Project Report

On

“Breast Cancer Detection Using Deep Learning”

Submitted in partial fulfillment of the requirements for the final year of

Bachelor of Technology

In

Computer Science & Engineering

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(2023-2024)

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CERTIFICATE OF APPROVAL

This is certify that Ashwani Yadav (2001660100017), Pallavi Singh (2001660100036), Ritik Mishra (2001660100047), Shivani Gupta (2001660100052) have successfully completed the project entitled: “Breast Cancer Detection using Deep Learning” Under the guidance of Mr. Sri Nath Dwivedi toward the fulfillment of the final year course in Computer Science & Engineering.

Internal Examiner

External Examiner

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Mr. Sri Nath Dwivedi

DECLARATION

I hereby certify that the work which is being presented in the report, entitled "Breast Cancer Detection using Deep Learning" in the partial fulfillment of the requirement for the final year of Bachelor in Technology and submitted to the institution is an authentic record of my own work carried out during the period March, 2024 to June, 2024 under the supervision of Mr. Sri Nath Dwivedi.

The matter presented in this report has not been submitted elsewhere for the final year from any institutions.

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This is to certify that the above statement made by the candidate is correct to the best of our knowledge.

Date: Signature of Project Guide:

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1.) ABSTRACT

Breast cancer is one of the major causes of death in women and it is difficult to prevent breast cancer as the main reasons underlying breast cancer remain unknown. Characteristics of breast cancer, such as masses and microcalcifications visible in mammograms, can be employed for early diagnosis and hence are highly beneficial for women who may be at risk of developing malignant tumors.

The principal check used for screening and early diagnosis is X-ray mammography and the proper interpretation of the clinical report is vital for breast cancer prediction, but the decision may be prone to error. Mammograms are difficult to interpret, especially in the screening context.

The sensitivity of screening mammography is affected by image quality and the radiologist's level of expertise. Digital image processing techniques such as image pre-processing, image segmentation, feature extraction and image classification are applied in this project on the digital mammogram images to achieve early and automated detection of breast cancer.

The objective of the project is todetect the initial phase tumors which shall not be prone to human error using image processing techniques such as image preprocessing, image segmentation, features extraction and selection and image classification. Firstly the image pre-processing of the mammogram is carried out which helps in removing noise in the image, if any. Second the segmentation techniques were used with which the tumor part dilates in the breast and erodes the remaining parts.

2.) INTRODUCTION

Breast cancer is a significant public health concern and one of the most common types of cancer affecting women worldwide. It arises when abnormal cells in the breast grow and divide uncontrollably, forming a tumor that can invade nearby tissues and, in some cases, spread to other parts of the body, a process known as metastasis. Although breast cancer predominantly affects women, it can also occur in men, though it is relatively rare in males.

The risk factors for breast cancer are diverse and multifactorial. Being female is the most significant risk factor, and the likelihood of developing breast cancer increases with age. Women with a family history of breast cancer, particularly those with mutations in the BRCA1 and BRCA2 genes, have a higher risk. Other risk factors include early menstruation, late menopause, having no children or having a first child after the age of 30, dense breast tissue, exposure to ionizing radiation, and long-term hormone replacement therapy. Lifestyle factors, such as obesity, alcohol consumption, and lack of physical activity, also play a role in increasing the risk of breast cancer.

Detection and diagnosis of breast cancer are crucial for early intervention and better treatment outcomes. Regular breast self-examinations and clinical breast exams by healthcare professionals are essential for detecting any abnormal changes in the breasts. Mammography, a type of low-dose X-ray, is the gold standard for breast cancer screening, particularly for women over the age of 40. Additional imaging tests, such as ultrasound and magnetic resonance imaging (MRI), may be used for further evaluation of suspicious findings.

Breast cancer is classified into various subtypes based on the presence or absence of specific receptors on the tumor cells. These receptors include estrogens receptors (ER), progesterone receptors (PR), and human epidermal growth factor receptor 2 (HER2). The classification helps guide treatment decisions, as different subtypes may respond differently to therapies.

Treatment options for breast cancer depend on the stage of the disease, the type of breast cancer, and the patient's overall health. Common treatment modalities include surgery, radiation therapy, chemotherapy, hormone therapy, and targeted therapy. In recent years, advancements in targeted therapies, such as HER2-targeted drugs like trastuzumab, have significantly improved outcomes for HER2-positive breast cancer patient.

Breast cancer awareness, early detection, and research have led to substantial progress in

reducing mortality rates and improving the quality of life for those affected. Regular screenings, healthy lifestyle choices, and increased understanding of risk factors are essential components in the ongoing fight against breast cancer. Additionally, ongoing research efforts continue to explore new treatment approaches and interventions to further advance breast cancer management and care.

a.) Objective:

The research objectives of using deep learning in breast cancer are aimed at improving various aspects of breast cancer detection, diagnosis, prognosis, and treatment. Deep learning, a subset of artificial intelligence (AI) and machine learning, has shown great potential in analyzing complex medical data and making accurate predictions. Some key research objectives include:

Automated Breast Cancer Detection: Developing deep learning algorithms to automatically detect and locate breast cancer in medical images, such as mammograms and ultrasounds. This can aid radiologists in early detection and reduce the chances of false negatives.

Segmentation of Tumor Regions: Using deep learning for tumor segmentation, which involves precisely delineating tumor boundaries in images. This can help in assessing tumor size, growth, and response to treatment.

Predicting Treatment Response: Deep learning can analyze patient data, including imaging, genetic information, and clinical records, to predict the likelihood of a patient responding positively to specific treatments. This enables personalized treatment plans.

Overall, leveraging deep learning in breast cancer research aims to improve early detection, enhance treatment decisions, and ultimately contribute to better patient outcomes and survival rates. However, it is essential to ensure the reliability and interpretability of deep learning models to gain the trust of medical professionals and ensure successful clinical translation.

Report Organization:

The organization of the report is as follows:

Chapter 2: This chapter contains the details about the literature survey that we did by looking at research papers from 2018 to 2023 before creating our convolutional neural network model.

Chapter 3: This chapter contains the information about the dataset.

