IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

Automated breast cancer diagnosis using deep learning model

Seema Keshri
School of Computer Science and Engineering
Vellore Institute of Technology, Chennai

Prof. Manas Ranjan Prusty
School of Computer Science and Engineering
Vellore Institute of Technology, Chennai

Abstract— **Breast cancer is one of the leading causes of death among women. There has been a lot of research done on the use of different image processing and classification algorithms for the diagnosis and detection of breast cancer. An automated breast cancer diagnosis system using a deep learning model involves training a neural network on a dataset of mammogram images, along with their corresponding labels (i.e. benign or malignant). The model can then be used to classify new mammogram images as either benign or malignant. A thorough experimental setup is constructed in order to train and test the CNN model. The dataset is split into training and testing sets, with the training set being enhanced using the proper data augmentation techniques. The approach for training deep learning models for breast cancer diagnosis is to use convolutional neural networks (CNNs), which are well-suited for image classification tasks. These models can learn to extract features from the mammogram images and use these features to make predictions. The use of CNN model helps to incorporate a lot more data which helps the model become more generic and makes the diagnosis more reliable. The outcomes show how successful the suggested CNN-based method is for finding breast cancer. The trained model exhibits good performance in differentiating between malignant and benign lesions and achieves high accuracy.**

Keyword—breast cancer detection, deep learning, convolutional neural network, training dataset, test dataset mammogram images.

I. INTRODUCTION

Breast cancer: A metastatic cancer that can spread to other organs in the body is breast cancer. The biggest cause of cancer-related fatalities in women globally is breast cancer. The likelihood of a successful course of treatment and recovery is significantly increased by early detection and diagnosis of breast cancer. Many person worldwide died in 2020 and 2021 as a result of breast cancer.

There are many reports that tells that women die due to breast cancer specially women and very rarely men. Men make up less percentage of breast cancer cases. Men with breast cancer are treated using the same management strategies as women.

When breast cancer is detected early, treatment can be extremely successful, with survival of greater probability. For the control of the disease in the breast, treatment typically comprises of surgery and radiation therapy.

The manual interpretation of mammograms, the current standard for breast cancer screening, takes a lot of time and is vulnerable to error, which can affect the results. Deep learning has recently gained popularity as a potent image analysis tool and has demonstrated promising results in a number of medical imaging applications. Deep learning models can recognise intricate patterns and features in photos, which makes them suitable for automated breast cancer diagnosis.

The objective of this study is to create and assess a deep learning model for mammogram-based automated breast cancer diagnosis. We will also look into the potential advantages of utilising deep learning to diagnose breast cancer in comparison to more conventional diagnostic techniques.

An example of a deep learning model that is particularly effective for image processing applications is convolutional neural networks (CNNs). They are frequently employed in a variety of medical imaging procedures, such as the detection of breast cancer.

CNNs are capable of learning from images and extracting elements like edges, textures, and forms that are pertinent to the task at hand. They can also immediately pick up on various levels of abstraction, from basic features like edges to more intricate ones like tumours. Because of this, CNNs are an effective technique for studying mammograms and identifying breast cancer.

Several studies have been done recently on the use of CNNs for mammogram-based breast cancer diagnosis. These investigations have demonstrated that CNNs are capable of excellent diagnosis accuracy, sometimes even outperforming radiologists. CNNs can also be applied to CAD systems, which help radiologists interpret mammograms by assisting in the diagnosing process.

CNNs offer the potential to increase the consistency and accuracy of breast cancer detection and have produced encouraging results for the identification of the disease. The potential of CNNs for the early diagnosis of breast cancer must still be fully realised through study and development, though.

A medical imaging procedure called mammography is used to find breast cancer in female patients. It entails using X-ray equipment to create precise photographs of the breast tissue that can be used to spot any unusual growths or lumps that might be signs of cancer.

Women over 50, those with a family history of breast cancer, as well as those with additional risk factors for the disease, are the typical candidates for the operation. The breast is crushed between two plates during the mammography in order to generate a clear image of the tissue.

It has been demonstrated that mammography is a reliable method for identifying breast cancer in its beginning stages, when it is most amenable to treatment. Studies have actually found that women who have routine mammograms had a greater chance of surviving from breast cancer than those who don't.

II. METHODOLOGY USED IN RELETED PAPER WORK

Machine learning techniques such as Support Vector Machines (SVMs), k-Nearest Neighbours (k-NN), Linear Discriminant Analysis (LDA), and Quadratic Discriminant Analysis (QDA) are commonly employed for classification tasks, including the detection of breast cancer.

