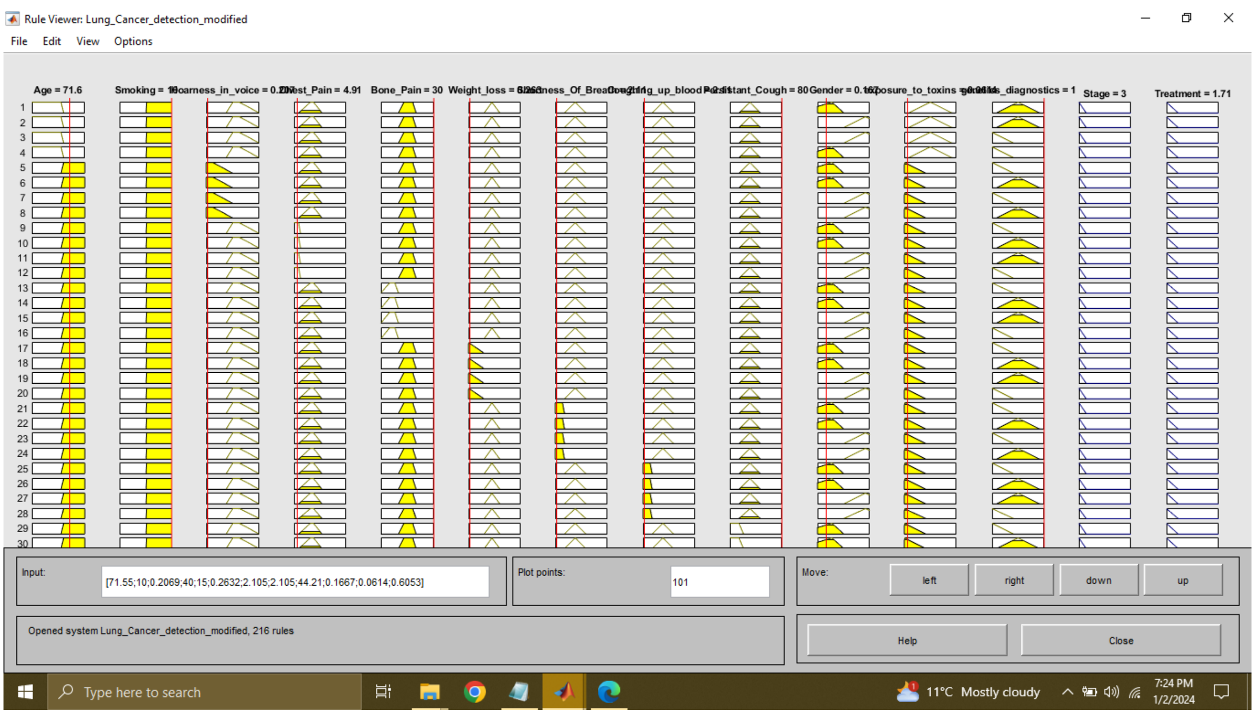

Figure 3(Inaccurate information from rule-5)

