PREMIER UNIVERSITY CHITTAGONG

Department of Computer Science & Engineering

Course Code : CSE-451

Course Title   : Neural Network and Fuzzy Logic Laboratory.

Report Name: Lung Cancer Prediction Model.

Date of Submission   : 14/03/2023

SUBMITTED BY

Mohiuddin Faysal ID:1903610201765
Prima Das ID: ID:1903610201766
Department : CSE
Semester: 7th
Section: C2
Session : Spring_ 2022

SUBMITTED TO

Faisal Ahmed
Assistant Professor
Department of CSE

Author's Declaration of Originality

We declare that the report work entitled "Lung Cancer Prediction Model" submitted to the Premier University, is a record of an original work done by us.
under the guidance of Mr. Faisal Ahmed, Assistant Professor, Department of Computer Science &Engineering, Premier University, Chittagong.
We can assure that the result of this report
has not been submitted to any other university.

_____

Mohiuddin Faysal
ID: 1903610201765

_____

Prima das
ID: 1903610201766

CERTIFICATION

The report entitled "Lung Cancer Prediction model" submitted by, Mohiuddin Faysal, ID: 1903610201765, Prima das, ID: 19036102021766, has been accepted as satisfactory in fulfillment of the course Neural Network and Fuzzy Logic Lab.

_____

Faisal Ahmed
Assistant Professor
Department of Computer Science & Engineering
Premier University, Chattogram

Table of Contents

Abstract

The major cause of deaths in human beings is Lung Cancer, Since the lung cancer symptoms appear in the advanced stages so it is hard to detect which leads to high mortality rate among other cancer types. Hence the early prediction of lung cancer is mandatory for the diagnosis process and it gives the higher chances for successful treatment. It is the most challenging way to enhance a patient's chance for survival.

In this paper, we developed an Artificial Neural Network (ANN) for detect the absence or presence of lung cancer in human body. Symptoms were used to diagnose the lung cancer, these symptoms such as Anxiety, Chronic Disease, Fatigue, Allergy, Wheezing, Coughing, Shortness of Breath, Swallowing Difficulty and Chest pain.

They were used and other information about the person as input variables for our ANN. Our ANN established, trained, and validated using data set, which its title is "lung cancer prediction". Model evaluation showed that the ANN model is able to detect the absence or presence of lung cancer with 82% % accuracy.

Our model is binary classification model. In this model we used 11 different input features. output layer is used both as single class model and Multiclass model. We used level encoding and min-max scaling method as preprocessing of the model.

Naive bayes, KNN, Decision tree are used as classifier for acquiring Model accuracy in both single class and multiclass output model. According to our analysis, DT displays higher precision when compared to others, while LR achieves better accuracy, precision, and F-score.

Keywords : Lung Cancer prediction , Neural Network, ANN, Naïve base, KNN, Level encoding, Min-max scaling, Activation function, Sigmoid, Softmax, Loss Function ,Binary Cross-entropy, Categorical Cross-entropy, epoch, Batch-size, Confusion matrix.

Chapter 01

Introduction

1.1 Background

Cancer is a wide term. It labels the illness that outcome once cellular changes cause the uncontrolled growth and division of cells. Most of the body's cells have particular functions and fixed lifetimes. However, cell death is part of a natural phenomenon called apoptosis. A cell takes directions to die so that the body can substitute it with a newer one that functions better. Cancerous cells lack the mechanisms that train them to stop dividing and to die. Thus, they grow in the body, using oxygen and nutrients that would usually feed other cells. Cancerous cells can form tumors, damage the immune system and cause other deviations that prevent the body from functioning right. Lung cancer is a malignant lung tumor considered by uncontrolled cell growth in lung tissues . Lung cancer is the primary cause of cancer-related death[1]. The primary goal of our research is to diagnose the presence of lung cancer cells based on attributes, which are set of human symptoms, and information. The study explores the possibility of using an Artificial Neural Network model to detect the presence of a lung cancer in someone's body. The purposes of this study are:

- To recognize some appropriate factors that cause lung cancer
- To model an Artificial Neural Network that can be used to detect the presence of lung cancer

Artificial neural networks are alike to our neural networks and offer a quite good technique, which solves the problem of classification and prediction . An ANN is a mathematical model that is encouraged by the organization and functional feature of natural neural networks, Neural networks involve input and output layers, as well as (in most cases) hidden layers that transform the input into something so the output layer can use . When a neural network used for cancer detections, the ANN Model go through two levels, training and validation. First, the network is trained on a dataset. Then the weights of the connections between neurons are fixed so the network is validated to determine the classifications of a new dataset . ANN Architecture is shown in figure 1. In this paper, we used about 80% of the total sample data for network training, and 20% for network validation.

We collected some document from difference types of ages persons. Outputs are categorized Cancer prediction YES or NO. We show our model both as single class and multi class output. We perform classification on the dataset using Naïve bayes , KNN, Decision Tree to acqure best model accuracy.

1.2 Motivation

Lung cancer is one of the cancer types that leads to death. The Lung diseases are the disorders which affect the lungs and it is unpredictable medical conditions worldwide . Lung cancer constitutes 12.8% of all cancer types worldwide, also it constitutes 17.8% of the cancer deaths and it increases by 0.5% every year globally worldwide. So it is one kind of hard challenge to detect cancer probability of an individual person. Artificial Neural Network model may solve this problem easily.