SVM: It is possible to employ SVMs, a form of supervised learning algorithm, for both classification and regression problems. In order to make predictions, they determine which boundary between the several classes is the best.

k-NN is a type of instance-based learning algorithm that makes predictions based on the closest training examples to a given test example.

LDA and QDA are both types of linear discriminant analysis, but QDA allows for non-linear decision boundaries while LDA assumes a normal distribution of the data and common covariance matrices for each class.

It is important to mention that the algorithm choosen will depend on the specific characteristics of the data set and the problem at hand. It is also important to evaluate the performance of the algorithm using appropriate evaluation metrics such as accuracy, precision, recall, and AUC.

Convolutional Neural Networks (CNNs) are a deep learning method frequently utilized for image classification tasks such as breast cancer detection. These networks are specifically designed to acquire hierarchical features from images in an automatic and adaptable manner.

Convolutional Neural Networks (CNNs) are a type of deep learning algorithm that are extensively used for image classification tasks, including the detection of breast cancer. CNNs can be applied to analyze medical images of breast tissue such as mammograms or ultrasound images, to categorize them as either normal or abnormal, such as cancerous.

Moreover, CNNs can also be utilized to detect and classify subtypes of breast cancer based on tissue characteristics presented in the images.

Compared to traditional machine learning techniques, CNNs have demonstrated high precision in detecting breast cancer. Nonetheless, CNNs demand a large amount of data for training, and it is usually required to perform considerable data pre-processing and feature engineering to develop a reliable CNN model for breast cancer detection.

Mammogram image pre-processing is an important step in **Computer-Aided Diagn (CAD)** systems for breast cancer detection. The goal of pre-processing is to enhance the quality of the mammogram images and to reduce the amount of noise and artifacts, making it easier for the CAD system to detect abnormalities.

Some common pre-processing techniques used in mammogram images include:

The following are common techniques used for improving the quality of mammogram images in computer-aided breast cancer detection systems:

- Image enhancement methods like contrast flexing, histogram equalization, and adaptive histogram equalization are utilized to improve the visibility of details in the mammogram images.
- Image denoising methods such as median filtering, Gaussian filtering, and wavelet denoising are employed to reduce the amount of noise in the images.
- Image registration is a technique that aligns multiple images of the same breast acquired at different times to enable comparison and detection of changes over time.
- Segmentation: This technique separates the breast tissue from the background and other irrelevant structures in the image, making it easier for the CAD system to focus on the area of interest.
- Normalization: It standardizes the images by adjusting the intensity values so that they have a consistent scale across images.

Digital breast tomosynthesis (DBT), also known as tomosynthesis, is an imaging technique that is gaining popularity in computer-aided diagnosis (CAD) systems for detecting breast cancer.

DBT uses X-rays to create a three-dimensional reconstruction of breast tissue by taking multiple low-dose images from different angles. This technique allows for a more detailed view of the tissue compared to traditional 2D mammography.

AB-MR (Automated Breast MR Image Interpretation) is an algorithm that uses machine learning techniques to automatically analyze breast MR images and identify potential abnormalities such as breast cancer.

The AB-MR algorithm typically involves the following steps:

- Image pre-processing: This step includes techniques such as noise reduction, intensity normalization, and registration to improve the quality of the MR images.
- Segmentation: This step separates the breast tissue from the background and other irrelevant structures in the image, making it easier for the algorithm to focus on the area of interest.
- Feature extraction: This step involves extracting relevant features from the

segmented images, such as shape, texture, and intensity, which will be used for classification.

- The classification stage involves the use of the extracted features to categorize the image as either normal or abnormal (cancerous). There are various machine learning techniques available for this purpose, such as support vector machines, k-nearest neighbors, and deep learning.
- Post-processing: The final step includes post-processing of the segmented results such as false positives reduction, lesion enhancement, and lesion boundary detection.

III. DATASET USED IN RELATED WORK

The term "dataset" refers to a grouping of data that is often arranged in a structured fashion, like a table or spreadsheet. It can be used for a variety of activities, including developing machine learning algorithms, running statistical analyses, and spotting patterns and trends. Datasets can be obtained from many different places, such as open access databases, for-profit vendors, or private repositories. They can be applied to a lot of tasks, including computer vision, natural language processing, and predictive analytics.