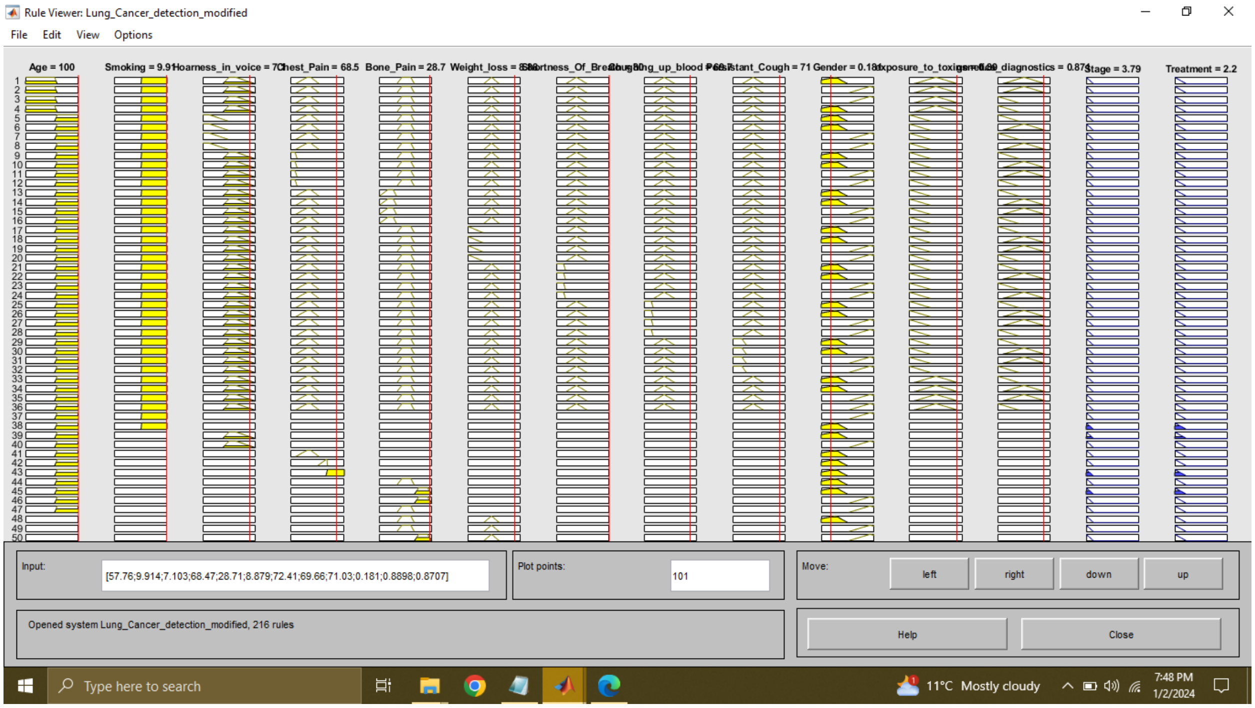

Figure 4(Even after changing multiple inputs the output not changing)

To enhance the accuracy and comprehensiveness of the fuzzy logic system, we varied the inputs to validate rules derived from expert knowledge. However, our attempts were met with limitations stemming from hardware degradation. As the number of inputs increased, the system struggled to maintain consistency, hampering its performance and hindering its real-time application. Also after varying the values of inputs the output were having no effect so we concluded that the fuzzy system are not feasible for this type of application.

Resources:

https://ieeexplore.ieee.org/document/8610976

After studying expert knowledge from following websites:

https://www.cancer.org/cancer/types/lung-cancer.html

https://www.cancer.gov/types/lung/hp

https://www.mayoclinic.org/departments-centers/lung-cancer-program/home/orc-20474481

We added more inputs some of the rules added newly are:
If a person has Med to high persistent cough and med-high smoking with high chest pain and is a male then he could have stage 1 cancer

The newly decided inputs were:

- Gender
- Genetics
- Exposure to toxins (Alcohol etc)

3. Neural Network Implementation:

In response to the limitations encountered with the fuzzy logic system, we turned to neural networks, a powerful class of machine learning algorithms known for their ability to model complex relationships within data. Our neural network architecture consisted of 10 hidden layers, and we employed two distinct training algorithms – Levenberg-Marquardt backpropagation and traingdx.

Code:

```
clear all;

data = readtable('survey lung cancer.csv');

toConvert = data.Properties.VariableNames(3:end-1);
data{:, toConvert} = data{:, toConvert} - 1;

data.GENDER = grp2idx(categorical(data.GENDER)) - 1;

data.LUNG_CANCER = grp2idx(categorical(data.LUNG_CANCER)) - 1;

data.AGE = normalize(data.AGE);

X = data(:, 1:end-1);
y = data.LUNG_CANCER;

rng(2012);
idx = randperm(size(X, 1));
trainRatio = 0.8;
trainIdx = idx(1:round(trainRatio * length(idx)));
testIdx = idx(round(trainRatio * length(idx)) + 1:end);

X_train = X(trainIdx, :);
y_train = y(trainIdx, :);
X_test = X(testIdx, :);
y_test = y(testIdx, :);

X_train_mat = table2array(X_train);
X_test_mat = table2array(X_test);

hiddenLayerSize = 10;
net = patternnet(hiddenLayerSize, 'trainlm');

net.divideParam.trainRatio = 80/100;
net.divideParam.valRatio = 1/100;
net.divideParam.testRatio = 19/100;

[net, tr] = train(net, X_train_mat', y_train');

y_pred = round(net(X_test_mat'))';

accuracy = sum(y_pred == y_test) / length(y_test);
disp(['Accuracy of the model used is : ', num2str(accuracy)]);
disp('Neural network training and evaluation completed successfully!');

view(net)

figure;
plot(tr.epoch, tr.perf);
xlabel('Epoch');
ylabel('Performance (Error)');
title('Training Performance');

figure, plotperform(tr)
```