1.3 Objective

We aim to analyze a repository of Cancer prediction articles to better identify ANN model and detect cancer prediction. The profundity of our work may not be supremely efficacious given our limited scope; however, it is a small step in the right direction to give the public a clearer perspective on the cancer prediction that they suffered.

1.4 Summary

In this report, we present a Binary classification model to detect the Cancer prediction. Where we applied some tools to detect Cancer prediction Yes or No. Here many stages will be followed, which are data leveling, data scaling. We used our model as single class and multiclass both. We performed classification on the dataset. After words we were able to choose the most actual model.

<div align="center">

Chapter 02

Related work

</div>

Lung cancer research is the most concerning region of enthusiasm for restorative field. The early diagnose of the cancer can help in expanding the death rate of people. This is very tedious, and their accurateness relies on the capacity of operator's. Chauhan *et.al* (2016) [2] has overviewed different methods to recognize lung cancer like ANN (Artificial Neural Network), picture handling, LDA (Linear Dependent Analysis), SOM (Self Organizing Map) and so on. From the conclusion, it is prescribed to utilization of Support vector machines as a classification tool. Support Vector Machine (SVM) are supervised learning models that analyze data and recognize patterns.

Krishnaiah *et.al* (2013) [3] gives an outline of the diagnosis on different lung cancer datasets by employing the data mining techniques and optimization techniques for the diagnosis of lung cancer. Knowledge Discovery in Databases (KDD), integrates data mining techniques to recognize and exploit the cancer patterns among large number of variables, and to predict the outcome of a disease using the certain medical cases stored within datasets.

Tiwari *et.al* (2016) [4] introduced an image processing technique for prediction of lung cancer and furthermore for early detection and treatment to prevent the lung cancer. To predict the lung cancer various features are extricated from the pictures along these lines, pattern recognition-based methodologies are valuable to predict the lung cancer. A far reaching audit for the expectation of lung cancer by past analyst utilizing image processing techniques was exhibited. The image processing techniques with the computational insight based methodologies are helpful for the prediction and decision making of lung cancer.

Kuruvilla et.al (2014) [5] presented a Computer Aided Diagnosis (CAD) classification method in Computed Tomography (CT) images for cancer detection based neural network. The whole lung is segmented from the CT images and the features are determined from the segmented image. The measurable parameters such as mean, standard deviation, skewness, kurtosis, fifth focal moment and 6th focal minute are estimated for cancer classification. The classification process is employed by feed forward back propagation neural networks for better classification.

Kaur et.al (2015) [6] assessed a new feature selection technique using hybrid genetic and particle swarm optimization and classification of lung CT images utilizing MLP-NN is investigated. It is connected to lung CT images engaged as the input. The guided image filter is connected to remove noises and the preprocessed images are given as input for feature extraction. Further the features are extracted utilizing MAD technique. Extracted features are chosen utilizing GAPSO algorithm. Furthermore, finally classify the features utilizing MLP-NN. Resulted image is acquired utilizing GAPSO-MLPNN. The experimental result indicates high Geometry Accuracy, high Bit Classification Rate and low Bit Error Rate in different testing data. This technique adequately functions admirably for the detection of lung diseases

Chapter 03

Data Collection

3.1 Data Source
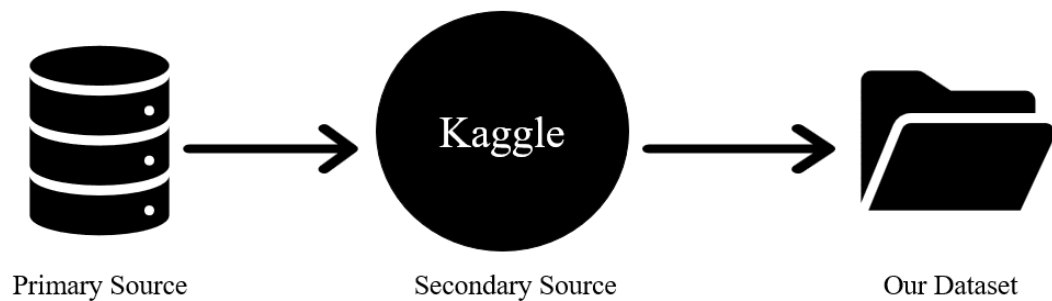
The Dataset was taken from secondary source www.kaggale.com .

3.2 Data Description

The dataset contains 309 different persons information according to age and smoking, Anexity, Peer_pressure, chronic disease, fatigue , allergy, coughing, shortness of breath, chest pain, Lung cancers value . Ten input features are used to find Lung cancer of a persons. And last feature of the dataset 'Lung_cancer 'is used as output.