BREAKHIS DATASET: A publicly accessible dataset of breast cancer histological pictures is called "Breast Cancer Histopathological Image Classification" (BreakHis) [3][4]. There are more than 7,000 pictures of benign and malignant tumours in breast tissue samples. The photos, which come in a variety of sizes and magnifications, were taken from surgical and fine-needle aspiration (FNA) specimens. The dataset is separated into two subsets: the masses (MA) subset, which includes photos of masses, and the micro-calcification (MC) subset [7][8], which includes images of micro-calcifications. A benign or malignant diagnosis is listed next to each photograph. The dataset is frequently used to test and train machine learning algorithms for the detection of breast cancer.

ISLES 2015 SISS DATASET: A dataset of magnetic resonance imaging (MRI) images of individuals with acute ischemic stroke is known as the ISLES (Ischemic Stroke Lesion Segmentation) 2015 SISS (Stroke Ischemic Segmentation) dataset [6]. The ISLES 2015 challenge, which sought to assess the effectiveness of algorithms for the automated segmentation of ischemic brain lesions in acute stroke, served as the impetus for its creation. The dataset consists of thirty patients' multi-modal MRI images (including T1, T2, and FLAIR), each with manual lesion segmentation supplied by specialists as ground truth. The information is intended for studies in medical picture analysis and computer-assisted stroke diagnosis.

PROGNOSTIC BREAST CANCER DATASET NC DATASET [14]: The collection contains genomic data, such as copy number variations, mutations, and levels of gene expression, as well as information on patient demographics, tumour features, therapy specifics, and survival results. The development of predictive models for breast cancer patients and the identification of molecular subgroups of the disease have both made extensive use of this dataset.

Dataset "Clinical Breast Cancer" [14] from the NCI's Cancer Data Service (CDS), which includes thorough clinical and treatment details on more than 5,000 breast cancer cases. This dataset can be used to investigate the link between therapy and patient outcomes and to find breast cancer patient predictive variables.

DMR-IR DATASET: Infrared (IR) imaging as a possible method for detecting breast cancer. In DBM-IR [9][17] heat is used as a contrast agent in IR imaging, a non-invasive method for identifying and visualising physiological changes related to cancer. Regions with aberrant blood perfusion, a sign of malignant tumours, can be found on the IR pictures.

IN BREAST AND DDSM DATASET: A publicly accessible collection of mammograms used to diagnose breast cancer is called INbreast[10]. It includes 119 women's digital mammograms, totaling 238 photos (left and right breast). The images, which comprise both craniocaudal (CC) and mediolateral oblique (MLO) views, were obtained using a digital mammography machine. The dataset also contains ground truth annotations on the presence and location of anomalies, as well as segmentation masks for the breast region (such as masses and microcalcifications). The dataset is frequently used to test and train machine learning algorithms for the detection of breast cancer.

Another mammography dataset for the diagnosis of breast cancer is the Digital Database[10][15]for Screening Mammography (DDSM). More than 2,620 mammography images, comprising both typical and atypical cases, are included. The images, which comprise craniocaudal (CC) and mediolateral oblique (MLO) views, were obtained using both film-screen and digital mammography devices. Along with data on patient demographics and mammography history, the dataset also includes ground truth annotations of the presence and location of abnormalities (such as masses and microcalcifications). The DDSM dataset is frequently used in studies on (CAD) of mammograms and the detection of breast cancer.

BI-RADS DATASET: Another publicly accessible dataset of mammograms for breast cancer diagnosis is the Digital Database for Screening Mammography (DDSM)[10][15]. It includes both typical and abnormal mammography photos, totaling approximately 2,620. Both views are included in the photos, which were taken using film-screen and digital mammography devices. The collection also contains demographic data about the patients and their mammography histories, as well as ground truth annotations of the presence and location of abnormalities (such as masses and microcalcifications). The DDSM dataset is frequently used in studies on mammography CAD and the detection of breast cancer.

Each breast imaging examination is given a score (from 1 to 5) by the BI-RADS[12][13][11] classification system depending on the risk of cancer. A score of 1 denotes a negative exam, a score of 2 benign findings, a score of 3 presumably benign, a score of 4 suspicious abnormality, and a score of 5 is strongly suggestive of cancer. On the basis of the BI-RADS score, the BI-RADS categorization system also contains advice for management and follow-up.