Figure 5(Nueral network implementation)

The Levenberg-Marquardt backpropagation algorithm, a popular choice for its fast convergence, demonstrated efficiency by requiring only 33 epochs for training. On the other hand, the traingdx algorithm, a gradient descent algorithm with momentum and adaptive learning rate, took 296 epochs to converge. Despite the longer training time, traingdx outperformed Levenberg-Marquardt in terms of accuracy, reaching an impressive 96%.

Results:

Results for Gradient descent algorithm with momentum and adaptive learning rate

```
Accuracy of the model used is : 0.96774
Neural network training and evaluation completed successfully!
```

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	293	1000
Elapsed Time	-	00:00:39	-
Performance	0.992	0.0355	0
Gradient	1.04	0.0268	1e-05
Validation Checks	0	6	6

Figure 6(Training process)

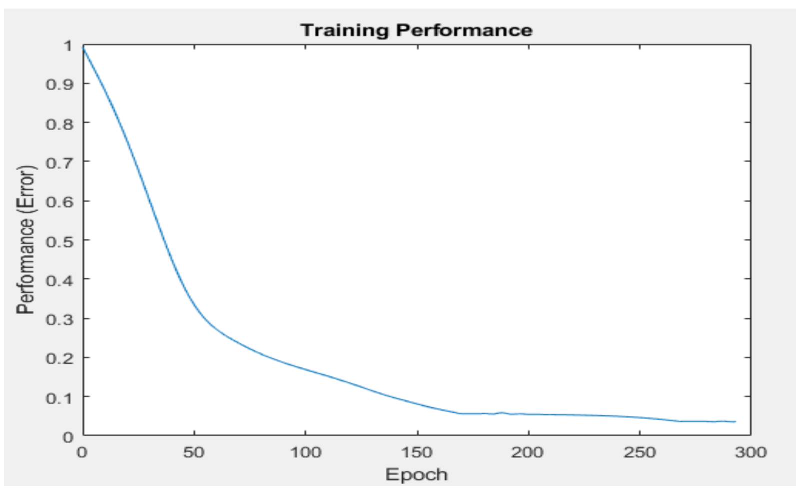

Figure 7(Epoch vs error)

