# 1.INTRODUCTION

Breast cancer is caused by abnormal cell growth, mutation, and uncontrolled growth of breast tissue. It is the most common type of cancer among women in both developed and underdeveloped countries and killed about 508,000 women in 2011 alone.

Accounting for 25% of all cancers and 15% of all cancers among women estimated to be diagnosed with breast cancer in 2012 [21]. Cancer imposes a heavy burden on society in terms of development and poor economic conditions.

Cancers are becoming more common due to an aging population and an increase in risk factors such as smoking, obesity, and physical inactivity. Early detection of cancer increases the risk of recurrence with effective treatment. Delay in diagnosis can lead to delayed admission, which can lead to reduced survival, increased medical costs, and even death.

The most common cancer diagnostic methods are X-ray mammography and Magnetic Resonance Imaging (MRI). However, current innovations have some disadvantages because they are very expensive, large and only available from large hospitals.

There are also some side effects and disadvantages of the mentioned process. However, thanks to the incredible amount of data generated and advances in biomedical science, machine learning has yielded great results. Machine learning helps extract data and information from experience and detect complex patterns from large and noisy data, providing accurate results in a short time. The use of machine learning in medicine has grown rapidly, especially due to its effectiveness in predicting and classifying breast cancer diagnosis and is now widely used in biomedical research.

# 2.PROBLEM STATEMENT

Breast cancer is a significant health concern worldwide, and early detection is crucial for successful treatment. Mammography is the most effective tool for breast cancer screening, but its interpretation relies on the subjective assessment of radiologists, leading to high false-positive and false-negative rates. Machine learning (ML) algorithms have shown promising results in improving the accuracy of mammogram analysis for early breast cancer detection. However, the optimal use of ML in mammography is still not well-defined, and several challenges need to be addressed, such as data quality, interpretability, and generalizability. Therefore, the problem statement of this report is to investigate the role of ML in mammogram analysis for early breast cancer detection, identify the challenges and limitations, and provide recommendations for future research and clinical practice.

However, there are still challenges to overcome in using machine learning for mammogram analysis. One challenge is the limited availability of high-quality labeled data, which is necessary for training accurate models. Another challenge is the need for interpretability of the model's predictions, so that medical professionals can understand how the model arrived at its diagnosis and make informed decisions about patient care.

The problem statement, therefore, is to develop a machine learning model for mammogram analysis that can accurately detect breast cancer lesions in mammogram images, while also addressing challenges such as limited data availability and interpretability of the model's predictions.

# 3.EXISTING SYSTEM

Mammography is the standard technology used to generate the images for breast cancer screening, diagnosis, and follow-up. It involves taking X-ray images of the breast tissue, which are then interpreted by radiologists to detect any suspicious lesions. However, mammography has several limitations that affect its performance, such as the high breast density, which reduces its sensitivity, and the subjective interpretation of the images, which can lead to inter-observer variability and diagnostic errors. Therefore, there is a need for more objective and accurate methods for mammogram analysis.

Machine learning (ML) algorithms have emerged as a promising approach to enhance the accuracy of mammogram analysis and reduce the false-positive and false-negative rates. ML algorithms can learn from large datasets of mammograms and patient characteristics to identify patterns and features that are relevant to breast cancer detection. Moreover, ML can be used to develop personalized risk models that can predict the likelihood of developing breast cancer and guide clinical decision-making.

Several studies have investigated the use of ML in mammogram analysis for breast cancer detection. For example, a recent study by McKinney et al. (2020) used deep learning algorithms to analyze mammograms from over 85,000 women and achieved a higher accuracy than radiologists in detecting breast cancer. Another study developed a machine learning model that combined mammography and clinical risk factors to predict the risk of developing breast cancer within the next 5 years. These studies demonstrate the potential of ML in improving the performance of mammography and advancing breast cancer screening and diagnosis.

However, despite the promising results, there are several challenges and limitations that need to be addressed in the use of ML for mammogram analysis. For example, the lack of standardized datasets and protocols for data collection and annotation can affect the quality and generalizability of ML models. Moreover, the interpretability of ML models is still a major concern, as they often rely on complex and opaque algorithms that are difficult to explain and validate. Therefore, there is a need for further research and development to overcome these challenges and maximize the benefits of ML in mammography.

# 4.PROBLEM ANALYSIS

## 4.1. PRODUCT DEFINITION

The product of this report is a comprehensive analysis of the role of machine learning (ML) in mammogram analysis for early breast cancer detection. The report aims to provide a thorough review of the existing literature on the use of ML in mammography, including its benefits, challenges, and limitations. The report also includes a critical evaluation of the current state-of-the-art in ML for mammogram analysis and provides recommendations for future research and clinical practice.

The product of this report is relevant to healthcare professionals, researchers, and policymakers who are interested in advancing breast cancer screening and diagnosis using state-of-the-art ML algorithms. The report can also benefit patients and the public by improving the accuracy and effectiveness of mammography and reducing the morbidity and mortality of breast cancer.

## 4.2. FEASIBILITY ANALYSIS

The feasibility of the product of this report can be assessed based on several criteria, such as technical feasibility, economic feasibility, and operational feasibility.

Technical feasibility: The product of this report is technically feasible, as it involves reviewing and analyzing the existing literature on the use of ML in mammography, which is widely available and accessible. Moreover, the ML algorithms and techniques used in mammogram analysis are well-established and can be easily implemented using standard programming languages and tools.

Economic feasibility: The product of this report is economically feasible, as it does not require significant financial resources. The main cost is the time and effort required to conduct a comprehensive literature review and analysis, which can be done using existing resources and tools. Moreover, the potential benefits of the product, such as improving the accuracy and effectiveness of mammography, can outweigh the costs in terms of healthcare outcomes and economic savings.

Operational feasibility: The product of this report is operationally feasible, as it does not require significant changes in the current healthcare system or clinical practice. The product can be integrated into existing mammography programs and workflows, and the recommendations can be implemented gradually based on the availability of resources and infrastructure.