Gender	Age	Smoking	Anexity	Peer pressure	Chronic Disease	Fatigui	Allergy	wheezing	cough	Short ness_ of Breath	Chest pain	Lung Cancer
M	69	1	2	1	1	2	1	2	2	2	2	Yes
M	74	2	1	1	2	2	2	1	1	2	2	Yes
F	59	1	1	2	1	2	1	2	2	2	2	No
M	63	2	2	1	1	1	1	1	1	1	2	No

Table 3.1. Glimpse of the dataset
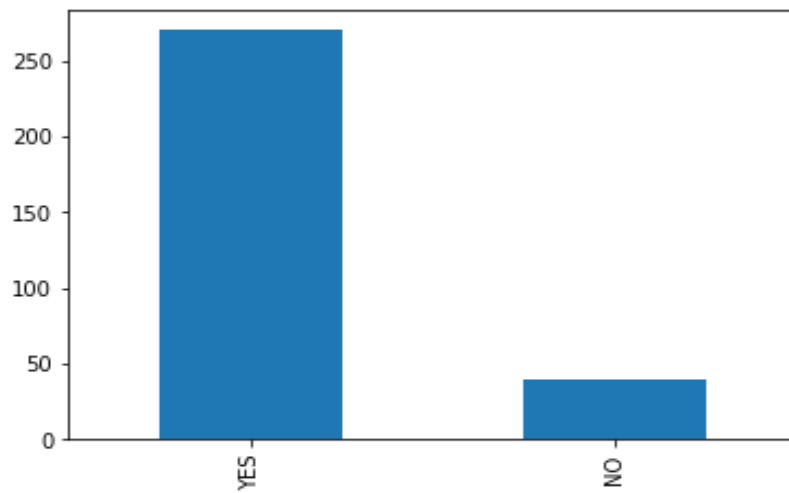
Daigram 3.1. Glimpse of the dataset result

<div align="center">

Chapter 04

Methodology

</div>

4.1 Preprocessing

Data preprocessing is an important step in the data mining process. It refers to the cleaning, transforming, and integrating of data in order to make it ready for analysis. The goal of data preprocessing is to improve the quality of the data and to make it more suitable for the specific data mining task.

> ➢ **Label Encoding**
>
> Label Encoding refers to converting the labels into a numeric form so as to convert them into   the machine-readable form. Machine learning algorithms can then decide in a better way how those labels must be operated. It is an important pre-processing step for the structured dataset in supervised learning.
>
> An attribute of having input classes 'Gender' . On Label Encoding, this column lets male is replaced with 1, female is replaced with 0. And an attribute having output class 'Lung Cancer' column lets 'Yes' replaced with 1, 'No' replaced with 0 by binary label transforming.

No	Gender	Lung_Cancer
01	Male	Yes
02	Male	Yes
03	Female	No
04	Male	No

No	Gender	Lung_Cancer
01	1	1
02	1	1
03	0	0
04	1	0

Before Encoding   After Encoding

> ➢ **Min-max scaling**
>
> Min-max normalization (usually called **feature scaling**) performs a linear transformation on the original data. This technique gets all the scaled data in the range (0, 1). The formula to achieve this is the following:

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

> Min-max normalization preserves the relationships among the original data values. The cost of having this bounded range is that we will end up with smaller standard deviations, which can suppress the effect of outliers. We applied the process on our dataset. The normalized dataset is following:

Here we show the 'Age ' column that is normalized by min-max scaling.