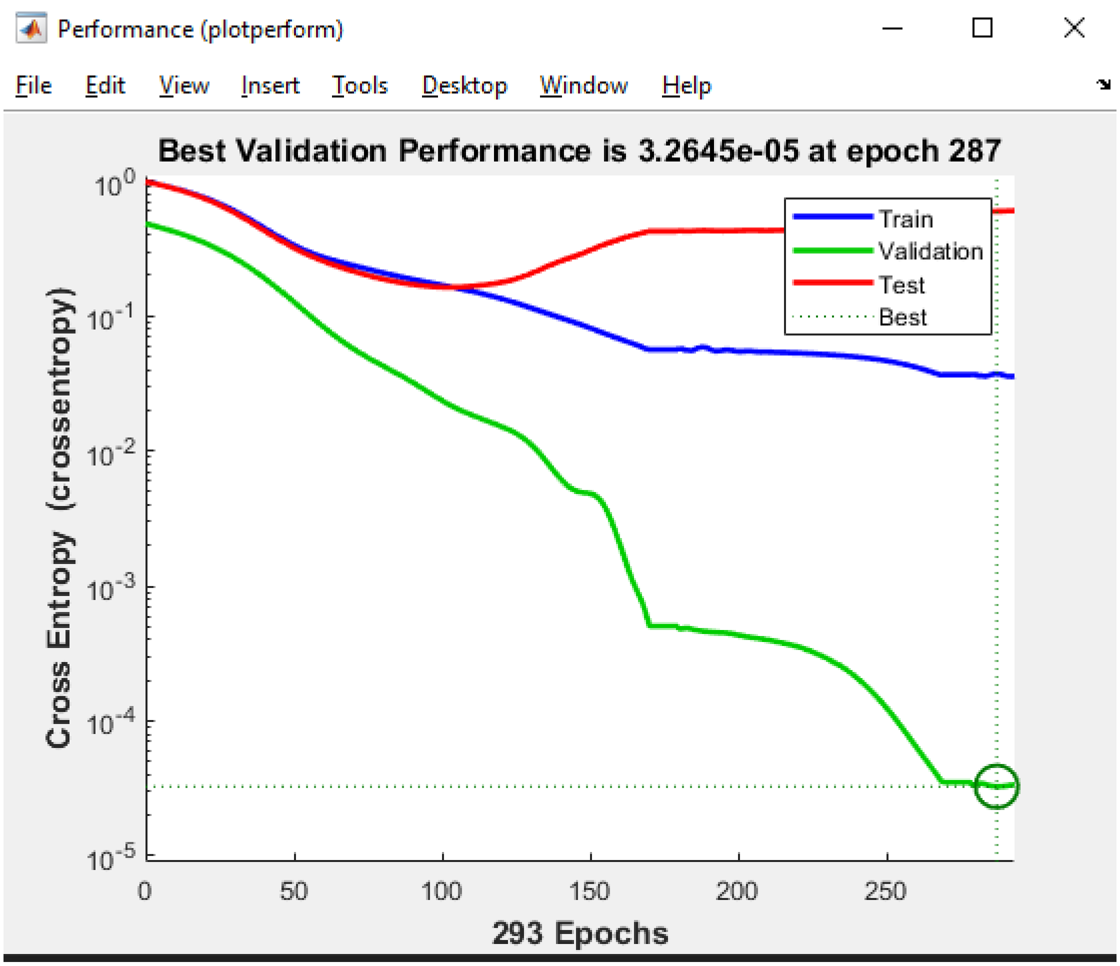

Figure 8(Performance graph epoch vs cross entropy)

Results for Levenberg-Marquardt algorithm:

Accuracy of the model used is : 0.93548
Neural network training and evaluation completed successfully!

Training Progress

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	35	1000
Elapsed Time	-	00:00:03	-
Performance	0.327	0.00579	0
Gradient	0.331	0.000878	1e-07
Mu	0.001	0.001	1e+10
Validation Checks	0	6	6

Figure 9(Training Process)