Chapter 4: This chapter talks about the Convolutional Neural Networks and the three Neural models. The results obtained after running the model codes are also discussed.

Chapter 5: This chapter contains a conclusion that contains our thinking about how the model

may assist pathologists in fully automating and accurate breast cancer detection from MRI images.

b.) Project Overview:

The suggested method uses a trained deep learning neural network system to categorize breast cancer subtypes. According to data from 221 actual patients, the findings have an accuracy of 90.50 to 94 %. Without needing any human intervention, this model can classify and identify breast cancer lesions. In this project the developing tools are prevent which captures, enumerates, and analyzes circulating tumors cells and associated cancer cells from blood. This project provides a platform to evaluate, predict survival in early-stage breast cancer patients.

c.) Benefits:

The primary benefits of mammography screening are a reduction in breast cancer mortality, years of life lost due to breast cancer, and morbidity of breast cancer treatment.

(i) Reduced Mortality

Several metrics describe the impact of breast cancer screening on mortality. All organizations that disseminate screening guidelines agree that more aggressive screening invariably results in fewer deaths.

Mortality reduction measures the percentage of deaths averted due to a specific screening strategy compared to an alternative screening strategy or no screening. As the screening age range expands and screening frequency increases, total mortality reduction improves. Annual screening mammography from ages 40 to 84 years yields a mortality reduction of 40% compared to no screening. The specific contribution to mortality reduction from annual screening ages 40 to 49 years is 12% to 29%.

The mortality ratio (observed breast cancer death rate divided by the expected death rate) is similar between women aged 40 to 49 at first screening, versus women over 50. Another common metric is the number needed to screen (NNS), which reports how many women need to be screened to prevent 1 breast cancer death. Since the incidence of breast cancer is higher in older women, the NNS decreases with age. Estimates from 1 systematic review provide a NNS of 753 for women ages 40 to 49 years, in comparison to 462 and 355 for women ages 50 to 59 and 60 to 69 years, respectively.

(ii) Reduced Years of Life Lost:

The mortality benefits of screening younger women are greater due to the longer life

expectancy and often greater family and career responsibilities than older women. An estimated 30% of years-of-life lost due to breast cancer occurs in women diagnosed in their 40s. Although breast cancer incidence increases with age, the increased incidence does not keep pace with shortened life expectancy. One year of life is gained for every 20 women in their 40s who undergo annual screening, while 45 women in their 70s must be screened biennially to gain 1 year of life. Now, no detailed studies are available that assess the socioeconomic impact of life-years gained from averting breast cancer deaths in young women compared to older women. However, it is safe to assume that the impact of breast cancer death on younger working-age women with families outweighs older women who are more likely to be retired from the workforce.

(iii) Reduced Treatment Morbidity:

Screening detects breast cancers at an earlier stage. Compared to symptomatic cancers, screen detected cancers are typically smaller and without lymph node involvement. This in turn affects prognosis with 5-year survival rates of 99% for localized disease, 86% for regional disease (eg, axillary lymph nodes), and only 27% for distant metastatic disease. Stage also influences treatment options with more extensive disease requiring more aggressive surgery and radiation therapy. This is reflected in data comparing treatment approaches between screened and unscreened women. Women ages 40 to 49 years who do not get screened are 3.4 times more likely to undergo a mastectomy, 4.6 times more likely to undergo axillary node dissection, and 2.5 times more likely to undergo chemotherapy, than screened women. More extensive surgery is associated with increased post-surgical complications including persistent pain and lymphedema. As a result, the detection of earlier stage cancer by screening can substantially reduce the morbidity associated with breast cancer treatment.

d.) Scope of Project:

The future of cancer diagnosis: AI, Virtual biopsies, and molecular profiling. In addition to CRISPR and precision medicine, approaches to imaging and detection could also shift in the future, to speed up diagnosis and cancer treatment.

e.) Details on Breast Cancer:

Breast cancer is a type of cancer that starts in the breast. Cancer starts when cells begin to grow out of control. Breast cancer cells usually form a tumor that can often be seen on an x-ray or felt as a lump. Breast cancer occurs almost entirely in women, but men can get breast cancer,

too.

It is important to understand that most breast lumps are benign and not cancer (malignant). Non-cancerous breast tumors are abnormal growths, but they do not spread outside of the breast. They are not life threatening, but some types of benign breast lumps can increase a woman's risk of getting breast cancer. Any breast lump orchange needs to be checked by a health care professional to determine if it is benign or malignant (cancer) and if it might affect your future cancer risk.

Where Breast Cancer Start:

Breast cancers can start from different parts of the breast. • Most breast cancers begin in the ducts that carry milk to the nipple (ductal cancers) • Some start in the glands that make breast milk (lobular cancers) • There are also other types of breast cancer that are less common like phyllodes tumor and angiosarcoma • A small number of cancers start in other tissues in the breast. These cancers are called sarcomas and lymphomas and are not really thought of as breast cancers**.**

Types of Breast Cancer:

There are many different types of breast cancer and common ones include ductal carcinoma in situ (DCIS) and invasive carcinoma. Others, like phyllodes tumours and angiosarcoma are less common. Once a biopsy is done, breast cancer cells are tested for proteins called estrogen receptors, progesterone receptors and HER2. The tumour cells are also closely looked at in the lab to find out what grade it is. The specific proteins found and the tumour grade can help decide treatment options.

How Breast Cancer Spread:

Breast cancer can spread when the cancer cells get into the blood or lymph system and are carried to other parts of the body. The lymph system is a network of lymph (or lymphatic) vessels found throughout the body that connects lymph nodes (small bean-shaped collections of immune system cells). The clear fluid inside the lymph vessels, called lymph, contains tissue byproducts and waste material, as well as immune system cells. The lymph vessels carry lymph fluid away from the breast. In the case of breast cancer, cancer cells can enter those lymph vessels and start to grow in lymph nodes. Most of the lymph vessels of the breast drain into: • Lymph nodes under the arm (auxiliary nodes) • Lymph nodes around the collar bone (supraclavicular [above the collar bone] and infraclavicular [below the collar bone] lymph

nodes) • Lymph nodes inside the chest near the breast bone (internal mammary lymph nodes). If cancer cells have spread to your lymph nodes, there is a higher chance that the cells could have travelled through the lymph system and spread (metastasized) to other parts of your body. The more lymph nodes with breast cancer cells, the more likely it is that the cancer may be found in other organs. Because of this, finding cancer in one or more lymph nodes often affects 6 your treatment plan. Usually, you will need surgery to remove one or more lymph nodes to know whether the cancer has spread. Still, not all women with cancer cells in their lymph nodes develop metastases, and some women with no cancer cells in their lymph nodes develop metastases later.