### 4.3. PROJECT PLAN

The project plan for the product of this report includes the following tasks:

Conduct a comprehensive literature review on the use of ML in mammography

Identify the benefits, challenges, and limitations of ML in mammogram analysis

Evaluate the current state-of-the-art in ML for mammography and compare it to conventional methods

Provide recommendations for future research and clinical practice

Write and format the report according to the given format

The project plan can be completed within a reasonable timeframe, depending on the availability of resources and the scope of the literature review. The estimated timeline for the project plan is as follows:

Literature review: 2-3 weeks

Selecting Data Set: 1 week

Analysis and evaluation: 2-3 weeks

Recommendation and report writing: 2-3 weeks

Revision and formatting: 1 week

Overall, the product of this report is feasible and can be completed within a reasonable timeframe with appropriate resources and effort.

# 5. Software Requirement Analysis

## 5.1. INTRODUCTION

The software requirement analysis for this report focuses on the tools and technologies required to conduct a comprehensive literature review and analysis of the use of machine learning (ML) in mammogram analysis for early breast cancer detection. The software requirements include a range of tools for literature search, data analysis, and report writing.

## 5.2. GENERAL DESCRIPTION

The general software requirements for this report include:

Web-based literature search engines and databases such as PubMed, Google Scholar, and Scopus to identify relevant articles and studies on the use of ML in mammography.

Data analysis software such as Python, R, or MATLAB for analyzing and visualizing the data extracted from the literature review.

Report writing and formatting software such as Microsoft Word or LaTeX for writing and formatting the report according to the given format.

## 5.3. Dataset

CBIS-DDSM is a database of mammographic images and related data designed to support research in the detection and diagnosis of breast cancer. it contains over 2,500 digitized film mammography cases, including both benign and malignant cases.

CBIS-DDSM includes a variety of imaging modalities, including both digital and digitized film mammography images, as well as clinical and radiological data for each case. The database also includes annotations and ground truth labels for each case, making it a valuable resource for developing and testing new algorithms and techniques for breast cancer detection and diagnosis.

Breast histopathology images are images of breast tissue that have been examined and analyzed by a pathologist to diagnose or confirm the presence of breast cancer or other breast conditions. The images are taken from tissue samples that have been collected during a breast biopsy or surgery.

The images path given to breast histopathology images. Here, Number of Images of no cancer: 198738, Number of Images of cancer: 78786, Total Number of Images: 277524 with accompanying labels indicating the presence or absence of breast cancer.

## 5.4. SPECIFIC REQUIREMENTS

The specific software requirements for this report are as follows:

Python: Python is a widely used programming language in analyzing the data and machine learning. It provides a range of libraries and frameworks for data analysis, such as NumPy, Pandas, and Matplotlib, and for machine learning, such as scikit-learn, TensorFlow, and Keras. Python can be used to extract and analyze data from the literature review and to implement and evaluate ML algorithms for mammogram analysis.

**5.5. Microsoft Word or LaTeX**: Microsoft Word is a widely used word processing software for report writing and formatting. It provides a range of tools for formatting, structuring, and referencing the report according to the given format. LaTeX is a typesetting system for technical and scientific documents that provides more advanced tools for formatting and referencing. LaTeX can be used to produce high-quality reports with complex equations, figures, and tables.

**5.6. Web-based literature search engines and databases**: Web-based writings like PubMed, Google Scholar, and Scopus can be used to identify relevant articles and studies on the use of ML in mammography. These tools provide advanced search options and filters for identifying high-quality and relevant articles.

**5.7. Reference management software**: Reference management software such as EndNote or Zotero can be used to organize and manage the references cited in the report. These tools provide features for importing and exporting references, generating citations and bibliographies, and collaborating with other researchers.

**5.8. Kaggle:** Kaggle is a web-based platform for data science and machine learning competitions. It provides access to a range of datasets, pre-trained models, and tools for data exploration, analysis, and modeling. Kaggle can be used to experiment with ML models for mammogram analysis, evaluate their performance, and compare them with existing approaches. Kaggle also provides a community of data scientists and machine learning practitioners who can provide feedback and insights on the analysis and modeling process.

Overall, the software requirements for this report are widely available and accessible, and the tools and technologies can be easily integrated into the literature review and analysis process. The specific requirements can be adapted based on the preferences and expertise of the researcher**.**

# 6.DESIGN

## 6.1. System Design

The system design includes the overall architecture of the machine learning model for mammogram analysis. The system architecture should be scalable, flexible, and robust to handle a large number of mammogram images and classify them accurately. The following components are part of the system design:

Data preprocessing: This component includes data cleaning, normalization, and augmentation. The input mammogram images may have different resolutions, brightness, and contrast. Preprocessing techniques such as resizing, grayscale conversion, histogram equalization, and noise removal can be used to standardize the input data.

Feature extraction: This component extracts relevant features from the preprocessed images. Features such as texture, shape, and intensity can be extracted using techniques such as the gray-level co-occurrence matrix (GLCM), local binary patterns (LBP), and Gabor filters.

Model training: This component trains the machine learning model using the extracted features. Here  ML algorithms we used is Convolutional neural networks can be used for classification.

Model evaluation: This component evaluates the performance of the trained model using metrics such as accuracy, precision, recall, and F1-score. The evaluation can be done using a hold-out validation or cross-validation technique.

## 6.3. Detailed Design

The detailed design describes the specific techniques and parameters used for each component of the system design. The following detailed design is proposed for the mammogram analysis system:

Data preprocessing: The input mammogram images are preprocessed using the following steps:

Conversion to grayscale

Resizing to a fixed size (e.g., 256x256 pixels)

Histogram equalization

**6.4. Model training**: Convolutional Neural Networks (CNNs) are a popular choice for analyzing medical images, including mammograms, for breast cancer detection. CNNs are a type of deep neural network that are capable of learning features from images by using convolutional layers, pooling layers, and fully connected layers.

Model evaluation: The performance of the trained model is evaluated using the Accuracy, Model Loss, Precision and F1-score metric on a hold-out validation set.