No	Age
01	69
02	74
03	59
04	63

Before scaling

No	Age
01	0.72727
02	0.80303
03	0.57575
04	0.63636

After Scaling

4.2 Training and Testing samples

30% Testing set

70% Training set

Data sample   Train & test data
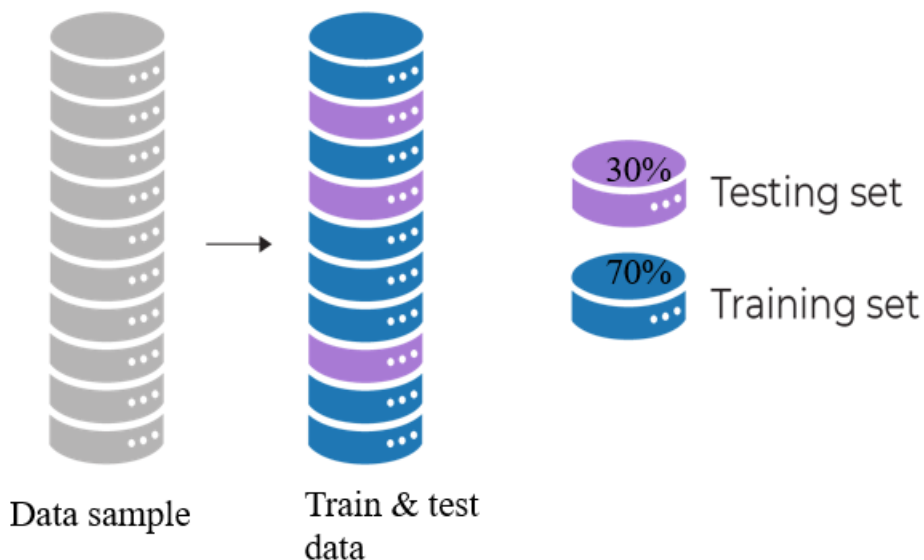
The input data samples are trained and tested by using neural network. Initially the weights of neural network of the input data are chosen randomly. The neural networks are trained with a sample data for learning and to perform classification process then with testing dataset. The classification result of the tested data is weighed to check the frequency error or the error rate which occur during classification process and the error are resolved by changing the weights in the dataset .we take 70% data for training and 30% for testing.
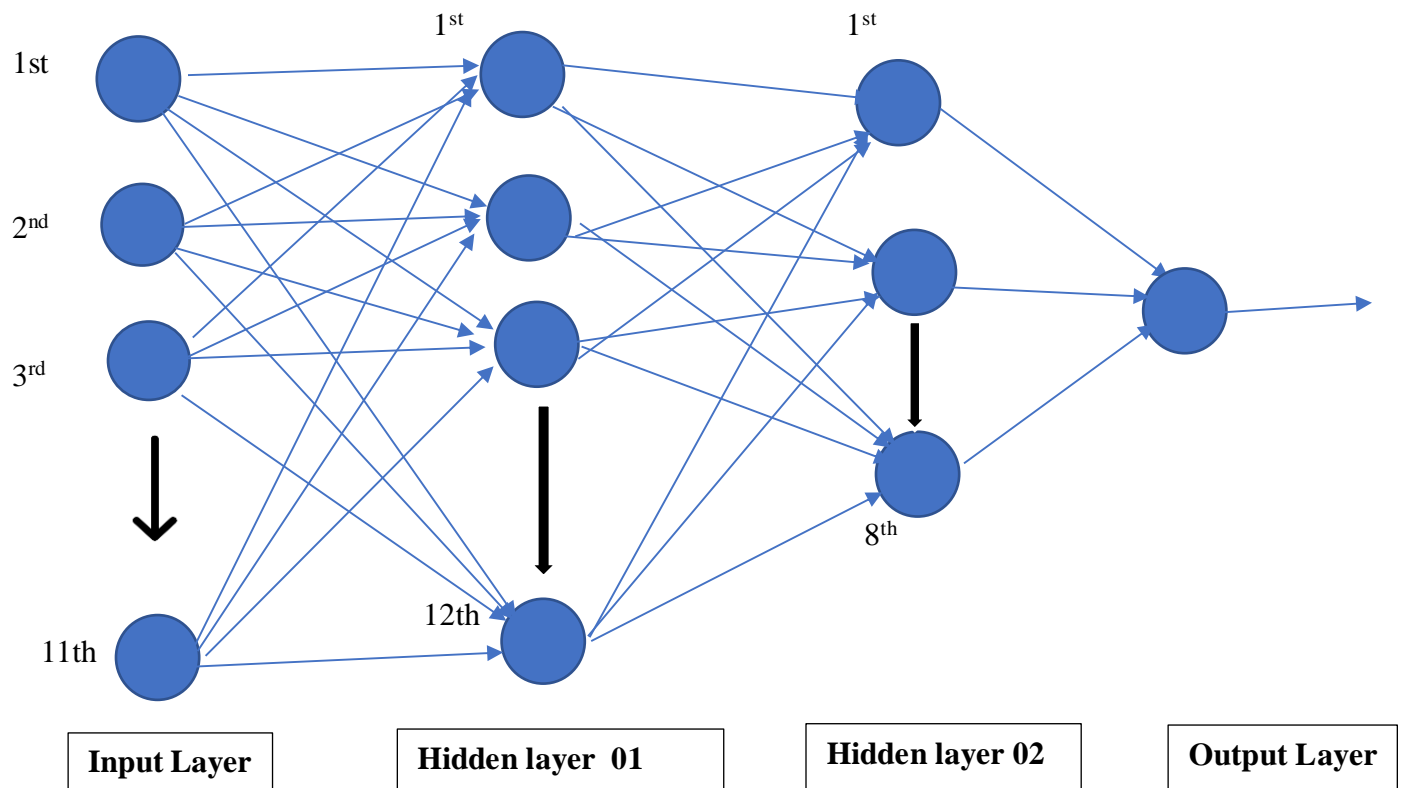
4.3 Neural network model

<div align="center">Fig: Binary classification model for single level</div>

4.3.1 Model design 1

```
model = Sequential()
model.add(Dense(12, input_dim=11, activation='relu'))
model.add(Dense(8, activation='relu'))

model.add(Dense(1, activation='sigmoid'))
# compile the keras model
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```

4.3.2 Model -01 summary

```
1 model.summary()
```

```
Model: "sequential_4"
_____
 Layer (type)                Output Shape              Param #
=================================================================
 dense_10 (Dense)            (None, 12)                144