How Common is Breast Cancer:

Breast cancer is the most common cancer in American women, except for skin cancers. The average risk of a woman in the United States developing breast cancer sometime in her life is about 13%. This means there is a 1 in 8 chance she will develop breast cancer. This also means there is a 7 in 8 chance she will never have the disease.

Current Year Estimates For Breast Cancer:

The American Cancer Society's estimates for breast cancer in the United States for 2021 are:

• About 281,550 new cases of invasive breast cancer will be diagnosed in women.

• About 49,290 new cases of ductal carcinoma in situ (DCIS) will be diagnosed.

• About 43,600 women will die from breast cancer.

Trends in Breast Cancer:

In recent years, incidence rates have increased by 0.5% per year.Breast cancer is the second leading cause of cancer death in women. (Only lung cancer kills more women each year.) The chance that a woman will die from breast cancer is about 1 in 39 (about 2.6%). Since 2007, breast cancer death rates have been steady in women younger than 50, but have continued to decrease in older women. From 2013 to 2018, the death rate went down by 1% per year. These decreases are believed to be the result of finding breast cancer earlier through screening and increased awareness, as well as better treatments. At this time there are more than 3.8 million breast cancer survivors in the United States. This includes women still being treated and those who have completed treatment

Breast Cancer Sign & Symptoms:

Knowing how your breasts normally look and feel is an important part of breast health.

Although having regular screening tests for breast cancer is important, mammograms do not find every breast cancer. This means it's also important for you to be aware of changes in your breasts and to know the signs and symptoms of breast cancer. The most common symptom of breast cancer is a new lump or mass. A painless, hard mass that has irregular edges is more likely to be cancer, but breast cancers can be tender, soft, or round. They can even be painful. For this reason, it's important to have any new breast mass, lump, or breast change checked by an experienced health care professional. Other possible symptoms of breast cancer include:

• Swelling of all or part of a breast (even if no lump is felt)
• Skin dimpling (sometimes looking like an orange peel)
• Breast or nipple pain
• Nipple retraction (turning inward)
• Nipple or breast skin that is red, dry, flaking or thickened
• Nipple discharge (other than breast milk)
• Swollen lymph nodes (Sometimes a breast cancer can spread to lymph nodes under the arm or around the collar bone and cause a lump or swelling there, even before the original tumor in the breast is large enough to be felt.) Although any of these symptoms can be caused by things other than breast cancer, if you have them, they should be reported to a health care professional so the cause can be found. Remember that knowing what to look for does not take the place of having regular mammograms1 and other screening tests2. Screening tests can help findbreast cancer early, before any symptoms appear. Finding breast cancer early givesyou a better chance of successful treatment.

Mammograms:

Mammograms are low-dose x-rays of the breast. Regular mammograms can help find breast cancer at an early stage, when treatment is most successful. A mammogram can often find breast changes that could be cancer years before physical symptoms develop. Results from many decades of research clearly show that women who have regular mammograms are more likely to 8 have breast cancer found early, are less likely to need aggressive treatment like surgery to remove the breast (mastectomy) and chemotherapy, and are more likely to be cured. Mammograms are not perfect. They miss some cancers. And sometimes a woman will need more tests to find out if something found on a mammogram is or is not cancer

Fig.1 Mammogram

There are two types of mammograms. A screening mammogram is used to look for signs of breast cancer in women who don't have any breast symptoms or problems. X-ray pictures of each breast are taken, typically from 2 different angles.Mammograms can also be used to look at a woman's breast if she has breast symptoms or if a change is seen on a screening mammogram. When used in this way, they are called diagnostic mammograms. They may include extra views (images) of the breast that aren't part of screening mammograms. Sometimes diagnostic mammograms are used to screen women who were treated for breast cancer in the past. In the past, mammograms were typically printed on large sheets of film. Today, digital mammograms are much more common. Digital images are recorded and saved as files in a computer.

Other Common Tests:

Breast MRI

Breast MRI (magnetic resonance imaging) uses radio waves and strong magnets to make detailed pictures of the inside of the breast. It is used: • To help determine the extent of breast cancer: Breast MRI is sometimes used in women who already have been diagnosed with breast cancer, to help measure the size of the 9 cancer, look for other tumors in the breast, and to check for tumors in the opposite breast. But not every woman who has been diagnosed with breast cancer needs a breast MRI. • To screen for breast cancer: For certain women at high risk for breast cancer, a screening MRI is recommended along with a yearly mammogram. MRI is not recommended as a screening test by itself because it can miss some cancers that a mammogram would find.

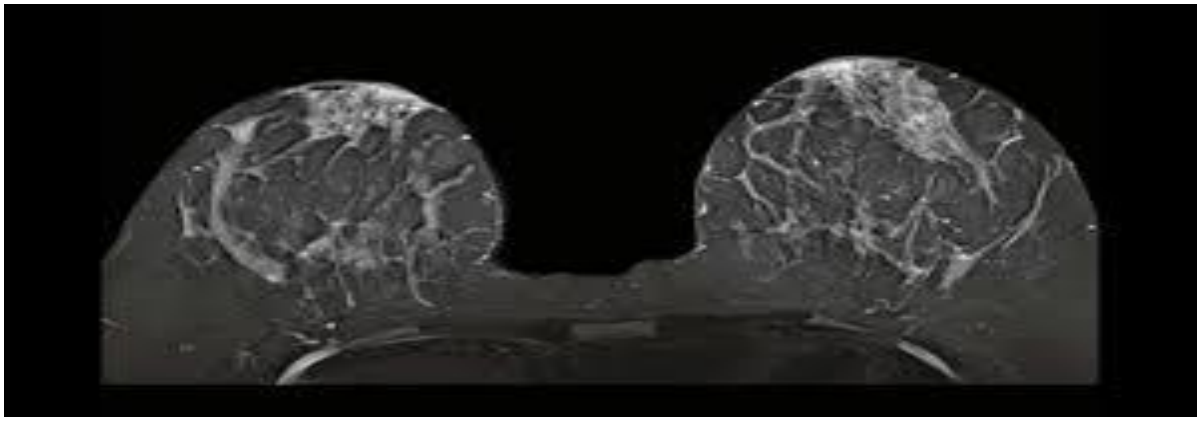


Fig.2 Breast MRI

Breast UltraSound:

Breast ultrasound uses sound waves to make a computer picture of the inside of the breast. It can show certain breast changes, like fluid-filled cysts, that are harder to identify on mammograms. It is used when:

• Ultrasound is useful for looking at some breast changes, such as lumps (especially those that can be felt but not seen on a mammogram) or changes in women with dense breast tissue. It also can be used to look at a suspicious area that was seen on a mammogram. 10

• Ultrasound is useful because it can often tell the difference between fluidfilled cysts (which are very unlikely to be cancer) and solid masses (which might need further testing to be sure they're not cancer)

. • Ultrasound can also be used to help guide a biopsy needle into an area so that cells can be taken out and tested for cancer. This can also be done in swollen lymph nodes under the arm.

• Ultrasound is widely available, easy to have, and does not expose a person to radiation. It also costs less than a lot of other options.

Breast Biopsy:

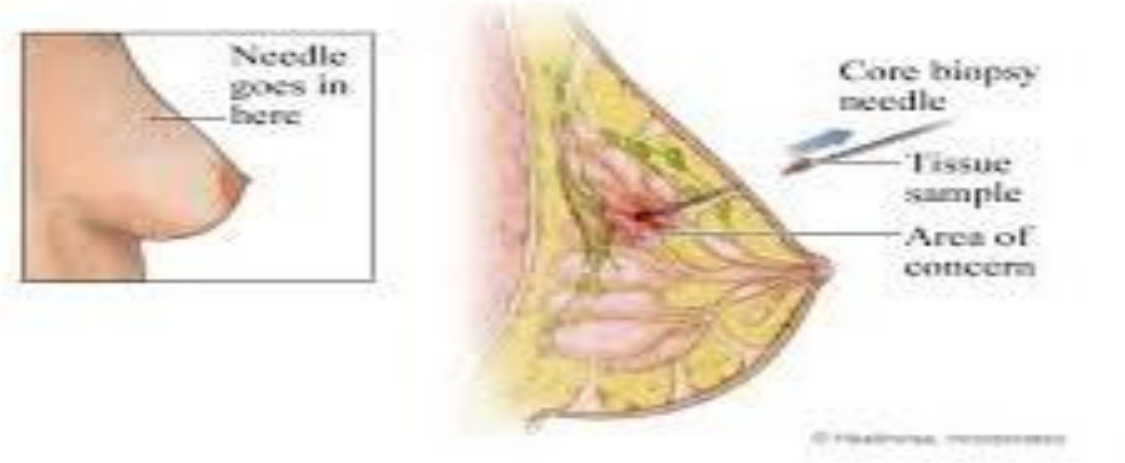
When other tests show that there is breast cancer, then biopsy is done. Needing a breast biopsy doesn't necessarily mean that there is cancer. Most biopsy results are not cancer, but a biopsy is the only way to find out for sure. During a biopsy, a doctor will remove small pieces from the suspicious area so they can be looked at in the lab to see if they contain cancer cells. There are different kinds of breast biopsies. Some are done using a hollow needle, and some use an incision (cut in the skin). Each has pros and cons.

• In an FNA biopsy, a very thin, hollow needle attached to a syringe is used to withdraw

(aspirate) a small amount of tissue from a suspicious area. The needle used for an FNA biopsy is thinner than the one used for blood tests.

• A core biopsy uses a larger needle to sample breast changes felt by the doctor or seen on an ultrasound, mammogram, or MRI. This is often the preferred type of biopsy if breast cancer is suspected. • In rare cases, surgery is needed to remove all or part of the lump for testing. This is called a surgical or open biopsy. Most often, the surgeon removes the entire mass or abnormal area as well as a surrounding margin of normal breast tissue

Fig-3 Breast Biopsy



3.) REQUIREMENT ANALYSIS

a.) Feasibility Study:

Descriptive statistics were used to assess feasibility outcomes, including participation rate, completion rate, survey administration time and medical recored abstraction time. Descriptive statistics were also used to describe the study population and knowledge perceptions.

Knowledge accuracy was determined by comparing participant responses with the medical record. Responses were considered accurate if they matched and inaccurate if they did not match.

b.) Technical Specification:

i)Hardware Requirement:

Choosing the right hardware to train and operate machine learning programs will greatly impact the performance and quality of a machine learning model.

Processors: CPUs, GPUs, TPUs, and FPGAs

A faster processor will reduce the time it takes to train a machine learning model and to generate predictions by as much as 100-fold or more.

CPU- a modern multicore processor like, an intel core i5 or i7.

GPU- GPUs are specialized computers that are used for machine learning infrastructure. For entry level deep learning models, a GPU memory of 4GB is enough.

RAM

A minimum of 8GB of RAM is required, but more may be required for larger datasets.

ii) Software Requirement:

Memory and Storage

In addition to processor requirements, memory and storage are other key considerations for the AI/ML pipeline.

To train or operate a machine learning model, programs require data and code to be stored in local memory to be executed by the processor. Some models, like deep neural networks, may require more fast, local memory because the algorithms are larger. Others, like decision trees, may be trained with less memory because the algorithms are smaller.

4.) PROJECT DESIGN METHODOLOGY

This section presents the recent developments in DL methods for breast cancer prediction. The DL-based breast cancer prediction techniques involves the following steps:

1.) Data Collection: Breast datasets are obtained from various sources such as medical institutions, public repositories, and research studies. These datasets consist of mammogram images, gene expression profiles, and clinical data.