**6.5. Pseudocode**

The following pseudocode describes the algorithm of the proposed mammogram analysis system:

1. Load mammogram dataset
2. Split dataset into training and validation sets
3. Preprocess mammogram images
4. Extract features from preprocessed images
5. Train machine learning model on extracted features
6. Optimize hyperparameters of the model using grid search
7. Evaluate model performance on validation set
8. Save trained model

### 6.6. Flow Chart

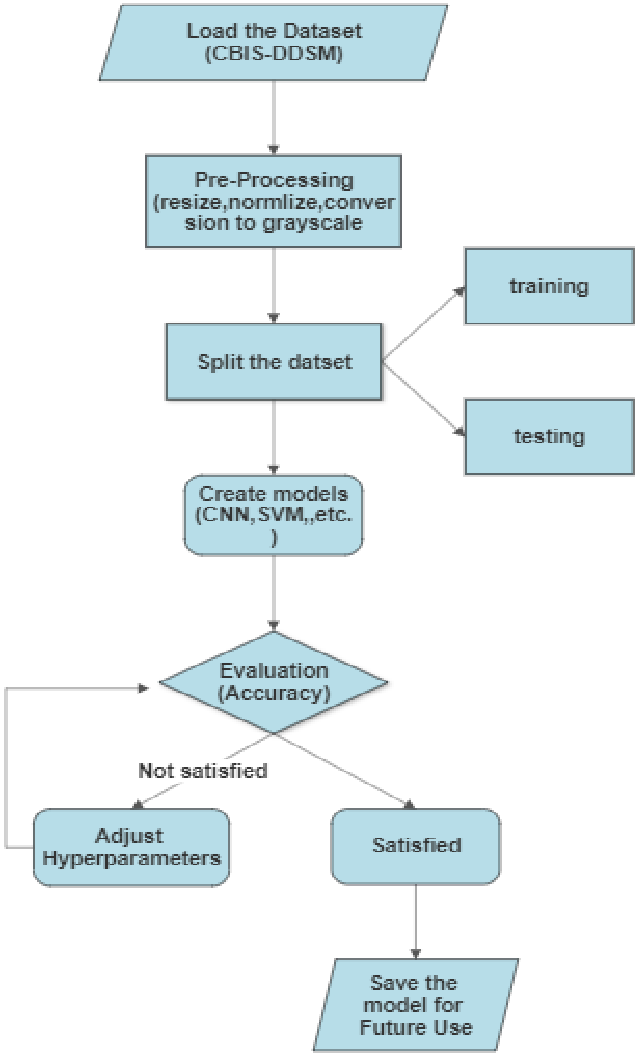



Figure 1: Flow Chart for Methodology

# 7.TESTING:

It ensures that the software product meets the desired quality standards and works as expected. In the case of machine learning models, testing is even more important because the accuracy and reliability of the model directly affect its usefulness in real-world scenarios.

In the context of the role of machine learning on mammogram analysis for early breast cancer detection, the testing phase should cover various aspects of the model, such as:

1.Functional testing: This type of testing proves that the model meets its requirements. In the case of mammogram screening, the examination will allow the sample to detect early signs of breast cancer from the mammogram images.

2.Structural testing: This type of testing verifies whether the model is structurally sound and free from any bugs or errors. It ensures that the model is working as intended and produces accurate results.

3.Levels of testing: The testing process should cover different levels of testing, such as unit testing, integration testing, and system testing, to ensure that the model performs as expected at every stage of its development.

4.Testing the project: In this phase, the entire project should be tested to ensure that it is working as intended, including the integration of different components, user interfaces, and system performance.

Overall, the testing phase should ensure that the machine learning model is accurate, reliable, and effective in detecting early signs of breast cancer from mammogram images.

# 8.IMPLEMENTATION

After designing and testing the machine learning model for mammogram analysis, the next phase is implementation. This phase involves deploying the model in a real-world scenario and making it available for use by end-users. The implementation phase consists of the following steps:

Implementation of the project: In this step, the machine learning model is integrated into the overall project and deployed in a production environment. This step involves installing and configuring the required software, hardware, and network infrastructure, ensuring the security of the system, and verifying that the system is working correctly.

Post-implementation and system maintenance: Once the system is implemented, it is essential to monitor its performance and maintain it over time. This step includes fixing bugs and errors, updating the system to incorporate new features or functionalities, and ensuring that the system continues to meet the user's needs.

**8.1 Convolutional Neural Network (CNN)**

Convolutional Neural Networks (CNNs) are a popular choice for analyzing medical images, including mammograms, for breast cancer detection. CNNs are a type of deep neural network that are capable of learning features from images by using convolutional layers, pooling layers, and fully connected layers.

To train a CNN model for mammogram analysis, the first step is to collect and preprocess a dataset of mammogram images. This dataset should be labeled with information about whether each image contains a breast cancer lesion or not.

Once the dataset is ready, the next step is to split it into training, validation, and testing sets. The training set is used to train the model, while the validation set is used to tune the model's hyperparameters and prevent overfitting. The testing set is used to evaluate the model's performance on unseen data.

The CNN model architecture should be designed based on the characteristics of the mammogram images. The architecture may include convolutional layers, pooling layers, and fully connected layers. The output layer should be a binary classifier that predicts whether an input mammogram image contains a breast cancer lesion or not.