IV. LITERATURE SURVEY TABLE

Reference paper	**Author**	**Proposed method**	**Dataset used**	**Accuracy rate**
[3]	Pendar Ali rezazadeh	CNN(Convolutional Neural Network)	BreaKHis dataset	**83.2%**
[4]	P.J. Sudharshan	Support Vector Machine	Public BreaKHis dataset	**88.23%**
[5]	Bikesh Kumar Singh	SVM,KNN,linear and quadratic discriminant	TVM dataset	**92.105%**
[6]	R. Karthik	CNN(Convolutional Neural Network)	ISLES 2015 SISS dataset	**89.6%**
[7]	Yubao Hou	convolutional neural network(CNN)	BreaKHis dataset	**91%**
[8]	Karan Gupta	(CNNs) , (SVM), (LR)	BreaKHis dataset	**93.2% app.**
[9]	Esraa A. Mohamed	(CNNs) , (SVM)	DMR-IR dataset	**97.2% app.**
[10]	Syed Jamal Safdar Gardezi et al.	Mammogram pre-processing in (CAD), CNN	Inbreast and [DDSM] datasets	**92.63%**
[11]	M Luke Marinovich et al.	Tomosynthesis in (CAD)	[BI-RADS] density 1 or 2	**95%(approx.)**
[12]	Christopher E. Comstock et al.	AB-MR interpretation algorithms and Tomosynthesis in (CAD)	BI-RADS; categories ranging from 1 [negative] to 5 [highly suggestive of breast cancer]	**79.0%(MRI)-99.2% (Tomosynthesis)**
[13]	Alejandro Rodriguez-Ruiz et al	Deep learning convolutional neural networks, Digital breast tomosynthesis	BI-RADS , DM = digital mammography, PoM = probability of malignancy.	**95%(approx.)**
[14]	Viswanatha Reddy Allugunti	CAD in The Convolutional Neural Network (CNN), the Support Vector	Prognostic Breast Cancer datasets, NC Dataset.	**98.1%**

		Machine (SVM), and Random Forest (RF).		
[15]	Dina A. Ragab et al.	The deep convolutional neural network (DCNN), support vector machine (SVM)	The digital database for screening mammography (DDSM); and The Curated Breast Imaging Subset of DDSM (CBIS-DDSM).	**94%(approx.)**
[16]	Zhiqiong Wang et al.	Convolutional neural network (CNN) in computer-aided diagnosis (CAD)	Real time dataset(experiment data)	**82.7%**
[17]	Sebastien Jean Mambou et al.	CAD in Support Vector Machine classifier (SVM) to perform the classification	Research Data Base (DMR) containing frontal thermogram images	**78%(approx.)**

V. PROBLEM DEFINITION

It is to minimise false detection results while identifying cancer in its earliest stages, when it is most curable.

Due to the variety of breast tissue, the existence of benign tumours, and the limits of current imaging equipment, this can be a difficult problem. It also has numerous features that can be used to diagnose breast cancer, such as the presence of a lump in the breast, the size and form of the lump, where the tumour is located, and many more.

Support Vector Machines (SVMs) and other methods are frequently used to identify breast tissue as normal or cancerous based on imaging data in breast cancer detection. The use of these algorithms for this task is not without its difficulties, though.

Given that breast cancer imaging often comprises a significant number of features that must be taken into account, one problem is the high dimensionality of the data. Overfitting may result from this and make it challenging to determine the most important elements for categorization.

VI. PROPOSED SYSTEM

Breast cancer screening using mammography pictures has been suggested as a potential application for convolutional neural networks (CNNs). Convolutional Neural Networks (CNNs) are highly efficient at image classification.

The ability of CNNs to dynamically learn characteristics from the data is one of the key benefits of utilizing them for breast cancer detection. This capability can be useful for finding patterns in mammography images that are symptomatic of malignancy. Additionally, CNNs are resilient to data fluctuations, which are frequent in mammography images, and can handle high-dimensional data.

CNNs have been demonstrated to diagnose breast cancer with excellent accuracy, frequently beating more conventional machine learning techniques. However, because CNNs need a lot of training data, it usually takes a lot of data pre-processing and feature engineering to build a reliable CNN model for detecting breast cancer.

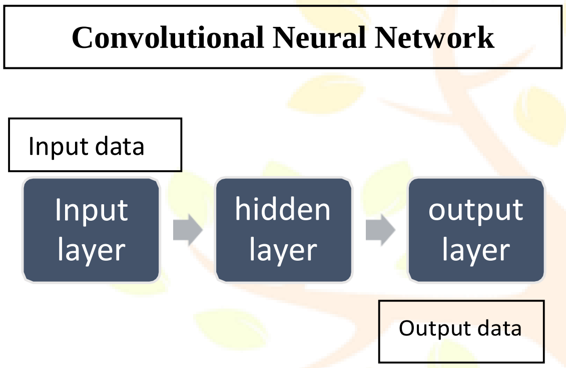
The CNN model incorporates a variety of learning algorithms, including Transfer Learning (a machine learning (ML) research subject that focuses on using knowledge gained while completing one task to another related task).