 dense_11 (Dense)            (None, 8)                 104

 dense_12 (Dense)            (None, 1)                 9

=================================================================
Total params: 257
Trainable params: 257
Non-trainable params: 0
_____
```
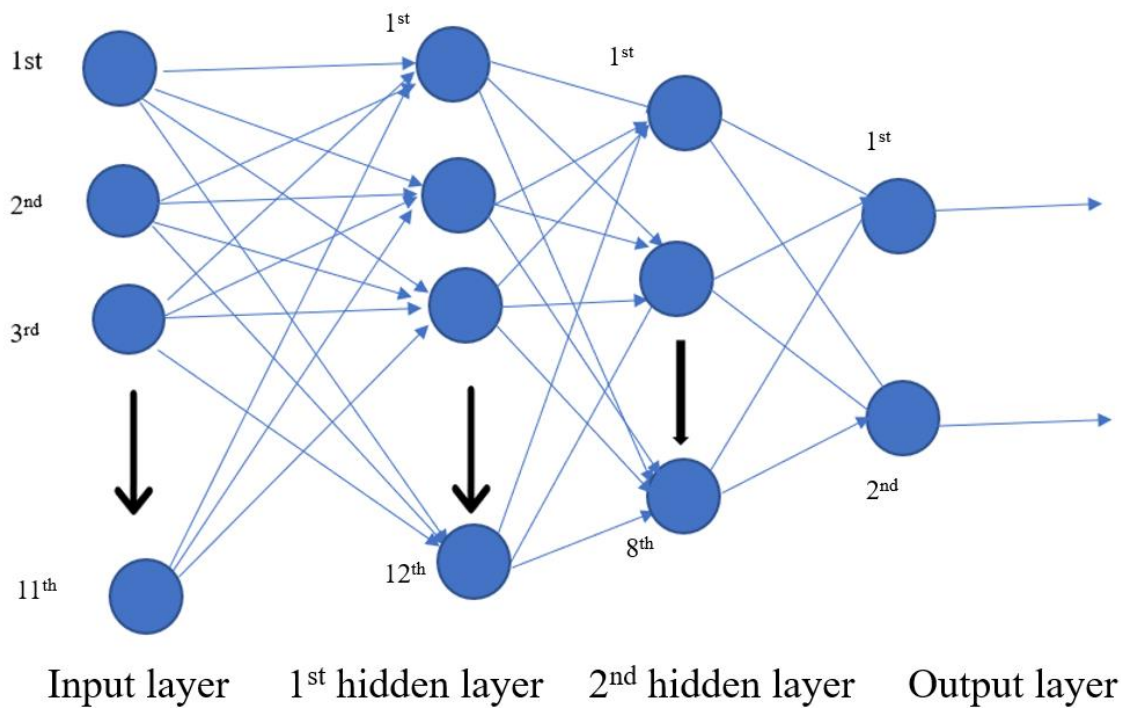

Fig: Binary classification model for multiclass

4.3.3 Model design-02

```
model2 = Sequential()
 model2.add(Dense(X_train.shape[1]*2, input_dim=X_train.shape[1], activation='relu'))
# model2.add(Dense(8, activation='relu'))

model2.add(Dense(2, activation='softmax'))
# compile the keras model
model2.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```

4.3.4 Model summary

```
1 model2.summary()

Model: "sequential_5"

_____
 Layer (type)                Output Shape              Param #
=================================================================
 dense_13 (Dense)            (None, 20)                220

 dense_14 (Dense)            (None, 2)                 42

=================================================================
Total params: 262
Trainable params: 262
Non-trainable params: 0
_____
```

4.4 Classification

We used Naïve Bayes classifier, KNN Classifier, Logistic Regression Classifier, And Decision Tree Classifier in our Experiment.

4.4.1 K-Nearest Neighbor Classifier: A straightforward technique called K-Nearest Neighbor categorizes incoming data or cases based on a similarity metric after storing all of the previous examples. A data point is often categorized using the classification of its neighbors. As a result, it forecasts value using a lazy learner. However, because of the relationship between classification time and data size, KNN is regarded as the slowest classifier. It makes predictions by using Euclidean distance to calculate the distance between the query point and the context in the samples. The values are categorized using training samples and attributes. Finally, the KNN predicts the model accuracy.

4.4.2 **Naive Bayes:** Naïve Bayes algorithm is a supervised learning algorithm, which is based on **Bayes theorem** and used for solving classification problems. It is a probabilistic classifier that predicts on the basis of the probability of an object. The formula for Bayes' theorem is given as:

$$P(A|B)= \frac{P(B|A)P(A)}{P(B)}$$

P(A|B) is Posterior probability and P(B|A) is Likelihood probability. In our dataset we used the Bernoulli Naive Bayes classifier. It is used when characteristic values are continuous in nature then an assumption is made that the values linked with each class are dispersed according to Gaussian, that is Normal Distribution.

4.4.3 **Logistic Regression:** Logistic regression is a Machine Learning classification algorithm which is used to predict the probability of certain classes based on some dependent variables. The outcome of the Logistic Regression is always between (0 and 1).

$$h_\Theta(X) = \frac{1}{1 + e^{-\Theta X}}$$

In the above formula θ is the parameter that we want to train and X is the input data. The output is the prediction value when the value is closer to 1, which means the instance is more likely to be a positive sample(y=1). If the value is closer to 0, this means the instance is more likely to be a negative sample(y=0). The formula for loss function is:

$$J(\Theta) = -\frac{1}{m} \sum_{m}^{i=1} (y^i \log(p^i) + (1 - y^i)\log(1 - p^i))$$

Here, m is the number of samples in the training data. y^i is the label of the itch sample, p^i I am the prediction value of the itch sample? We use this loss function to optimize our work.

<div align="center">

Chapter-05

Experiment and Results

</div>

5.1 Performance Measurement

Performance metrics are a part of every machine learning pipeline. They tell us if we're making progress, and put a number on it. All machine learning models, whether it's linear regression, or a SOTA technique like BRET, need a metric to judge performance.
Every machine learning task can be broken down to either *Regression* or *Classification*, just like the performance metrics. There are dozens of metrics for both problems, but we're going to discuss popular ones along with what information they provide about model performance. It's important to know how our model sees our data!