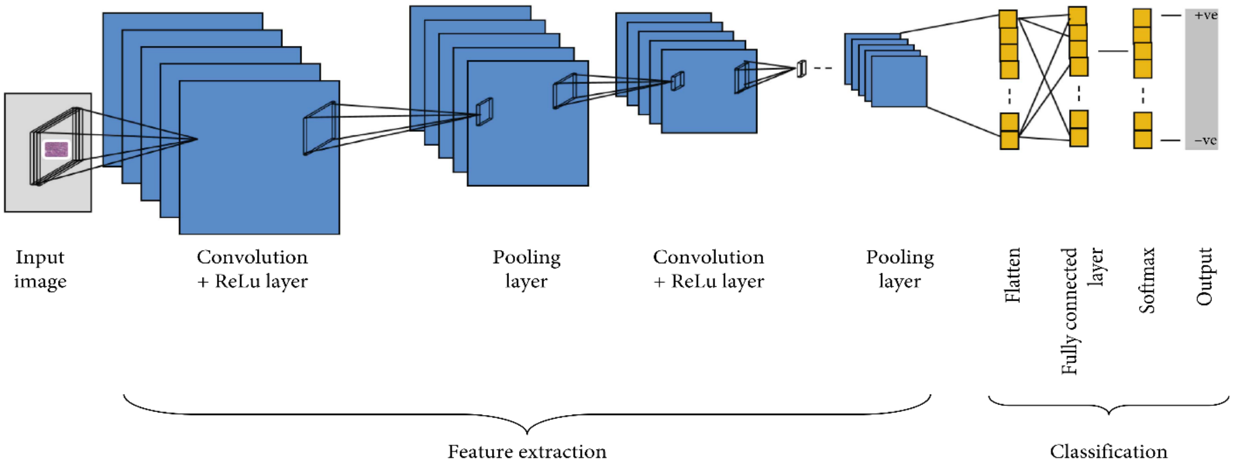



Figure 2: Schematic view Of Convolutional Neural Network

# 9.RESULT ANALYSIS

The algorithm was performed differently with and without PCA applied to the data. The performance evaluation and comparison of CNN model metrics used in testing the data were evaluated over various performance criteria.

**Performance Metrics**

In mammogram analysis for breast cancer detection using machine learning, common performance metrics include:

## 9.1. Confusion matrix

A confusion matrix is one of the simplest and easiest measures to find an accurate and correct model. It is used in classification problems where the output can be of two or more types, so it is suitable for this article. Table or matrix layouts can be useful for visualizing the performance of algorithms. Each row of the matrix in Table 1 represents an instance in the real class and each row represents an instance in the predicted class and vice versa .

Table 1: Structure of Confusion Matrix

| | Predictive Negative | Predictive Positive |
|---|---|---|
| Actual Negative | True Negative (TN) | False Positive (FP) |
| Actual Positive | False Negative (FN) | True Positive (TP) |

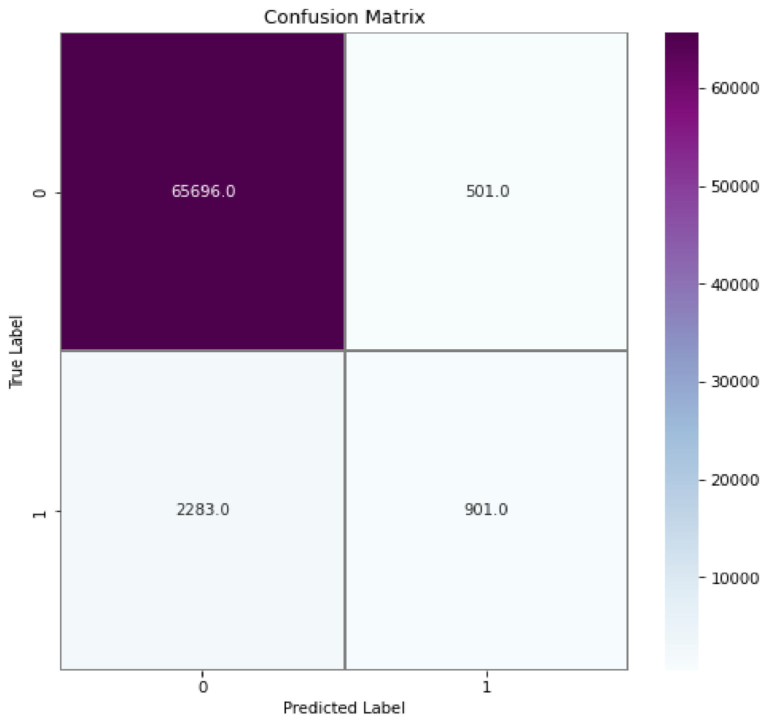



Figure 3: Confusion Matrix

**Confusion matrix points:**

Ideal (TP): Actual outcome is the condition that the data point class is correct (1) and the prediction correct (1) Cancer (1) Classify tumor and its data as Cancer. (1) really good.

True Negatives (TN): True negatives are cases where the true category of the data point is False (0) and the estimate is False (0). For example: a situation where a person has a benign (0) tumor and the standard classification of their data as benign (0) is actually negative.

False Positive (FP): A false positive is a situation where the data class indicates false (0) but the prediction is correct (1). Errors due to model prediction errors and positives due to class prediction accuracy (1).

For example: A person has a benign tumor (0) and the pattern (1) that classifies it as malignant is negative.

False Negative (FN): A false negative is a situation where the data class indicates true (1) but predicted false (0). Incorrect because the model prediction is incorrect, and negative because the class prediction is negative (0). For example: A person has a Cancer (1) and the model that classifies not having Cancer (0) tumor negative.

The best data for this model is 0 negative and 0 false negative. Accuracy

### 9.2. Accuracy

In the context of mammogram analysis for breast cancer detection using machine learning, accuracy is an important metric because it gives an indication of how well the model is performing overall. However, accuracy can be misleading when the dataset is imbalanced, meaning that there are many more non-cancerous images than cancerous images (or vice versa). In such cases, a model that always predicts the majority class (e.g., non-cancerous) can achieve high accuracy, but it will not be useful for detecting cancer.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

### 9.3. Precision

Precision is a performance metric that measures the proportion of true positive results (correctly classified cancerous mammogram images) out of all the images that the model classified as positive (both true positives and false positives). Precision is important because it measures the ability of the model to avoid false positives.

For example, suppose a machine learning model classifies 100 mammogram images as positive for cancer, but only 60 of them are actually cancerous (true positives). The remaining 40 are non-cancerous (false positives). The precision of this model would be 60/100 = 0.6 or 60%. This means that 60% of the images that the model classified as cancerous were actually cancerous, while the remaining 40% were false positives.

$$Precision = \frac{TP}{TP + FP}$$

### 9.4. Recall or Sensitivity

Return is a measure of the percentage of patients with malignancies diagnosed as malignant by the algorithm. The diagnostic criteria for true (cancer patients are TP and FN) and malignancy are TP. So if we want to focus on minimizing the downside, we want our return to be as close to 100% as possible.

$$Recall = \frac{TP}{TP + FN}$$

### 9.5. F1 Score

F1 score is a common performance metric used in binary classification tasks, including mammogram analysis for breast cancer detection. It combines precision and recall into a single score that represents the harmonic mean of the two.