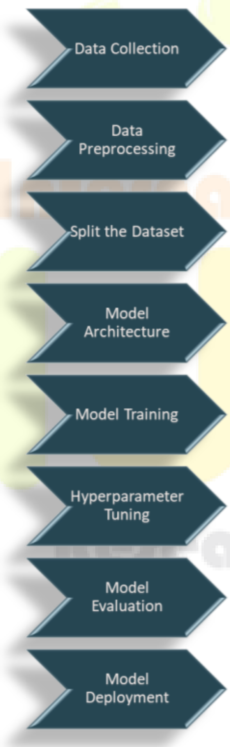
An input layer at the top of a conventional CNN design that uses mammography images to detect breast cancer would be receiving the mammography images as input. Then, using a succession of convolutional layers, the images are run through to extract features. These layers provide feature maps, which are then processed through pooling layers to condense their spatial dimensions.
The feature maps are then sent via one or more fully linked layers, where the final classification is made, after passing through the pooling layers. These layers provide a series of output neurons, each of which represents the likelihood that the image is malignant or normal.

The output layer then generates the network's final prediction, which is the class with the highest probability.

The size of the filters, the quantity of filters, the size of the pooling layers, and the quantity of neurons in the fully connected layers can all be changed in this architecture to enhance the performance of the network.

This is a simplified explanation of the architecture, and that there is other more approaches to improving network performance and avoiding overfitting.





The CNN architecture used in the project consists of the following layers:

- Convolutional Layer 1: This layer applies 32 filters to the input image with a kernel size of (3, 3). The ReLU activation function is applied to introduce non-linearity.
- MaxPooling Layer 1: It performs downsampling by taking the maximum value in each 2x2 region of the previous layer's output. This reduces the spatial dimensions of the feature maps.
- Dropout Layer 1: Dropout is a regularization technique that randomly sets a fraction (0.25) of the input units to 0 during training. It helps prevent overfitting by forcing the network to learn more robust and generalizable features.
- Convolutional Layer 2: Similar to the first convolutional layer, this layer applies 64 filters with a kernel size of (3, 3) and ReLU activation.

ReLU

$$f(x) = max\ (0, x)$$

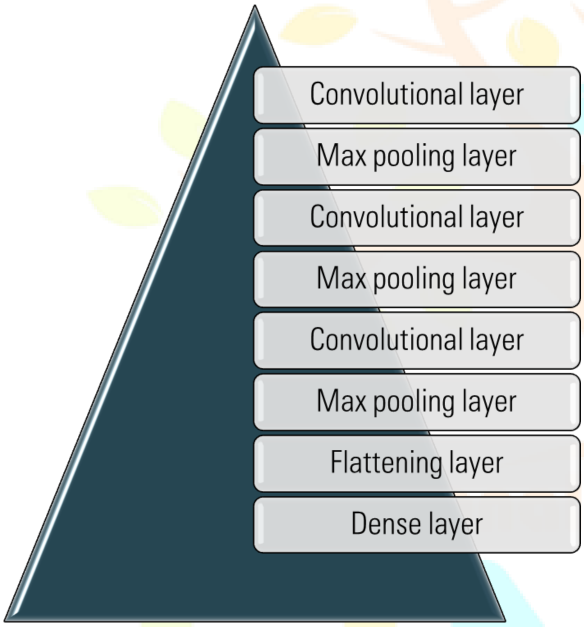
- MaxPooling Layer 2: Another max pooling layer is applied, further reducing the spatial dimensions.
- Dropout Layer 2: Another dropout layer with a dropout rate of 0.25.
- Convolutional Layer 3: This layer applies 128 filters with a kernel size of (3, 3) and ReLU activation.
- MaxPooling Layer 3: Max pooling is applied again.
- Dropout Layer 3: Another dropout layer with a dropout rate of 0.25.
- Convolutional Layer 4: This layer applies 256 filters with a kernel size of (3, 3) and ReLU activation.
- MaxPooling Layer 4: Max pooling is applied.
- Dropout Layer 4: Another dropout layer with a dropout rate of 0.25.
- Flatten Layer: The output from the previous layer is flattened into a 1D vector. This prepares the data for the subsequent fully connected layers.
- Dense Layer 1: This fully connected layer consists of 64 units with ReLU

activation. It learns high-level features from the flattened input.