5.1.1 Accuracy: Accuracy is a metric that generally describes how the model performs across all classes. It is useful when all classes are of equal importance. It is calculated as the ratio between the numbers of correct predictions to the total number of predictions.

$$\text{Accuracy} = (TP+TN) / (TP+FP+FN+TN)$$

- True Negatives (TN): These are the accurately predicted negative values, meaning the current class value is no, and the expected class value is no as well;
- False Positives (FP): When the real class is negative, and the class is expected to be positive;
- False Negatives (FN): The real class is positive, but the class is expected to be negative.

5.1.2 Precision: The precision is calculated as the ratio between the numbers of Positive samples correctly classified to the total number of samples classified as Positive. The precision measures the model's accuracy in classifying a sample as positive.

$$\text{Precision} = TP/ (TP+FP)$$

5.1.3 Recall: The recall is calculated as the ratio between the numbers of Positive samples correctly classified as Positive to the total number of Positive samples. The recall measures the model's ability to detect Positive samples. The higher the recall, the more positive samples detected.
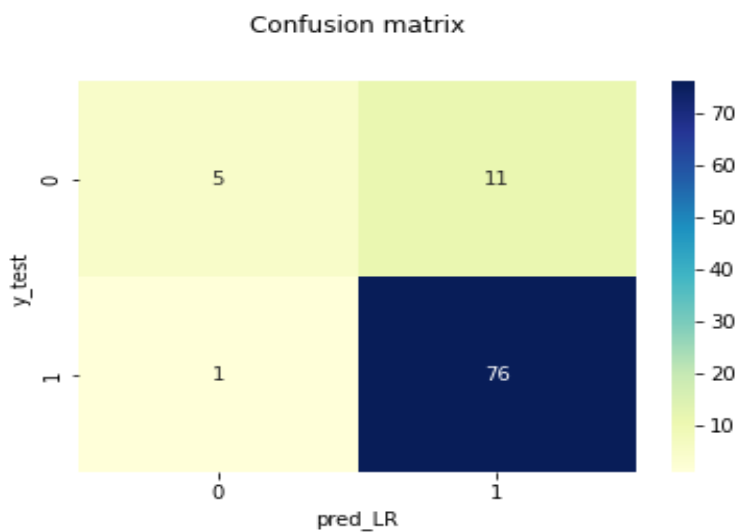
$$\text{Recall} = TP / (TP+FN)$$

5.1.4 **F1-score**: F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account.

$$\text{F1-score} = 2*(\text{Recall} * \text{Precision}) / (\text{Recall} + \text{Precision})$$
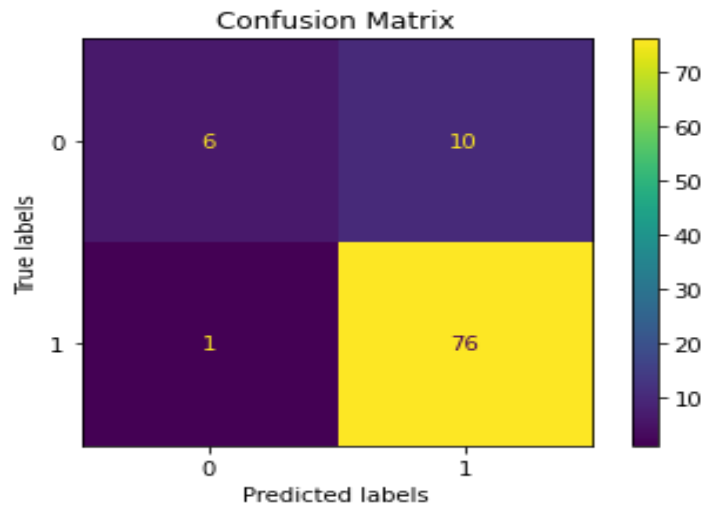
5.2 Result for single neuron in output class.
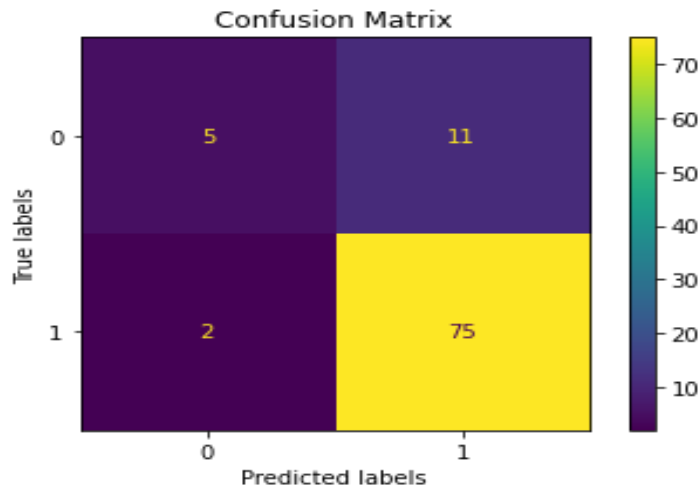
Fig 5.1 Confusion matrix for KNN classifier

Fig 5.2 Confusion matrix for logistic regression

Fig 5.3 Confusion matrix for Naïve bayes classifier

Classifier	Lung Cancer	Precision	Recall	F1-score	Accuracy
Naive Bayes	0 1	0.86 0.88	0.38 0.99	0.52 0.93	0.88
Logistic Regression	0 1	0.83 0.87	0.31 0.99	0.45 0.93	0.87
KNN	0 1	0.71 0.87	0.31 0.97	0.43 0.92	0.86

Table 5.1. Generated result from all the classifiers

The table-4.1 shows precision, recall, f1-score, and accuracy of all the classifiers . We see that, Naïve bayes classifier gives the accuracy of 88% which is better than other classifiers.