In mammogram analysis for breast cancer detection, a high F1 score indicates that the model is accurately detecting both positive and negative cases, without producing many false positives or false negatives. Therefore, F1 score is an important performance metric to consider when evaluating the effectiveness of a machine learning model for breast cancer detection.

## 10.Model Performance:

Based on the provided true positive, true negative, false positive, and false negative values, it is difficult to make a comprehensive analysis of the CNN model's performance. However, we can still draw some conclusions and make some observations: The model's accuracy is high (96%), indicating that the model is making correct predictions for most of the instances in the test set. The model's precision is moderate (71%), which means that when the model predicts a positive class label, it is correct about 71% of the time. The model's recall is low (28.3%), indicating that the model is not able to identify all the positive instances in the test set. The model's F1 score is also relatively low (39.1%), which means that the model's precision and recall are not well balanced.

Overall, these results suggest that the model may be overestimating the number of negative instances and underestimating the number of positive instances. This could be due to several reasons, such as an imbalance in the dataset and the images are not precise or clear way.

```
In [122]: model.summary()

Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 50, 50, 32)        896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 25, 25, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 25, 25, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 12, 12, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 12, 12, 128)       73856
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 5, 5, 128)         0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 5, 5, 128)         147584
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 2, 2, 128)         0
_________________________________________________________________
flatten (Flatten)            (None, 512)               0
_________________________________________________________________
dense (Dense)                (None, 128)               65664
_________________________________________________________________
dense_1 (Dense)              (None, 2)                 258
=================================================================
Total params: 306,754
Trainable params: 306,754
Non-trainable params: 0
_________________________________________________________________
```

**Table 02: Results of Model Metrics**

| TRUE POSITIVE | 901 |
|---|---|
| TRUE NEGATIVE | 65696 |
| FALSE POSITIVE | 501 |
| FALSE NEGATIVE | 2283 |
| ACCURACY | 96% |
| PRECISION | 71% |
| LOSS | 0.11 |

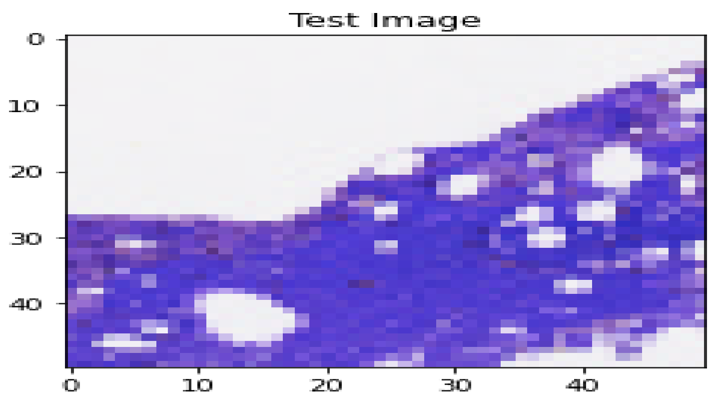



**Figure 4: Test Image**

```
Predicted Value using  cnn model 0
True Value 0
```

**Figure 5: Output for Test Image**

# 11.PROJECT LEGACY

The project legacy phase involves evaluating the current status of the project, identifying any remaining areas of concern, and documenting the technical and managerial lessons learned throughout the project's lifecycle. This phase ensures that the project's success factors are identified, documented, and used for future reference.

The following are the key components of the project legacy phase:

Current status of the project: In this step, the project team assesses the current status of the project to determine whether it has met its goals and objectives. This includes evaluating the accuracy and reliability of the machine learning model, the efficiency of the project development process, and the user's satisfaction with the project.

Remaining areas of concern: Once the current status of the project is evaluated, the project team should identify any remaining areas of concern. This includes identifying any issues with the machine learning model's performance, potential security vulnerabilities, or any unresolved technical issues.

Technical and managerial lessons learned: Finally, the project team should document the technical and managerial lessons learned throughout the project's lifecycle. This includes documenting any issues that arose during the development process, the solutions used to overcome these issues, and any best practices that were identified.

The documentation of the project legacy provides a roadmap for future projects that can build on the successes and lessons learned from the current project. It helps to identify areas of improvement, document best practices, and ensure that the project team can apply the knowledge gained during the project's lifecycle in future projects..

## 12. DATA VISUALIZATION

### 12.1. Histogram

It consists of a set of rectangles whose area is proportional to the frequency of the variable being measured. The rectangles are typically adjacent to each other and have equal widths, so that the height of each rectangle represents the frequency density of the data within that particular interval.. You can use histograms to show the shape and distribution of continuous data. Figure 3 shows the classification of Patients with Cancer and without Cancer.

There are about 78,000 cancers, accounting for about 38%, and about 200,000 other cancers, accounting for 62% of the rest of the predicted group. The properties of nuclei can be plotted against diagnosis,the importance of these restrictions increased, they were found to be associated with violence. Average of texture, smoothness, symmetry, or fractal dimension doesn't favor one thing.

