***DATA SCIENCE PROJECT***

***DATASET:*** BREAST CANCER WISCONSIN

***ALGORITHM:*** NAÏVE BAYES



***SUBMITTED BY:***

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***INTRODUCTION TO TOPIC***

Breast cancer is a common type of cancer, affecting more than a million people annually in India alone. There are 2 types of tumors associated with breast cancer namely benign and malignant tumors. A benign tumor is just a non-cancerous mass of abnormal tissue that doctors prefer to leave instead of removing unless it causes pain or gets too large. A malignant tumor is a cancerous and aggressive growth that doctors because they might invade and destroy neighboring tissues. When a tumor is diagnosed as malignant, doctors perform a biopsy and remove the mass.

If a mass is undetected or is incorrectly diagnosed, then it can cause serious risk to the patient’s life. Hence it is critical to correctly diagnose and if possible, predict the type of growth a patient has. This is where Machine Learning comes into play.

By using Machine Learning and classification algorithms, it can be possible to detect a malignant growth before it gets dangerous and can possibly save a person’s life.

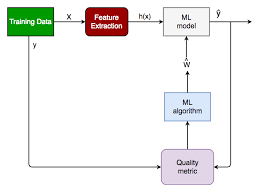
***CLASSIFICATION IN MACHINE LEARNING***

**Classification** is the process of discovering a model/function which helps in separating the given data into multiple categorical classes. In classification, data is categorized under different labels according to some parameters given in the input and then the labels are predicted for the data. This data may simply be bi-class, or it may be multi-class. A few examples of classification problems are speech recognition, spam classification, binary classification, prediction etc.

We have few types of classification algorithms in machine learning:

1. Linear Classifiers: Logistic Regression, Naive Bayes Classifier
2. Nearest Neighbour
3. Support Vector Machines
4. Decision Trees

In this project we will be implementing Naïve Bayes Classifier, so let us take a further look at that.

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***NAÏVE BAYES CLASSIFIER***

This classifier works on the conditional probability principle of Bayes Theorem. According to Bayes Theorem, the conditional probability can be calculated as follows:

P(Y|X) = [P(X|Y) \* P(Y)] / P(X)

A Naive Bayes classifier assumes that the presence of one feature in a class is unrelated to the presence of any other feature or that all these properties have independent contribution to the probability. This family of classifiers is relatively easy to build and particularly useful for very large data sets as it is highly scalable and easy to implement.

There are 3 types of Naïve Bayes classifiers:

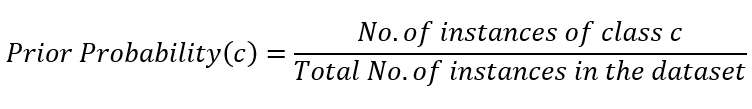
## 1. Multinomial Naive Bayes

2. Bernoulli Naïve Bayes

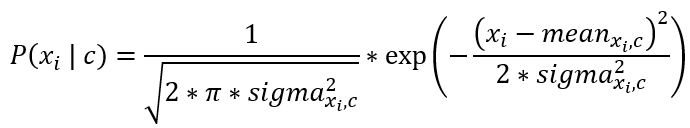
3. Gaussian Naïve Bayes

We have used Gaussian Naïve Bayes as our classifier model.

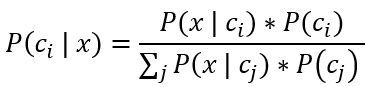
Gaussian Naïve Bayes is a classification algorithm using probabilistic approach. It involves prior and posterior probability calculation of the classes in the dataset and the test dataset respectively.



We then obtain the conditional probabilities of the test data features:



Then the conditional probability of each class given a test instance is calculated using Bayes Theorem.



This last step is repeated for all classes and the class showing the highest probability is declared as the predicted result.

![A picture containing clock, meter

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generated](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEAYABgAAD/4ST6RXhpZgAATU0AKgAAAAgABgALAAIAAAAmAAAIYgESAAMAAAABAAEAAAExAAIAAAAmAAAIiAEyAAIAAAAUAAAIrodpAAQAAAABAAAIwuocAAcAAAgMAAAAVgAAEUYc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAFdpbmRvd3MgUGhvdG8gRWRpdG9yIDEwLjAuMTAwMTEuMTYzODQAV2luZG93cyBQaG90byBFZGl0b3IgMTAuMC4xMDAxMS4xNjM4NAAyMDIwOjA0OjEwIDE3OjE5OjIxAAAGkAMAAgAAABQAABEckAQAAgAAABQAABEwkpEAAgAAAAMwMAAAkpIAAgAAAAMwMAAAoAEAAwAAAAEAAQAA6hwABwAACAwAAAkQAAAAABzqAAAACAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA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**Advantages of Gaussian Naïve Bayes classifier:**

* Easy to implement.
* It requires less training data.
* It is highly scalable.
* Can handle both continuous and discrete data.