5.3 Result for two neuron in output class:

We applied KNN on multiclass

```
              precision    recall  f1-score   support

           0       1.00      0.20      0.33        10
           1       0.87      1.00      0.93        52

   micro avg       0.87      0.87      0.87        62
   macro avg       0.93      0.60      0.63        62
weighted avg       0.89      0.87      0.83        62
 samples avg       0.87      0.87      0.87        62

Accuracy Score: 0.8709677419354839
[[[52  0]
  [ 8  2]]

 [[ 2  8]
  [ 0 52]]]
```

Naïve bayes:

```
              precision    recall  f1-score   support

           0       0.80      0.40      0.53        10
           1       0.89      0.98      0.94        52

    accuracy                           0.89        62
   macro avg       0.85      0.69      0.73        62
weighted avg       0.88      0.89      0.87        62

Accuracy Score: 0.8870967741935484
[[[52  0]
  [ 8  2]]

 [[ 2  8]
  [ 0 52]]]
```

So we see for two neuron in binary classification we got 87% model accuracy using KNN classifier .

<div align="center">

Chapter-06

Analysis

</div>

The analysis of a lung cancer prediction model report typically includes an evaluation of the model's performance in terms of its accuracy, precision, recall, F1 score.

Accuracy refers to the proportion of correctly predicted cases among all cases, while precision refers to the proportion of true positives (correctly predicted lung cancer cases) among all predicted lung cancer cases. Recall refers to the proportion of true positives among all actual lung cancer cases, and the F1 score is the harmonic mean of precision and recall, providing a balanced evaluation of the model's performance.

The AUC of the ROC curve is a measure of the model's ability to distinguish between positive and negative cases. A value of 1 indicates a perfect model, while a value of 0.5 indicates a model that performs no better than random guessing.

In addition to these metrics, the report may also include a confusion matrix, which displays the number of true positives, false positives, true negatives, and false negatives. This can provide insights into the model's strengths and weaknesses in correctly identifying lung cancer cases.

Overall, the analysis of a lung cancer prediction model report aims to provide a comprehensive evaluation of the model's performance, helping to determine its potential usefulness in clinical settings for identifying individuals at high risk of lung cancer.

Our model lung cancer prediction is a binary classification model. We did experiment to determine the model accuracy by two ways.
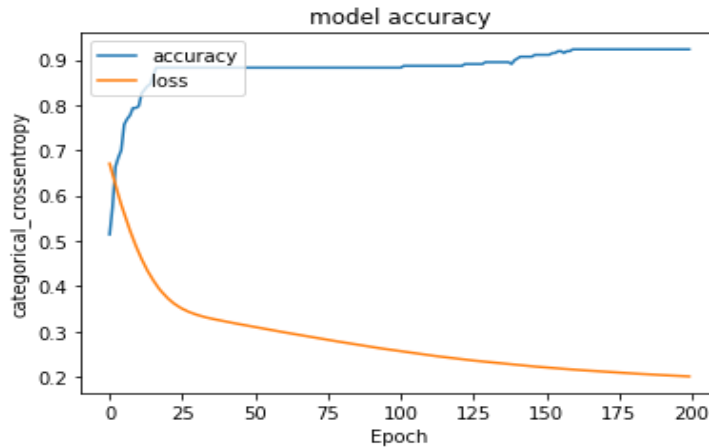
1. **Single neuron in output**:   For epochs=100, batch_size=200 we got accuracy and loss .
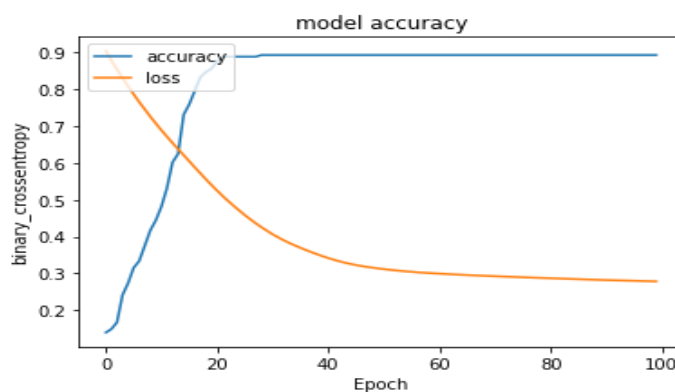
Here we got loss: 0.3911 - accuracy: 0.8280

2. **Two neuron in output:**

For epochs=200, batch_size=128 we got our model accuracy and loss

Here we got   loss: 0.3436 - accuracy: 0.8548

On the other hand considering to the KNN classifier we got best model accuracy for multiclass binary classification that is 87% where single class model accuracy.