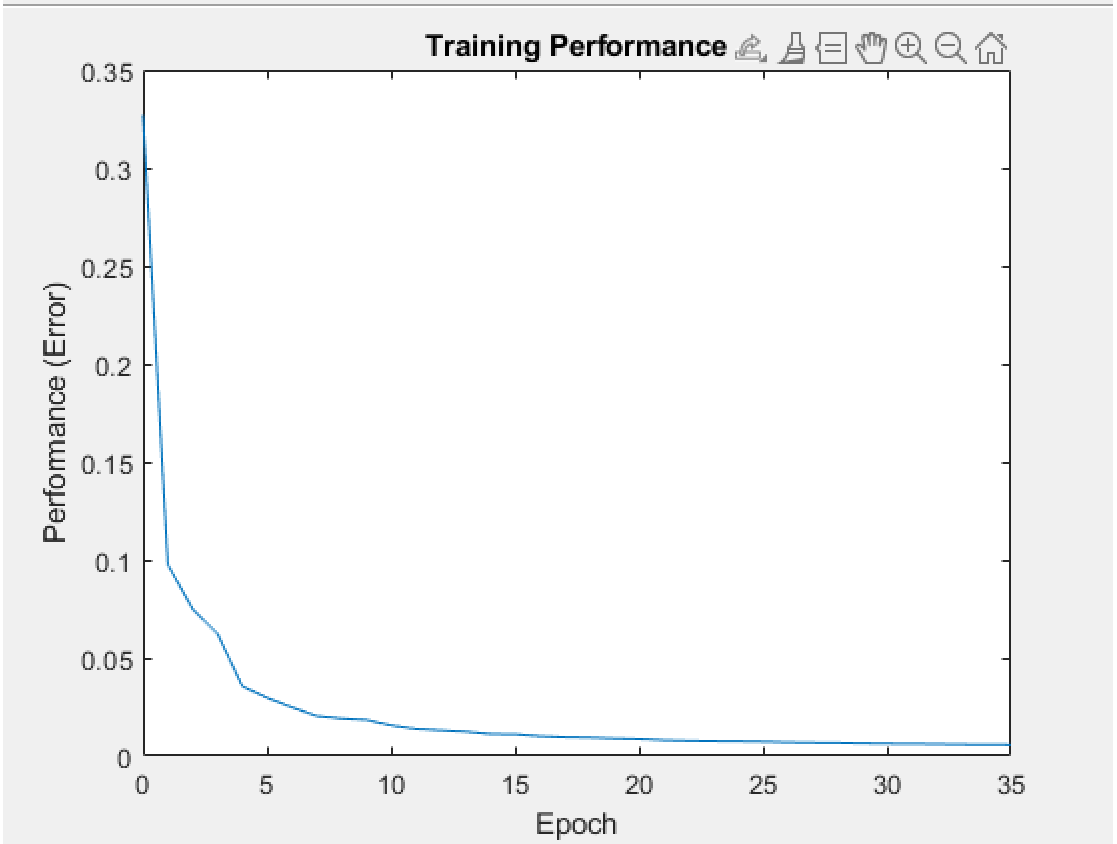

Figure 10(Epoch vs Erms)

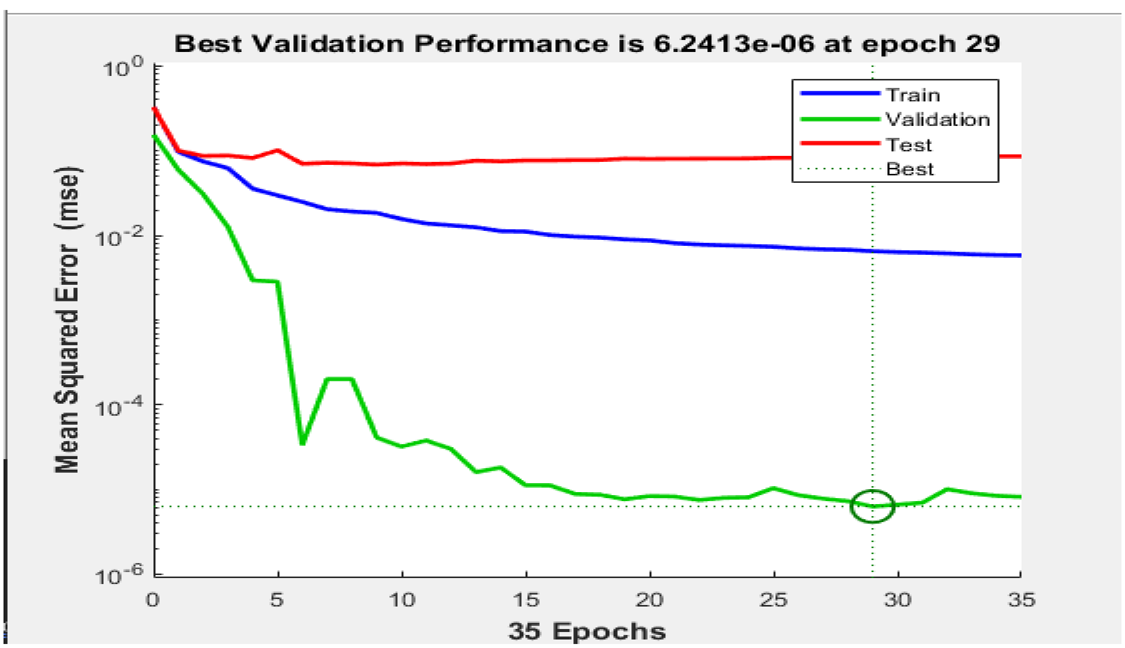

Figure 11(Performance plot)