- Dropout Layer 5: Another dropout layer with a dropout rate of 0.25.
- Dense Layer 2: The final layer consists of 3 units with softmax activation. It produces the probability distribution over the 3 classes, indicating the predicted class for each input image.

Softmax function ⁝

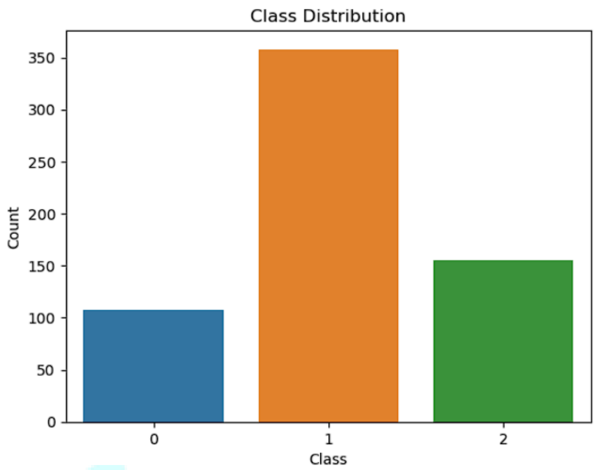
$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$



This architecture follows a common pattern in CNNs, where convolutional layers are used to extract features from the input image, followed by down sampling through max pooling, and then fully connected layers for classification. Dropout layers are inserted to prevent overfitting by randomly dropping out a fraction of the units during training.

The input shape for each convolutional layer is (128, 128, 1), indicating that the input images are grayscale with a size of 128x128 pixels.

There are 3 class labels in the dataset used: normal, benign and malignant.



Normal is denoted with 0,
Benign is denoted with 1,
Malignant is denoted with 2.

VII. RESULTS AND ANALYSIS:

The proposed system was using a collection of images divided into three classes—normal, benign, and malignant. On this dataset, the previously disclosed CNN architecture was trained, and encouraging results were obtained. The confusion matrix, training and testing loss graphs, and accuracy curves are all included in this presentation of the results.

CONFUSION MATRIX:

A table that summarises how well a classification model performed on a set of test data is called a confusion matrix. It gives a thorough breakdown of the predictions made by the model and the actual labels that correlate to them.

Format:

Class A | TN | FP | FP |
Class B | FP | TN | FP |
Class C | FP | FP | TN |

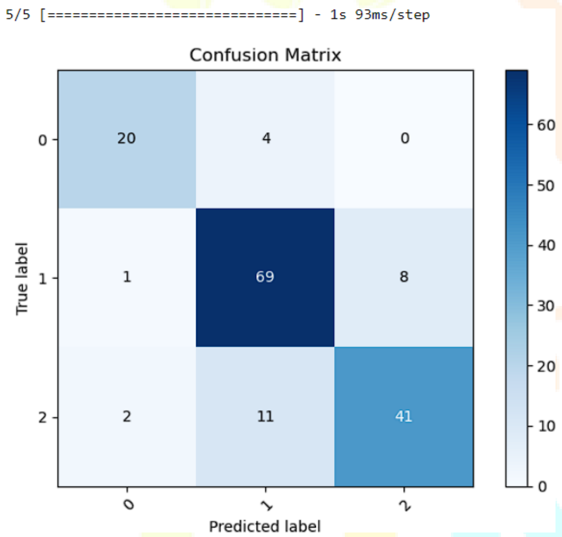
In the matrix of confusion,

- The number of instances that were correctly identified as belonging to a specific class is known as True Positives (TP).
- The number of occurrences that were accurately identified as not being within a specific class is known as True Negatives (TN).
- The number of occurrences that were mistakenly identified as belonging to a certain class is known as false positives (FP).

- The number of instances that were wrongly identified as not being under a specific class is known as False Negatives (FN).

The examples in a true class are represented by each row in the matrix, while the occurrences in a predicted class are represented by each column. The accurate predictions (TP and TN) are represented by the diagonal elements (top-left to bottom-right), whilst the wrong guesses (FP and FN) are represented by the off-diagonal elements.

The performance of the model can be examined in great depth using the confusion matrix. It offers information about any patterns or biases in the forecasts and aids in identifying which classes are being misclassified. To further evaluate the model's effectiveness, other assessment metrics including accuracy, precision, recall, and F1-score can be derived from the confusion matrix.