Accuracy finding by Classification

Accuracy for single neuron in output

Classifiers	Accuracy
KNN	0.86
Naïve bayes	0.88
Logistic regression	0.87

Accuracy for two neuron in output

Classifiers	Accuracy
KNN	0.87
Naïve bayes	0.88

Limitation: we have very small dataset. That's why that is not possible to determine cancer prediction for a individual person very strongly. In future we will try to collect more data. And we will try to determine accuracy of the model more best.

Chapter-07

Discussion

Lung cancer prediction using neural networks is an active research area with significant potential for improving the accuracy of diagnosis and treatment of lung cancer. Neural networks are powerful tools for predicting outcomes and have been used successfully in various fields, including healthcare.

To build a neural network model for lung cancer prediction, researchers typically start by collecting data on patient demographics, medical history, smoking status, and other relevant factors. This data is then used to train the neural network to recognize patterns and make predictions about the likelihood of developing lung cancer.

Our project is binary classification model. And we worked here with small number of peoples information. If we train our model with a large number of information may we get more better prediction. This actually a challenge for us.

In this project we actually worked about model accuracy. We got different accuracy on the basis of different machine learning algorithm.

One challenge in developing neural network models for lung cancer prediction is the need for large and diverse datasets. This requires collaboration among researchers and healthcare providers to ensure that sufficient data is available for training and testing the model.

Another challenge is ensuring that the neural network model is both accurate and interpretable. Interpretability is important because clinicians need to understand how the model arrived at its predictions in order to make informed decisions about patient care.

Despite these challenges, there have been promising results in using neural networks for lung cancer prediction. For example, a study published in the Journal of Thoracic Oncology found that a neural network model outperformed traditional statistical models in predicting lung cancer recurrence after surgery.

In summary, lung cancer prediction using neural networks is a promising area of research that has the potential to improve patient outcomes. However, further research is needed to overcome the challenges associated with developing accurate and interpretable models.

Chapter-08

Conclusion

In conclusion, lung cancer prediction using neural networks is an exciting area of research that has the potential to improve the accuracy of diagnosis and treatment of lung cancer. Neural networks can be trained on large and diverse datasets to recognize patterns and make predictions about the likelihood of developing lung cancer.

However, the development of accurate and interpretable models is challenging and requires collaboration among researchers and healthcare providers. Despite these challenges, there have been promising results in using neural networks for lung cancer prediction, and further research is needed to improve the accuracy and interpretability of these models. With continued efforts, lung cancer prediction models using neural networks may eventually become a valuable tool for healthcare professionals in the fight against lung cancer.

The fact that the ANN lung cancer prediction model achieved an accuracy of 88% with a small dataset is a promising result. This suggests that the model has learned meaningful patterns in the data and can make accurate predictions about the likelihood of developing lung cancer. However, it is important to note that the small dataset size may limit the generalizability of the model to larger and more diverse datasets. Further research is needed to validate the model's performance on larger datasets and to ensure that it can be used effectively in clinical practice. Additionally, the model's interpretability should be evaluated to ensure that clinicians can understand and trust the predictions it produces. Overall, while the model's initial performance is promising, continued research and validation is needed to ensure that it can be used effectively in practice.

Chapter-09

References

[1] R. Nall, "Medical News Today," 12 11 2018. [Online]. Available: https://www.medicalnewstoday.com/articles/323648.php. [Accessed 14 3 2019].

 [2] Chauhan, D., Solan, H.P. and Jaiswal, V., Development of Computational Tool for Lung Cancer Prediction Using Data Mining .

[3] Krishnaiah, V., Narsimha, D.G. and Chandra, D.N.S., 2013. Diagnosis of lung cancer prediction system using data mining classification techniques. International Journal of Computer Science and Information Technologies, 4(1), pp.39-45. .

[4] Tiwari, A.K., 2016. Prediction of lung cancer using image processing techniques: a review". Advanced Computational Intelligence: An International Journal (ACII), 3(1).

[5] Kuruvilla, J. and Gunavathi, K., 2014. Lung cancer classification using neural networks for CT images. Computer methods and programs in biomedicine, 113(1), pp.202-209.

[6] kaur, T. and Gupta, E.N., 2015. Classification of Lung Diseases using Particle Swarm Optimization. Image, 4(9).

<div align="center">

Chapter-10

Appendices

</div>

An appendix for a lung cancer prediction model report might include additional details about the model, data used for training and evaluation, and technical specifications.

1. **Description of input features:** we used 11 input features in our model where 'Gender' is categorical and rest of the inputs are numerical .

2. **Model architecture and specifications:** our model binary classification lung cancer prediction is used with two ways. Where one neuron is used in output layer and another is two neuron in output layer. Besides we used two hidden layer where 12 neuron in 1st hidden layer and 8 neuron in 2nd hidden layer.

3. **Performance metrics:** we used KNN, Naïve bayes , Logistic regression classifiers to find our model accuracy . Where Naïve bayes gives us best accuracy for this model.

4. **Code and software:** we used google Colab for creating the model with python language.