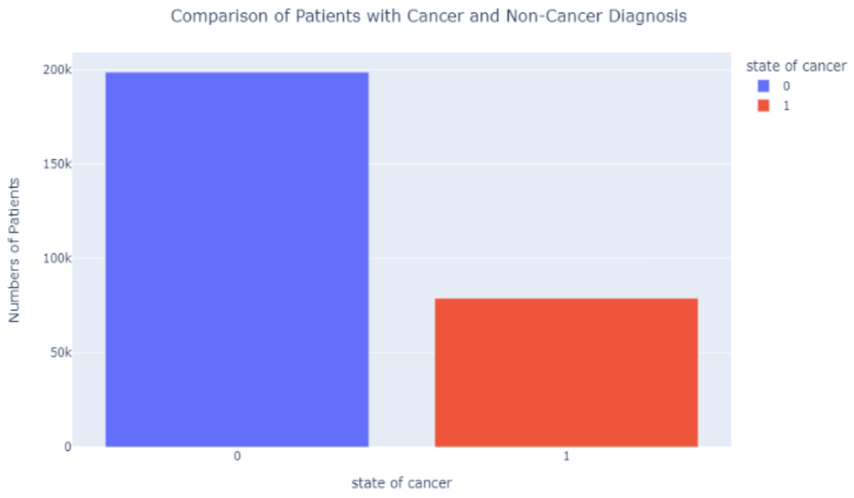



Figure. 06 : Classification

### 12.2. GRAY SCALE:

Grayscale refers to an image or visual representation that is composed solely of shades of gray or black and white, without any colors. In a grayscale image, each pixel's brightness level is represented by a single value in bits form. Shades of gray are created by varying the intensity of this brightness level. Grayscale is a range of shades of gray without apparent color. In digital imaging, a grayscale image is an image in which the value of each pixel is a single sample representing only an amount of light .

Grayscale images are commonly used in a variety of applications, including otography, printing, and digital imaging. They are often used to simplify images and remove color distractions, making it easier to focus on the overall composition and contrast of an image. Grayscale images can also be useful for image processing and analysis, as they can be more easily manipulated and processed than full-color images.

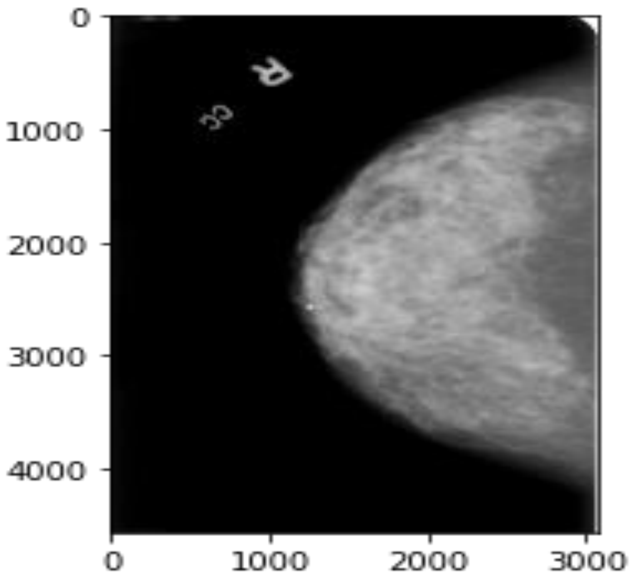



Figure 07: Images on Gray Scale

### 12.3. LINE CHART :

A line chart that shows the model accuracy and model loss over multiple epochs is a common way to visualize the performance of a machine learning model during training.

In such a chart, the horizontal axis represents the epochs, which are the number of times the model has gone through the entire training dataset. The vertical axis represents the model's accuracy and loss, which is a measure of how well the model performs on the test data.

As the model is trained, the accuracy is computed for each epoch, and a point is plotted on the chart to represent the accuracy at that epoch. These points are then connected by a line to show the trend in the model's accuracy over time.

Ideally, the line on the chart would trend upward over time, indicating that the model is improving and becoming more accurate with each epoch. However, the line may also have fluctuations or plateaus, indicating that the model is struggling to improve or has reached a limit in its performance.

Ideally, the line on the chart would trend downward over time, indicating that the model is reducing its error and becoming more accurate with each epoch.
However, the line may also have fluctuations or plateaus, indicating that the model is struggling to improve or has reached a limit in its performance.