2.) Data Preprocessing: The collected datasets are preprocessed to eliminate noise, normalize, and standardize the data. This step involves data cleaning, feature extraction, and data augmentation.

3.)Model Building: DL models, such as CNNs, RNNs, DBNs, and autoencoders, are developed using the preprocessed breast cancer datasets. These models are trained and optimized using training and validation datasets.

4.) Model Evaluation: The trained DL models are assessed using a separate test dataset to determine their performance. Performance metrics, including sensitivity, specificity, accuracy, precision, F1 score, and AUC, are used for evaluation.

5.) Model Interpretation: The interpretability of the DL models is evaluated using techniques such as Grad-CAM, saliency maps, and feature visualization. These techniques help identify which features of the input data are utilized by the DL models for making predictions.

6.) Deployment: The DL model is deployed in a clinical setting to predict breast cancer in patients. The performance of the model is regularly monitored and updated to enhance accuracy and efficiency**.**

By utilizing DL techniques, breast cancer prediction can be significantly improved, leading to better detection and treatment outcomes.

Data preprocessing techniques and evaluation:

Preprocessing techniques :

When applying DL algorithms to analyze breast images, noise can have a negative impact on the accuracy of the image classifier. To address this issue, several image denoising techniques have been developed. These techniques, including the Median filter, Wiener filter, Non-local means filter, Total variation (TV) denoising, Wavelet-based denoising, Gaussian filter, anisotropic diffusion, BM3D denoising, CNN, and autoencoder, aim to reduce image noise while preserving important features and structures that are relevant for breast cancer diagnosis.

After denoising, a normalization method, such as min-max normalization, is typically employed to rescale the images and reduce the complexity of the image datasets before feeding them into the DL model. This normalization process ensures that the model can effectively learn meaningful patterns from the images and improve its ability to accurately classify them.

Performance metrics :

Several performance metrics are utilized to evaluate DL algorithms for breast screening. The selection of a specific metric depends on the task at hand and the objectives of the model. Some of the most commonly employed metrics include:

1.) Accuracy: measures the proportion of correct predictions made by the model.

Precision: measures the proportion of true positive predictions out of all positive predictions made by the model.

2.) Sensitivity: measures the proportion of true positive predictions out of all actual positive cases in the dataset.

3.) F1 score: a composite metric that balances precision and sensitivity.

4.) Area under the curve (AUC): distinguishes between positive and negative points across a range of threshold values.

5.) Mean Squared Error (MSE): measures the average squared difference between predicted and actual values in a regression task.

6.) Mean Absolute Error (MAE): measures the average absolute difference between the predicted and actual values in a regression task.

The commonly used equation for calculating accuracy, as stated in reference (40), is:

$$\textbf{Accuracy}=(TP+TN)/(TP+TN+FP+FN) \quad \textbf{--- (1)}$$

Where TP and TN are the numbers of true positives and true negatives, FP and FN are the numbers of false positives and false negatives, respectively.

$$\textbf{Precision}=TP/(TP+FP) \quad \textbf{---(2)}$$

$$\textbf{Sensitivity}=TP/(TP+FN) \quad \textbf{---(3)}$$

$$\textbf{F1 score}=2*(\textbf{Precision} * \textbf{Sensitivity})/(\textbf{Precision}+\textbf{Sensitivity}) \text{ ---- (4)}$$

AUC is typically computed by plotting the true positive rate against the false positive rate at different threshold values and then calculating the area under this curve.

$$MSE=(1/n)*\sum(ytrue-ypred)2 \text{ ----(5)}$$

$$MAE=(1/n)*\sum|ytrue-ypred| \text{---- (6)}$$

Where y_{tru} is the true value and y_{pred} is the predicted value, and n is the number of samples.

Equations 1 – provide a general idea of how performance metrics are computed, but the actual implementation may vary depending on the specific task and the software.

DataSet

Breast datasets play a crucial role in evaluating DL approaches. These datasets offer a comprehensive collection of high-quality and labelled breast images that can be utilized for training and testing DL algorithms. **Table1** presents commonly utilized publicly available breast datasets in mammography for breast screening.

Breast image dataset.

Year	Country	Dataset	Sample Number	Human Number	Task
1998 (41)	US	Digital Database for Screening Mammography (DDSM)	2,620	N/A	Breast cancer detection
1998 (42)	US	Mammographic Image Analysis Society (Mini-MIAS)	322	N/A	Breast cancer classification
2012 (43)	US	INbreast	410	N/A	Breast cancer detection
2017 (44)	US	Breast Cancer Digital Repository (BCDR)	1,224	N/A	Breast cancer classification
2017 (45)	US	Curated Breast Imaging Subset of DDSM (CBIS-DDSM)	753	N/A	Breast cancer detection
2011 (46)	US	BCDR-F01	362	N/A	Breast cancer classification
2018 (47)	USA	DDSM	2,620	N/A	Classification, segmentation
2016 (48)	Netherlands	Mammographic Image Analysis Society (MIAS)	322	N/A	Classification, segmentation
2012 (49)	Multi-country	BCDR	1,875	N/A	Classification, density

Table-1

Breast lesion segmentation :

The Nottingham Histological Grading (NHG) system is currently the most commonly utilized tool for assessing the aggressiveness of breast cancer . According to this system, breast cancer scores are determined based on three significant factors: tubule formation, nuclear pleomorphism , and mitotic count . Tubule formation is an essential assessment factor in the NHG grading system for understanding the level of cancer. Before identifying tubule formation, detection or segmentation tasks need to be performed. Pathologists typically conduct these tasks visually by examining whole slide images (WSIs). Medical image segmentation assists pathologists in focusing on specific regions of interest in WSIs and extracting detailed information for diagnosis. Conventional and AI methods have been applied in medical image segmentation, utilizing handcrafted features such as color, shapes, and texture. Traditional manual tubule detection and segmentation techniques have been employed in medical images. However, these methods are challenging, prone to errors, exhaustive, and time-consuming.