**Disadvantages of Gaussian Naïve Bayes classifier:**

* The assumption about the features being independent is hardly true in real life applications.
* Data scarcity.
* Chances of loss of accuracy.
* Zero Frequency i.e. if the category of any categorical variable is not seen in training data set then model assigns a zero probability to that category and then a prediction cannot be made.

***DATASET DESCRIPITON***

The data has been collected by the University of Wisconsin. The features are computed from a digitized image of a fine needle aspirate (FNA) of a breast mass. They describe characteristics of the cell nuclei present in the image. Relevant features were selected using an exhaustive search in the space of 1-4 features and 1-3 separating planes.

Attribute Information:

1) ID number  
2) Diagnosis (M = malignant, B = benign)  
3-32)

Ten real-valued features are computed for each cell nucleus:

a) radius (mean of distances from centre to points on the perimeter)  
b) texture (standard deviation of grey-scale values)  
c) perimeter  
d) area  
e) smoothness (local variation in radius lengths)  
f) compactness (perimeter^2 / area - 1.0)  
g) concavity (severity of concave portions of the contour)  
h) concave points (number of concave portions of the contour)  
i) symmetry  
j) fractal dimension ("coastline approximation" - 1)

The mean, standard error and largest (mean of the three  
largest values) of these features were computed for each image,  
resulting in 30 features. All feature values are recoded with four significant digits.

***DATA VISUALIZATION***

Data visualization is the representation of data or information in a graph, chart or any other visual format. It communicates relationships of the data with images. We need data visualization because a visual summary of information makes it easier to identify patterns and trends than looking through thousands of rows on a spreadsheet. Since the purpose of data analysis is to gain insights, data is much more valuable when it is visualized. Even if a data analyst can pull insights from data without visualization, it will be more difficult to communicate the meaning without visualization.

The various data visualization techniques we have used are:

**1. Box plot-** A boxplot is a standardized way of displaying the distribution of data based on a five-number summary (min, max, Q1, Q3, median). It can tell you if your data is symmetrical, how tightly your data is grouped, and if and how your data is skewed. Here we have plotted a box plot of all features including whether the diagnosis is benign or malignant.

A picture containing pencil

Description automatically generated

**2. Bar Graph-** A bar chart or bar graph is a chart or graph that presents categorical data with rectangular bars with heights or lengths proportional to the values that they represent. The bars can be plotted vertically or horizontally. Here we plot the number of benign tumours vs malignant tumours in the dataset.