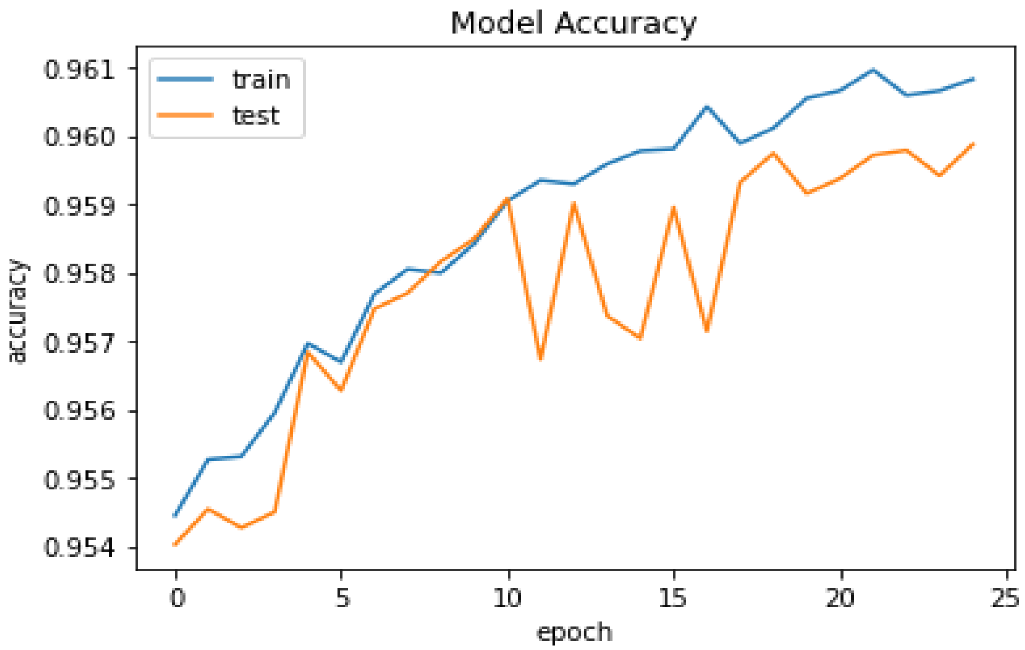



Figure 08 : Model accuracy vs epoch

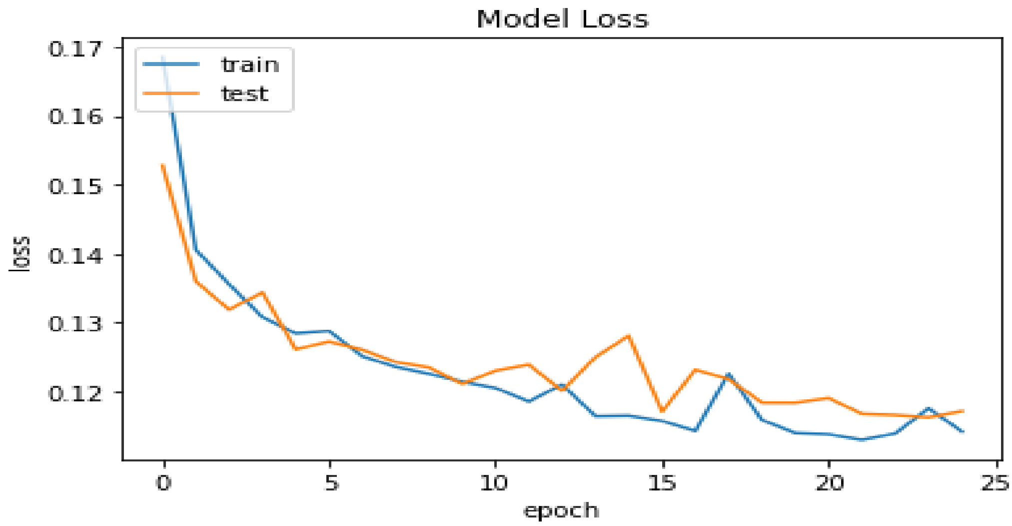


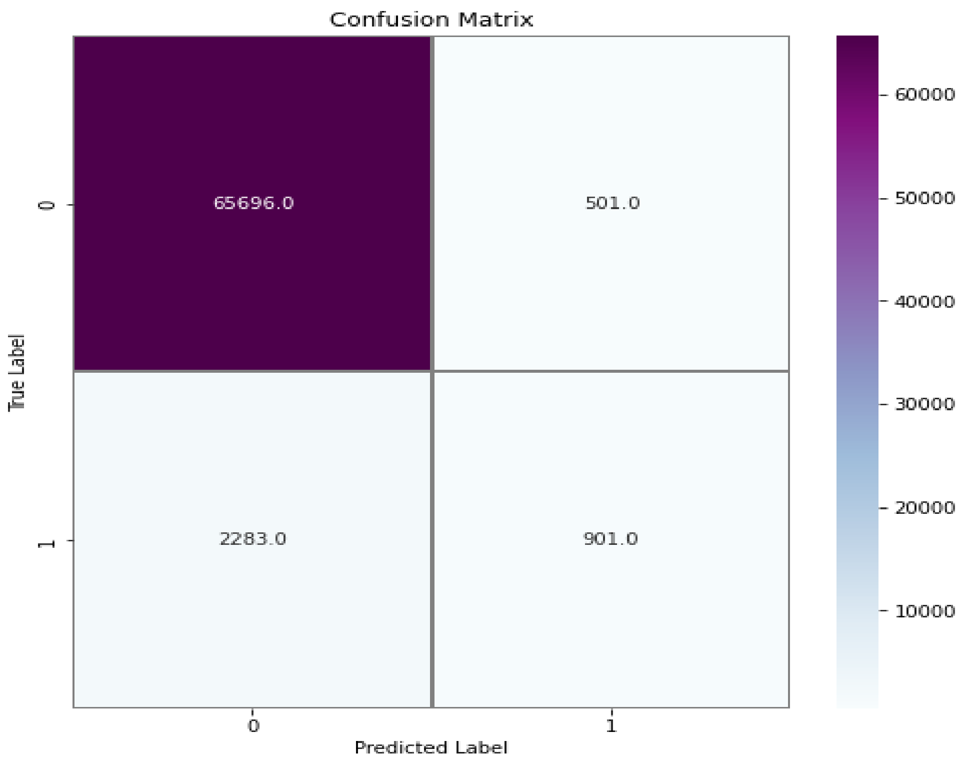

Figure 09 : Model Loss vs Epoch

### 12.4. HEAT MAP:

In a heatmap, each cell of the confusion matrix is color-coded according to its value, with darker colors indicating higher values. The diagonal cells (true positives and true negatives) are often highlighted with a different color to draw attention to them.

Heatmaps can be useful for quickly identifying patterns in the confusion matrix, such as areas of high false positives or false negatives. They can also be used to compare the performance of different models or algorithms side by side.

Heatmaps are often used to visualize large datasets with multiple variables. They are particularly useful in data analysis and visualization for identifying patterns, trends, and anomalies.




.