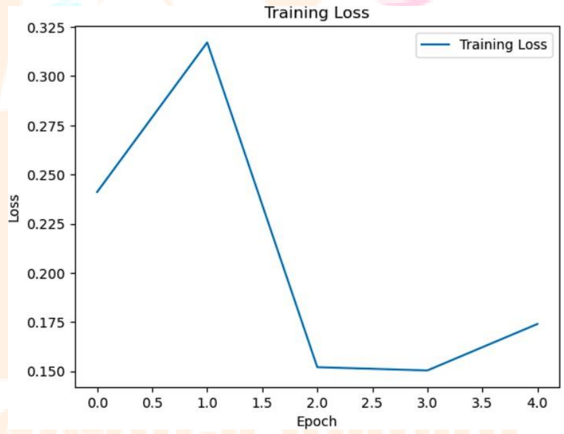


TRAINING LOSS GRAPHS:

The training and testing loss graphs show how the loss has changed over time. The error on the training set is represented by the training loss, whereas the error on the testing set is represented by the testing loss. Better model performance and improved convergence are indicated by a smaller loss.

The value of the loss function on the training data over many iterations or epochs is displayed in the training loss graph. It offers a visual representation of how well the model fits the practise data. The training loss should ideally be decreasing over time, demonstrating that the model is picking up new information and increasing its performance on the training set. It may be a sign of overfitting, when the model gets overly specialised to the training data and performs badly on unseen data, if the training loss keeps dropping but the validation loss (or testing loss) starts to rise.

The loss function value on a different validation or testing dataset is displayed on the testing loss graph, also known as the validation loss graph. This dataset is used to assess how well the model generalises to new data but is not used to train the model. Understanding the model's performance on data that it hasn't been trained on is made easier by looking at the testing loss graph. The testing loss should ideally start out decreasing and then stabilise or show a progressive reduction. The model is overfitting and not performing well on unobserved data if the testing loss starts to rise.



The number of epochs is normally represented on the x-axis, and the loss value is typically plotted on the y-axis, for both the training and testing loss graphs. Utilising several Python charting tools like Matplotlib or Seaborn, the graphs can be produced.

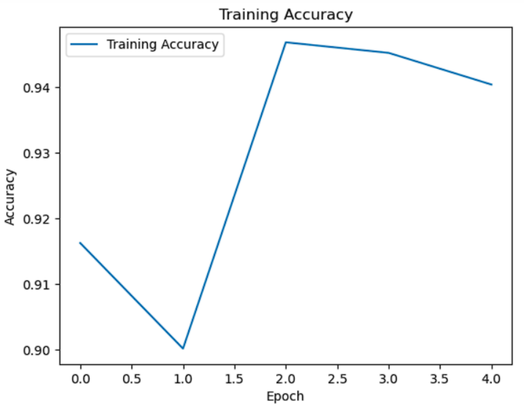
ACCURACY GRAPH:

Accuracy curves provide insights into the performance of a machine learning or deep learning model during training and evaluation phases. These curves visualize how the accuracy of the model changes over time, allowing us to analyse its learning progress and generalization capabilities.

The accuracy curve shows the model's classification accuracy on the training and testing data over multiple iterations or epochs. The accuracy is typically calculated as the percentage of correctly classified samples out of the total number of samples.

Classification Report:

	precision	recall	f1-score	support
0	0.87	0.83	0.85	24
1	0.82	0.88	0.85	78
2	0.84	0.76	0.80	54
accuracy			0.83	156
macro avg	0.84	0.83	0.83	156
weighted avg	0.83	0.83	0.83	156



Test Loss: 0.572771430015564
Test Accuracy: 0.8333333134651184

Specificity for Class 1: 0.8333333333333334
Specificity for Class 2: 0.8846153846153846
Specificity for Class 3: 0.7592592592592593

Several insights can be gained by examining the training and testing loss graphs and Accuracy graphs:

- Overfitting: It is indicated if the training loss keeps down while the testing loss rises or stays high. When a model becomes overfit, it begins to memorise the training data rather than learning broader patterns.
- Underfitting: Underfitting is present when both the training and testing losses are substantial and do not considerably decline. Underfitting happens when the model performs badly on both the training and testing sets and is unable to recognise the underlying patterns in the data.
- Model convergence: A model is converging and effectively learning the patterns in the data if both the training and testing losses over time reduce and stabilise.
- Optimal number of epochs: The graphs can be used to determine the ideal number of epochs to use when training the model. At this time, the model has picked up the patterns without overfitting, and the testing loss is at its lowest level.