A screenshot of a cell phone

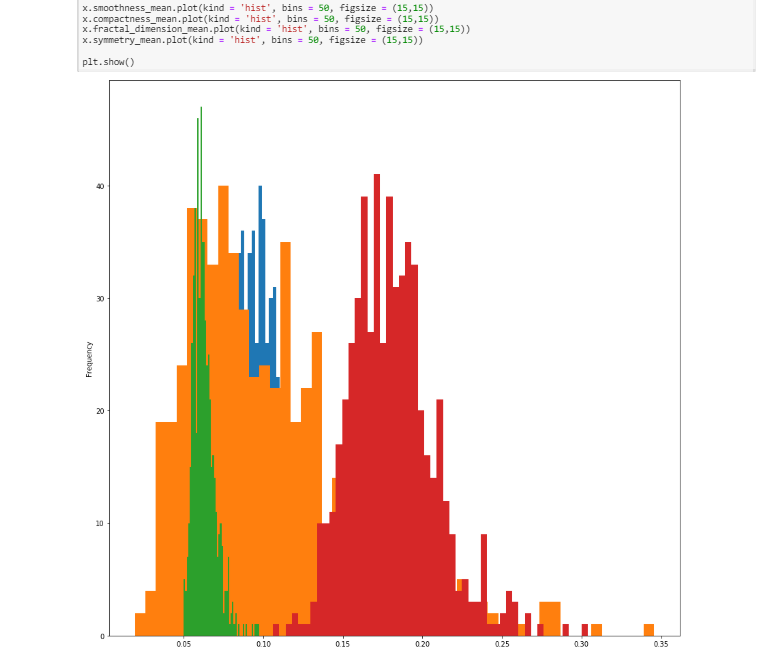
Description automatically generated

**3. Pairplot-** A pairplot plot a pairwise relationships in a dataset. The pairplot function creates a grid of Axes such that each variable in data will by shared in the y-axis across a single row and in the x-axis across a single column. In this project, we have created a pairplot of the main 10 features of a tumour/mass.

A close up of a flag

Description automatically generated

**4. Histogram-** A histogram is used to summarize discrete or continuous data. It provides a visual interpretation of numerical data by showing the number of data points that fall within a specified range of values (called “bins”). It is like a vertical bar graph, but, unlike a vertical bar graph, a histogram shows no gaps between the bars. Here we have created a histogram of the mean of 4 important features given in the dataset (smoothness, compactness, fractal dimensions and symmetry)



***IMPLEMENTATION AND EFFECTIVENESS OF ALGORITHM***

**STEP 1-** Create a function that calculates effectiveness of the algorithm based on 11 parameters- accuracy, precision, recall, f1\_measure, sensitivity, specificity, false positive rate, false negative rate, negative predictive values, false discovery rate and Matthews correlation coefficient.  
Import all libraries required and split data into given training and test data set percentages. Call the Gaussian classifier then fit the training data into the classifier. After this, store the predicted output of the test data in ‘y\_pred’.  
Then calculate the values of all 11 parameters and return them in a list.

A screenshot of a social media post

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**STEP 2-** To show the difference in results we have achieved due to the different train/test ratios, we have a graphical representation of each parameter for each train/test ratio. These bar graphs are a simpler way of visualizing the results.  
 Parameter 1- Accuracy:

(Accuracy = No. of correct predictions/Total predictions)

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Parameter 2- Precision:

(Precision = No. of correct positives predicted/Total no. of positives predicted)

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Parameter 3- Recall:

(Recall = No. of correct positives predicted/Total no. of correct predictions)

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Parameter 4- F1-measure:

(F1-measure is the Harmonic Mean between precision and recall)

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Parameter 5- Sensitivity:

(Sensitivity = True Positive/True Positive + False Negative)

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Parameter 6- Specificity:

(Specificity = True Negative/True Negative + False Positive)

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Parameter 7- False Positive Rate:

(FPR = False Positive/False Positive + True Negative)

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Parameter 8- False Negative Rate:

(FNR = False Negative/False Negative + True Positive)

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Parameter 9- Negative Predictive Values:

(NPV = True Negative/True Negative + False Negative)

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Parameter 10- False Discovery Rate:

(FDR = False Positive/False Positive + True Positive)

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Parameter 11- Matthews’ Correlation Coefficient:

(MCC = ((tp\*tn) - (fp\*fn))/sqrt((tp+fp) \* (tp+fn) \* (tn+fp) \* (tn+fn)) )

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**STEP 3-** Represent the differences in the results achieved for each train/test dataset ratio in a tabular format to further clarify the outcome.

TABLE 1:

|  |  |  |  |
| --- | --- | --- | --- |
| Algorithms 🡪  Measures: | Train : Test Ratio-  70: 30 | Train: Test Ratio-  80 : 20 | Train : Test Ratio-  90 : 10 |
| Accuracy | 94.15% | 97.36% | 98.24% |
| Precision | 0.9344 | 1.0000 | 1.0000 |
| Recall | 0.9047 | 0.9302 | 0.9411 |
| F1-measure | 0.9193 | 0.9638 | 0.9696 |
| Sensitivity | 0.9047 | 0.9302 | 0.9411 |
| Specificity | 0.9629 | 1.0000 | 1.0000 |
| False Positive Rate | 0.0370 | 0.0000 | 0.0000 |
| False Negative Rate | 0.0952 | 0.0697 | 0.0588 |
| Negative Predictive Values | 0.9454 | 0.9594 | 0.9756 |
| False Discovery Rate | 0.0655 | 0.0000 | 0.0000 |
| Matthews’ Correlation Coefficient | 0.8737 | 0.9447 | 0.9582 |

From the above table, we can clearly see that as the percentage of data used for training our model increases, the effectiveness and efficiency of the model increases as well.   
Having a specificity of 1.00 for train/test ratio 80:20 and 90:10 means that, the model with that data was able to correctly identify every person who does not have the target disorder (Breast cancer) i.e. not predict anyone from the health group as sick.  
Also we can see that we have a perfect precision score for 80:20 and 90:10 train/test ratios, which leads us to believe that every prediction made by the Gaussian Bayes’ model was relevant i.e. all the predictions made by the model with the data it had in terms of positive cases, was correctly identified as positive/malignant.