Figure 10: Confusion Matrix

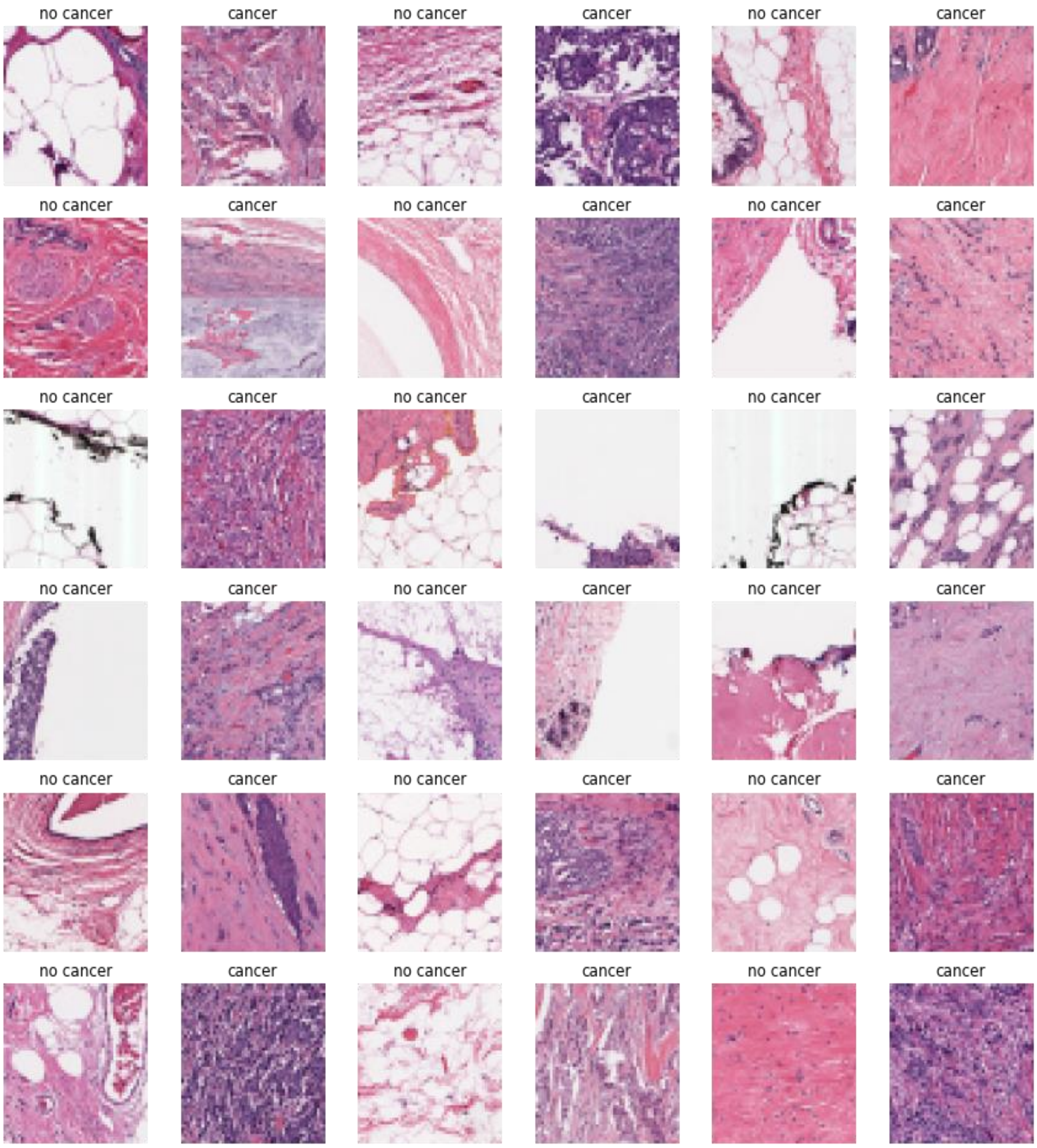


Figure 11 : Images of Cancer and No Cancer

# 13.CONCLUSION

In conclusion, machine learning has shown great potential in aiding the early detection of breast cancer through mammogram analysis. Convolutional neural networks (CNNs) have proven to be most effective in classifying breast Cancer mammogram images as either cancerous or non-cancerous and have shown improved performance over traditional methods.

By using machine learning for mammogram analysis, healthcare professionals can potentially detect breast cancer earlier, leading to better treatment outcomes and improved patient survival rates. However, it is important to continue research in this area to improve the accuracy and reliability of machine learning models for breast cancer detection.

Furthermore, it is important to consider the ethical implications of using machine learning in healthcare, including issues such as data privacy and potential biases in the data or models. Collaboration between healthcare professionals and machine learning experts is crucial to ensure that these models are developed and used responsibly, with the goal of improving patient outcomes.

Therefore, the study recommends that government agencies and other organizations help the areas where there are no proper mammography tools with expertise on use. The study also recommends further research to uncover the relationship between different screening methods and for age groups to make clear the problem of false positives and false negatives. The study also suggest research on knowledge and useof mammography in rural developing countries.

# 14.SOURCE CODE SNAPSHOTS

```
import pandas as pd
import numpy as np
import cv2
import PIL
import matplotlib.pyplot as plt
import plotly.express as px
import seaborn as sns
import glob
import random
import os
from os import listdir
random.seed(100)
np.random.seed(100)
```

Code 1 : Used Libraries

```
non_can_num = len(non_can_img)  # No cancer
can_num = len(can_img)   # Cancer

total_img_num = non_can_num + can_num

print('Number of Images of no cancer: {}' .format(non_can_num))   # images of Non cancer
print('Number of Images of cancer : {}' .format(can_num))   # images of cancer
print('Total Number of Images : {}' .format(total_img_num))
```

```
Number of Images of no cancer: 198738
Number of Images of cancer : 78786
Total Number of Images : 277524
```

Code 2: Data set Overview

```
import tensorflow as tf
tf.random.set_seed(100)
```

Code 3: Importing TensorFlow

```python
from sklearn.model_selection import train_test_split
from keras.utils.np_utils import to_categorical

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 42)

rate = 0.5
num = int(X.shape[0] * rate)

y_train = to_categorical(y_train, 2)
y_test = to_categorical(y_test, 2)


print('X_train shape : {}' .format(X_train.shape))
print('X_test shape : {}' .format(X_test.shape))
print('y_train shape : {}' .format(y_train.shape))
print('y_test shape : {}' .format(y_test.shape))
```

Code 4: Splitting Data for Training and Testing

```python
model = tf.keras.Sequential([
tf.keras.layers.Conv2D(32, (3, 3), padding = 'same', activation = 'relu', input_shape = (50, 50, 3)),
tf.keras.layers.MaxPooling2D(strides = 2),
tf.keras.layers.Conv2D(64, (3, 3), padding = 'same', activation = 'relu'),
tf.keras.layers.MaxPooling2D((3, 3),strides = 2),
tf.keras.layers.Conv2D(128, (3, 3), padding = 'same', activation = 'relu'),
tf.keras.layers.MaxPooling2D((3, 3),strides =2),
tf.keras.layers.Conv2D(128, (3, 3), padding = 'same', activation = 'relu'),
tf.keras.layers.MaxPooling2D((3, 3),strides =2),
tf.keras.layers.Flatten(),
tf.keras.layers.Dense(128, activation = 'relu'),
tf.keras.layers.Dense(2, activation = 'softmax')
])
```

Code 5: Implementing CNN Model

```python
history = model.fit(X_train, y_train, validation_data = (X_test, y_test), epochs = 25 , batch_size = 75)
```

Code 6 : Fitting the Model

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