VIII. CONCLUSION

In summary, employing mammography images and Convolutional Neural Networks (CNNs) can enhance the effectiveness and speed of breast cancer screening, which may enhance the accuracy of diagnosis. CNNs are a type of deep learning algorithm that can automatically learn features from the images, making them well-suited for analyzing mammography images.

Mammography images are widely used in breast cancer detection, as they provide detailed images of the breast tissue. However, mammography images can be affected by noise and artifacts, making it difficult for radiologists to identify abnormalities. By using CNNs to analyze mammography images, it is possible to automatically identify and classify abnormalities, which can help to improve diagnostic accuracy and reduce the number of false positives.

IX. REFERENCES

[1] P. Giri and K. Saravanakumar, "Breast Cancer Detection using Image Processing Techniques," An International research journal of Computer Science and Technology, vol. 14, 2017

[2] V. Goel, "Building a Simple Machine Learning Model on Breast Cancer Data," Published in Towards Data Science, vol. 1, 2018

[3] P. A. rezazadeh, B. Hejrati, A. Monsef-Esfahani, and A. Fathi, "Representation learning-based unsupervised domain adaptation for classification of breast cancer histopathology images," ScienceDirect, vol. 23, 2018

[4] P. J. Sudharshan, C. Petitjean, F. Spanhol, L. E. Oliveira, L. Heutte, and P. Honeine, "Multiple instances learning for histopathological breast cancer image classification," ScienceDirect, vol. 117, 2019

[5] B. K. Singh, "Determining relevant biomarkers for prediction of breast cancer using anthropometric and clinical features: A comparative investigation in machine learning paradigm," ScienceDirect, vol. 39, 2019

[6] R. Karthik, R Menaka, M Hariharan and Daehan Won "Ischemic Lesion Segmentation using Ensemble of Multi-Scale Region Aligned CNN," Computer Methods and Programs in Biomedicine, vol. 1, 2021

[7] Y. Hou, "Breast cancer pathological image classification based on deep learning," Journal of X-Ray Science and Technology, ScienceDirect, vol. 28, 2020

[8] K. Gupta and N. Chawla, "Analysis of Histopathological Images for Prediction of Breast Cancer Using Traditional Classifiers with Pre-Trained CNN," vol. 167, 2020

[9] E. A. Mohamed, E. A. Rashed, T. Gaber, and O. Karam, "Deep learning model for fully automated breast cancer detection system from thermograms," PLoS ONE, vol. 17, 2022

[10] S. J. S. Gardezi, A. Elazab, B. Lei, and T. Wang, "Breast Cancer Detection and Diagnosis Using Mammographic Data: Systematic Review," Journal of medical internet research, vol. 21, 2019

[11] M. L. Marinovich, K. E. Hunter, P. Macaskill, and N. Houssami, "Breast Cancer Screening Using Tomosynthesis or Mammography: A Meta-analysis of Cancer Detection and Recall," JNCI: Journal of the National Cancer Institute, vol. 110, 2018

[12] C. E. Comstock, C. Gatsonis, and G. M. Newstead, "Comparison of Abbreviated Breast MRI vs Digital Breast Tomosynthesis for Breast Cancer Detection Among Women With Dense Breasts Undergoing Screening," JAMA, vol. 8, 2020

[13] A. Rodriguez-Ruiz et al., "Stand-Alone Artificial Intelligence for Breast Cancer Detection in Mammography: Comparison With 101 Radiologists," JNCI: Journal of the National Cancer Institute, vol. 111, 2019

[14] V. R. Allugunti, "Breast cancer detection based on thermographic images using machine learning and deep learning algorithms," research gate, vol. 4, 2022

[15] D. A. Ragab, M. Sharkas, S. Marshal, and J. Ren, "Breast cancer detection using deep convolutional neural networks and support vector machines," journal peerJ, vol. 7, 2019

[16] Z. Wang et al., "Breast Cancer Detection Using Extreme Learning Machine Based on Feature Fusion with CNN Deep Features," IEEE publisher, vol. 7, 2019

[17] S. J. Mambou, P. Maresova, O. Krejcar, A. Selamat, and K. Kuca, "Breast Cancer Detection Using Infrared Thermal Imaging and a Deep Learning Model," sensors, vol. 18, 2018