Table 2 provides a comparison of recently developed DL methods in mammography for breast lesion segmentation. These methods include the Conditional Random Field model (CRF), Adversarial Deep Structured Net, Deep Learning using You-Only-Look-Once , Conditional Residual U-Net (CRU-Net), Mixed-Supervision-Guided (MS-ResCU-Net) and Residual-Aided Classification U-Net Model (ResCU-Net) , Dense U-Net with Attention Gates (AGs) (, Residual Attention U-Net Model (RU-Net) , Modified U-Net , Mask RCNN , Full-Resolution Convolutional Network (FrCN) , U-Net , Conditional Generative Adversarial Networks (cGAN) , DeepLab , Attention-Guided Dense-Upsampling Network (AUNet), FPN , modified CNN based on U-Net Model , deeply supervised U-Net , modified U-Net , and Tubule-U-Net . Among these DL methods, U-Net is the most commonly employed segmentation method.

Deep learning approaches in mammography for breast lesion segmentation.

Year	Model	Evaluation Dataset	Noise remove method	Performance Metrics (results)
2015 (59)	CRF	INbreast and DDSM-BCRP	NA	The method achieved an 89.0% Dice index in 0.1.
2018 (60)	adversarial deep structured net	INbreast and DDSM-BCRP	NA	The method achieved a segmentation rate of 97.0%.
2018 (61)	deep learning using You-Only-Look-Once	INbreast	NA	The method achieved detection rate of 98.96%, Matthews correlation coefficient (MCC) of 97.62%, and F1 score of 99.24%.
2018 (62)	CRU-Net	INbreast and DDSM-BCRP	NA	The CRU-Net achieved a Dice Index DI of 93.66% for INbreast and a DI of 93.32% for DDSM-BCRP.
2019 (63)	MS-ResCU-Net and ResCU-Net	INbreast	NA	The MS-ResCU-Net achieved an accuracy of 94.16%, sensitivity of 93.11%, specificity of 95.02%, DI of 91.78%, Jac of 85.13%, and MCC of 87.22%, while ResCU-Net correspondingly achieved 92.91%, 91.51%, 94.64%, 90.50%, 83.02%, and 84.99%.
2019 (64)	dense U-Net with AGs	DDSM	NA	The method achieved 82.24% F1 score, 77.89% sensitivity, and overall accuracy of 78.38%.
2019 (65)	RU-Net	DDSM, BCDR-01, and INbreast	cLare filter	The proposed model achieved a mean test pixel accuracy of 98.00%, a mean Dice coefficient index (DI) of 98.00%, and mean IOU of 94.00%.
2019 (66)	modified U-Net	DDSM	Laplacian filter	The method produced 98.50% of the F-measure and a

Table - 2

Naik et al.developed a likelihood method for the segmentation of lumen, cytoplasm, and nuclei based on a constraint: a lumen area must be surrounded by cytoplasm and a ring of nuclei to form a tubule. Tutac et al.introduced a knowledge-guided semantic indexing technique and symbolic rules for the segmentation of tubules based on lumen and nuclei. Basavanhally et al. developed the O'Callaghan neighborhood method for tubule detection, allowing for the characterization of tubules with multiple attributes. The process was tested on 1226 potential

lumen areas from 14 patients and achieved an accuracy of 89% for tubule detection. In reference, the authors applied a k-means clustering algorithm to cluster pixels of nuclei and lumens. They employed a level-set method to segment the boundaries of the nuclei surrounding the lumen, achieving an accuracy of 90% for tubule detection. Romo-Bucheli et al. developed a Convolutional Neural Network (CNN) based detection and classification method to improve the accuracy of nuclei detection in tubules, achieving an accuracy of 90% for tubule nuclei detection. Hu et al. proposed a breast mass segmentation technique using a full CNN (FCNN), which showed promising results with high accuracy and speed. Abdelhafiz et al. studied the application of deep CNN for mass segmentation in mammograms and found increased performance in terms of accuracy. Tan et al.recently developed a tubule segmentation method that investigates geometrical patterns and regularity measurements in tubule and non-tubule regions. This method is based on handcrafted features and conventional segmentation techniques, which are not effective and efficient for tubule structures due to their complex, irregular shapes and orientations with weak boundaries.

Deep learning approaches in mammography for breast lesion detection and classification

DL approaches have garnered considerable attention in mammography for the detection and classification of breast lesions, primarily due to their ability to automatically extract high-level features from medical images. Numerous popular DL algorithms have been employed in mammography for breast screening, including convolutional neural networks (CNN), deep belief networks (DBN), recurrent neural networks (RNN), autoencoders, generative adversarial networks (GAN), capsule networks (CN), convolutional recurrent neural networks (CRNN), attention mechanisms, multiscale CNN, and ensemble learning (EL).

CNN proves highly effective in extracting and classifying image features into distinct categories. DBN is particularly advantageous in identifying subtle changes in images that may be challenging for human observers to discern. RNN utilizes feedback loops to facilitate predictions, thereby aiding in the analysis of sequential data. Autoencoders are utilized for unsupervised feature learning, which aids in the detection and classification of mammography images. GAN is exceptionally effective in generating synthetic mammography images for training DL models. Multiscale CNN analyzes images at multiple scales, proving invaluable in detecting and classifying images with complex structures and patterns at varying scales. EL combines multiple DL models to enhance accuracy and reduce false positives.

Table 3analyzes the recently developed DL methods for breast lesion detection using mammography. These methods have the potential to greatly enhance the accuracy and efficiency of breast cancer diagnosis. However, it is important to note that most DL methods for biomedical imaging applications come with certain limitations.

DL-based mammography for breast tumor detection.