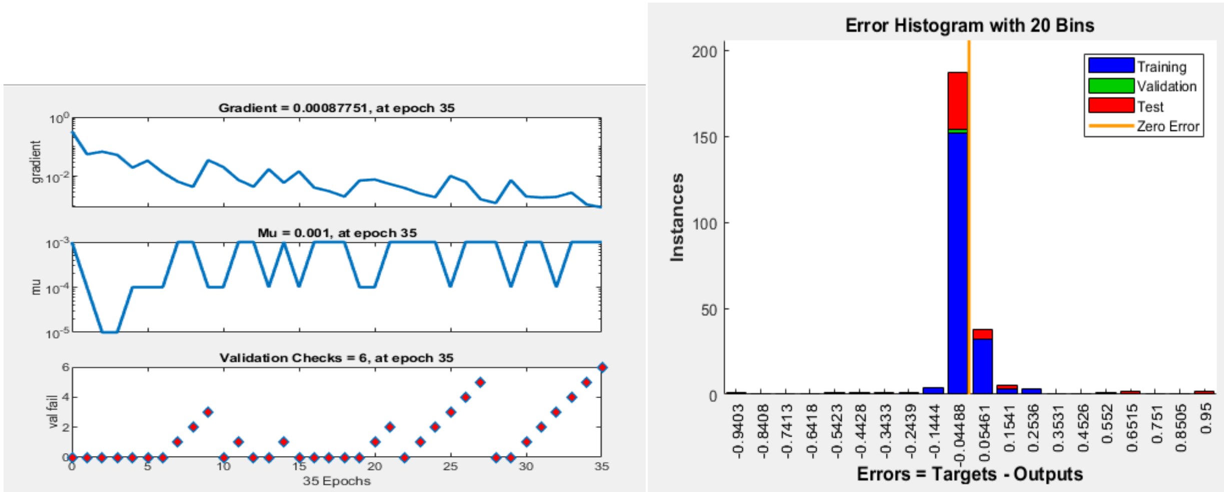

Figure 12(Error histogram and training state)

4. Comparison:

Comparison Aspect	Fuzzy Logic System	Neural Network-Based System
Effectiveness in Fewer Inputs	Effective in scenarios with fewer inputs.	Showcased remarkable resilience and adaptability.
Challenges with Increased Inputs	Faced challenges when dealing with an increased number of variables.	Demonstrated capacity to handle a multitude of inputs.
Hardware Constraints	Hardware constraints hindered overall accuracy and real-time applicability.	No indication of specific hardware constraints.
Training Algorithm Comparison	N/A	Levenberg-Marquardt backpropagation exhibited faster convergence but was surpassed by traingdx in accuracy. The traingdx algorithm dynamically adjusted the learning rate and leveraged momentum, achieving a notable 96% accuracy.
Adaptability and Resilience	N/A	Neural network exhibited adaptability to complex patterns in the data.
Promising Solution for Lung Cancer Detection	N/A	Positioned as a promising solution for lung cancer detection due to its capacity to handle a multitude of inputs and adapt to complex patterns in the data.
Intuitiveness and Interpretability	Intuitive and interpretable.	No specific mention of interpretability; however, neural

		networks are generally considered less interpretable than fuzzy logic systems.
Optimization Requirement	Requires further optimization to accommodate a larger set of inputs and overcome hardware constraints.	No indication of specific optimization requirements.

5. Conclusion:

In conclusion, the comparative analysis of fuzzy logic and neural network-based lung cancer detection systems underscores the importance of choosing a methodology that aligns with the specific demands of the application. The fuzzy logic system, although effective in simpler scenarios, faces challenges in scaling to accommodate a higher number of inputs and may require hardware upgrades for optimal performance.

On the other hand, the neural network-based approach, particularly leveraging the traingdx algorithm, emerges as a robust and accurate solution for lung cancer detection. The neural network demonstrated its adaptability to intricate data patterns and exhibited superior accuracy, albeit with a longer training time. The choice between these methodologies should consider factors such as computational resources, the complexity of the problem, and the trade-off between interpretability and predictive power.

Further research is warranted to enhance the robustness of the fuzzy logic system and explore additional optimization strategies. The potential for hybrid systems that integrate the interpretability of fuzzy logic with the predictive capabilities of neural networks could represent the next frontier in lung cancer detection research.

In summary, the study provides valuable insights into the strengths and limitations of fuzzy logic and neural network-based approaches, contributing to the ongoing efforts to enhance early detection methods for lung cancer and ultimately improve patient outcomes.