**STEP 4-** Now we will display a confusion matrix for each train/test ratio. A confusion matrix is a table that is often used to describe the performance of a classification model on a set of test data for which the true values are known. It allows the visualization of the performance of an algorithm. It is one of the most popular and effective ways to evaluate and visualise the effectiveness of a machine learning algorithm.

Confusion Matrix 70:30-

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Confusion Matrix 80:20-

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Confusion Matrix 90:10-

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**STEP 5-** The next step is to plot a loss and accuracy graph for the model.   
A loss function is used to optimize a machine learning algorithm. The loss is calculated on training and validation and its interpretation is based on how well the model is doing in these two sets. It is the sum of errors made for each example in training or validation sets. Loss value implies how poorly or well a model behaves after each iteration of optimization.  
An accuracy metric is used to measure the algorithm’s performance in an interpretable way. The accuracy of a model is usually determined after the model parameters and is calculated in the form of a percentage. It is the measure of how accurate your model's prediction is compared to the true data.  
We plot these metrics against epochs.  An epoch is one complete presentation of the data set to be learned to a learning machine. To implement loss/accuracy vs epoch, we use Artificial Neural Networks (ANN).   
ANN is a concept in AI that is like the human brain. You feed data to the program, it evaluates the data and comes up with output. Then based on that output, the neural network tries to correct itself and tries to improve the accuracy of the output. Each time an output is produced, one epoch is completed.

Train/Test ratio- 70:30

Accuracy vs epoch graph-

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Loss vs Epoch graph-

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Train/Test ratio- 80:20

Accuracy vs Epoch Graph-

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Loss vs Epoch Graph:

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Train/Test ratio- 90:10

Accuracy vs Epoch Graph-

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Loss vs Epoch Graph-

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In the above graphs, we can see that there is much more fluctuation in the graphs which have train/test ratio 70:30 and 90:10 as compared to the graphs with train/test ratio 80:20. The most likely reason for this is overfitting. Overfitting happens when a model learns the detail and noise in the training data to the extent that it negatively impacts the performance of the model on new data. This means that the random fluctuations in the training data is picked up and learned as concepts by the model. We can fix it by adding more layers to the network or by using regularization techniques.

We can also compare the accuracy of each train/test ratio using the mean squared error. It is simply the average of the square of the difference between the original values and the predicted values. It is the evaluation measure to check the performance of the classification model.

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**STEP 6-** The final way we will evaluate the performance of our classification model is by plotting a ROC curve for each training dataset percentage. ROC or Receiver Operating Characteristic curves summarize the trade-off between the true positive rate and false positive rate for a predictive model using different probability thresholds which basically means that it plots the false alarm rate versus the hit rate.  
We want to achieve a skilful model and a ROC curve is a good way of judging if our model is skilful or not. A skilful model will assign a higher probability to a randomly chosen real positive occurrence than a negative occurrence on average. This is what we mean when we say that the model has skill. Generally, skilful models are represented by curves that bow up to the top left of the plot.   
Let us see if our ROC curves show that our model is skilful.

ROC Curve for train/test ratio 70:30

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ROC Curve for train/test ratio 80:20

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ROC Curve for train/test ratio 90:10

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***CONCLUSION AND FURTHER WORK***

After evaluating the ROC curves, we see that as the training data increases, the model becomes more skillful. We can confirm this because the classifier curve moves to the top left as the training data increases, indicating a higher true positive rate and AUC (Area Under Curve).   
This statement is further backed by evidence from previous steps performed, which show that the parameters indicate higher values as the train/test ratio increases.   
To get a closer look and in-depth analysis, we would have to feed the model with more data and to improve the model even more, a larger neural network would have to be used with more layers and units to avoid overfitting which we saw. A regularization technique and loss optimizer function would also have to be applied to tune the model further.