Reference	Year	Method	Database	Number of images	Accuracy	AUC	Sensitivity	Specifi
(88)	2016	Deep CNN	DDSM	600	96.7%	NA	NA	NA
(89)	2016	AlexNet	FFDM	607	NA	86%	NA	NA
(90)	2016	CNN	BCDR-F03	736	NA	82%	NA	NA
(91)	2016	SNN	UCI, DDSM	NA	89.175%, 86%	NA	NA	NA
(92)	2016	ML-NN	ED(US)	NA	98.98%	98%	NA	NA
(93)	2016	DBN	ED(US-SWE)	NA	93.4%	94.7%	88.6%	97.1%
(94)	2017	Deep CNN	FFDM	3185	82%	88%	81%	72%
(95)	2017	CNN (COM)	INbreast	115	95%	91%	NA	NA
(96)	2017	Deep CNN	SFM, DM	2242	NA	82%	NA	NA
(97)	2017	CNN-CT	IRMA	2796	83.74%	83.9%	79.7%	85.4%
(97)	2017	CNN-WT	IRMA	2796	81.83%	83.9%	78.2%	83.3%
(98)	2017	VGG19	FFDM	245	NA	86%	NA	NA
(99)	2017	Custom CNN	FFDM	560	NA	79%	NA	NA
(100)	2017	VGG16	IRMA	2795	100%	100%	NA	NA
(101)	2017	SNN	DDSM	480	79.5%	NA	NA	NA
(101)	2017	CNN (COM)	MIAS, CBIS-INBreast	NA	57%	77%	NA	NA
(96)	2017	Multitask DNN	ED(Mg),DDSM	1057 malignant, 1397 benign	82%	NA	NA	NA
(102)	2017	CNN (COM)	ED (HP)	NA	95.9% (2 classes), 96.4% (15 classes)	NA	NA	NA
(103)	2017	ImageNet	BreakHis	NA	93.2%	NA	NA	NA
(104)	2018	GoogLeNet	BCDR-F03	736	81%	88%	NA	NA

Table – 3

Table 4 presents a comprehensive list of the latest DL-based mammogram models developed for breast lesion classification. DL models offer numerous benefits, including

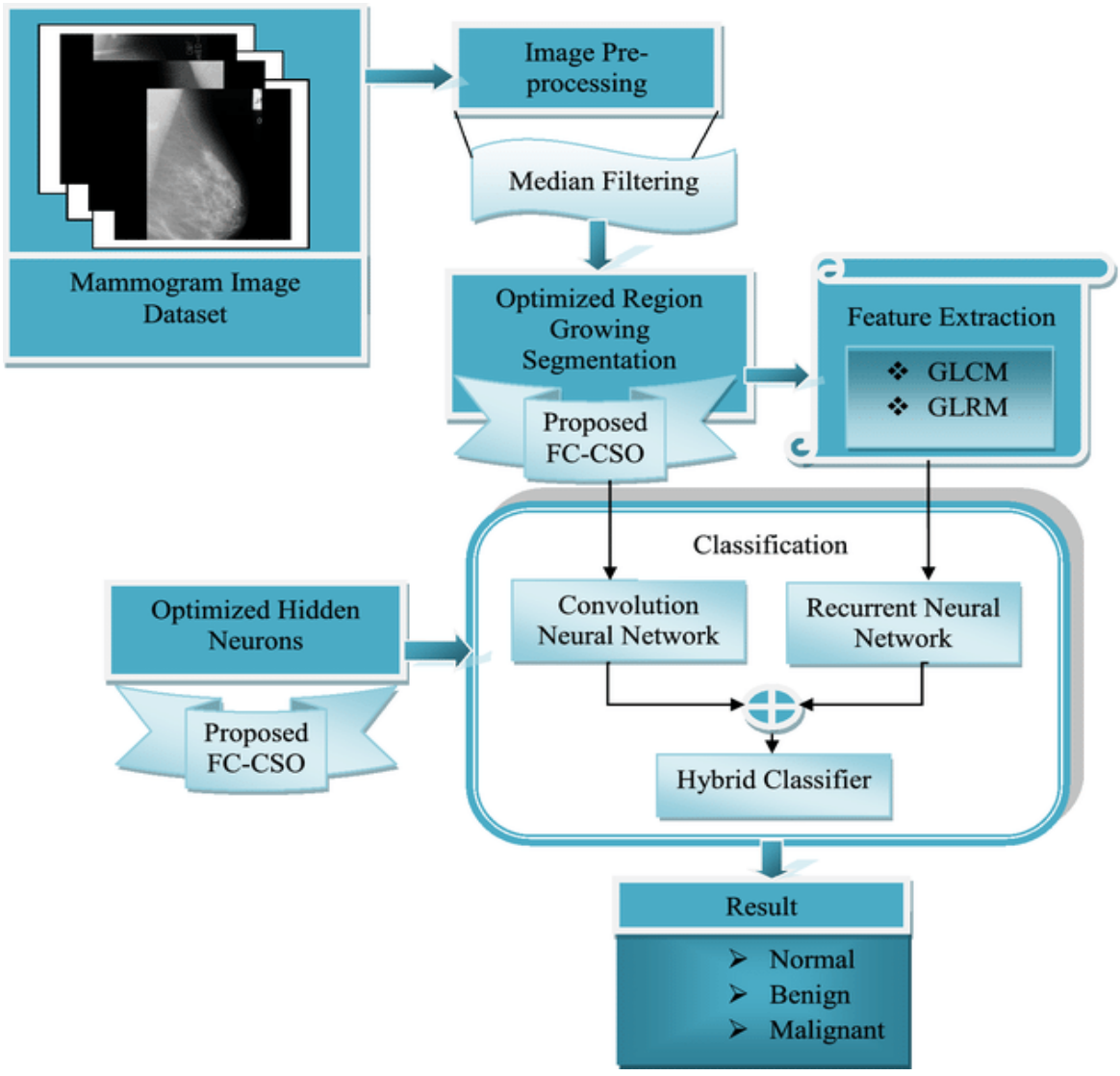
)L-based mammography for breast tumor classification.

Reference	Year	Method	Database	Number of images	Accuracy	AUC	Sensitivity	Precision
(95)	2017	Transfer learning, Random Forest	INbreast	108	90%	NA	98%	70%
(124)	2018	Deep GeneRAtive Multitask	CBIS-DDSM	NA	89%	0.884	NA	NA
(125)	2019	VGG, Residual Network	CBIS-DDSM	NA	NA	NA	86.10%	80.10%
(126)	2019	DCNN, Alexnet	CBIS-DDSM	1696	75.0%	0.80	NA	NA
(127)	2019	MA-CNN	MIAS	322	96.47%	0.99	96.00%	NA
(128)	2019	DCNN, MSVM	MIAS	322	96.90%	0.99	NA	NA
(129)	2019	CNN Improvement (CNNI-BCC)	MIAS	NA	90.50%	0.90	89.47%	90.71%
(130)	2020	MobileNet, VGG, Resnet, Xception	CBIS-DDSM	1696	84.4%	0.84	NA	NA
(131)	2020	MobilenetV1, MobilenetV2	CBIS-DDSM	1696	74.5%	NA	NA	70.00%
(132)	2020	DE-Ada*	CBIS-DDSM	NA	87.05%	0.9219	NA	NA
(133)	2020	AlexNet	MIAS	68	98.53%	0.98	100%	97.37%
(133)	2020	GoogleNet	MIAS	68	88.24%	0.94	80%	94.74%
(134)	2020	Inception ResNet V2	INbreast	107	95.32%	0.95	NA	NA
(132)	2020	De-ada*	INbreast	NA	87.93%	0.9265	NA	NA
(135)	2021	CNN	CBIS-	1592	91.2%	0.92	92.31%	90.00%

Table - 4

exceptional accuracy and optimal performance achieved with fewer parameters. However, it is important to acknowledge certain limitations associated with existing DL methods for breast tumor classification using mammographies. These limitations include the substantial computational power and extensive datasets required for training the models, which can be computationally expensive, intricate, and time-consuming.

c.) FLOW DIAGRAM:



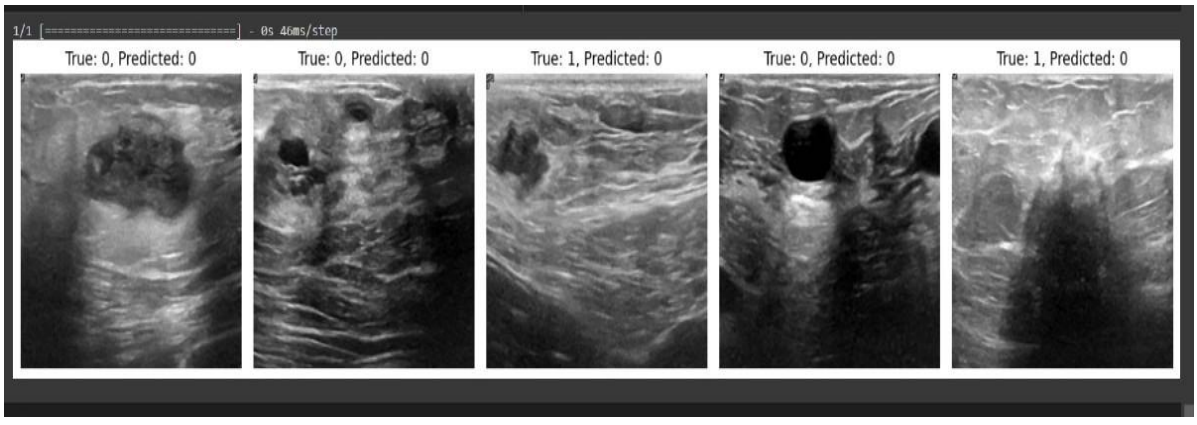
5.) TESTING

a.) Model Evaluation:

```
+ Code  + Text

from sklearn.metrics import precision_score, recall_score

# Calculate precision and recall for each class
precision = precision_score(y_test, svm_predictions, average=None)
recall = recall_score(y_test, svm_predictions, average=None)
from sklearn.metrics import confusion_matrix

# Get the confusion matrix
cm = confusion_matrix(y_test, svm_predictions)

# Calculate specificity
specificity = cm[0, 0] / (cm[0, 0] + cm[0, 1])  # Specificity for class (benign)

print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1 Score:", f1)
print("Specificity:", specificity)
```

```
Accuracy: 0.8466257668711656
Precision: [0.9266055  0.68518519]
Recall: [0.8559322  0.82222222]
F1 Score: 0.8505568645564862
Specificity: 0.8559322033898306
```

b.) Prediction:



6.) RESULT

Results obtained using different architectures are as follows-:

a.)DenseNet121

DenseNet121 is a Dense Convolutional Network (DenseNet)comprised of 121 layers. DenseNet is a special kind of CNN that was originally proposed by Huang et al. It achieved state-of-the-art results on several image classification datasets, such as Cifar-10 and SVHN. In a DenseNet architecture, layers are connected with dense blocks, meaning that each layer utilizes inputs from all previous layers in order to create a feature map that will send data to all of the following layers. Therefore, the h -layer receives all previous features maps (0 ,1 , … … ,−1) as inputs: = ([0 ,1 , … … ,−1])Here, [0 ,1 , … … ,−1] represents the concentration of all previous feature maps of h - layer. Is the output of the h layer, and represents h layer, which is a composition function consisting of three successive operations including batch normalization, a ReLU activation function, and convolution. DenseNet is similar to methods such as ResNet, but the latter combines previous layers with future layers while DenseNet concatenates layers instead. DenseNet approaches the problem of vanishing gradients by reusing features which also reduces the number of parameters. As shown in Fig. 2, DenseNet-121 utilizes four dense blocks. Between each block is a transition layer that utilizes down-sampling on the feature maps to create a 1× 1 convolution as well as a 2× 2 average pooling layer. The dense blocks comprise multiple convolutional layers, which are connected in series and serve as cross-layer connections between distant layers. To increase non-linearity, DenseNet-121 utilizes a ReLU activation.

The deep DenseNet-121 model requires a large training set to increase its accuracy rate, but collecting labelled br images is difficult. Transfer learning (TL) has been proposed as a common technique to address this limitation. The TL strategy pre-trains a model on a large, labelled dataset and then transfers the gained knowledge (learned weights) to other related tasks within the same architecture design. It treats the model as a starting point in the target task's training, which avoids the process of training the model from scratch with random weight initializations. Once TL is complete, the last layer must be altered to the number of required classes and then fine-tuned on the target dataset of interest. Recent research has demonstrated that TL improves performance rates compared to training a model from scratch on a small dataset. In addition, TL enhances generalization, reduces both overfitting training time, and decreases the labeled

data required. Recently, TL has been applied widely in computer vision and natural language processing application.

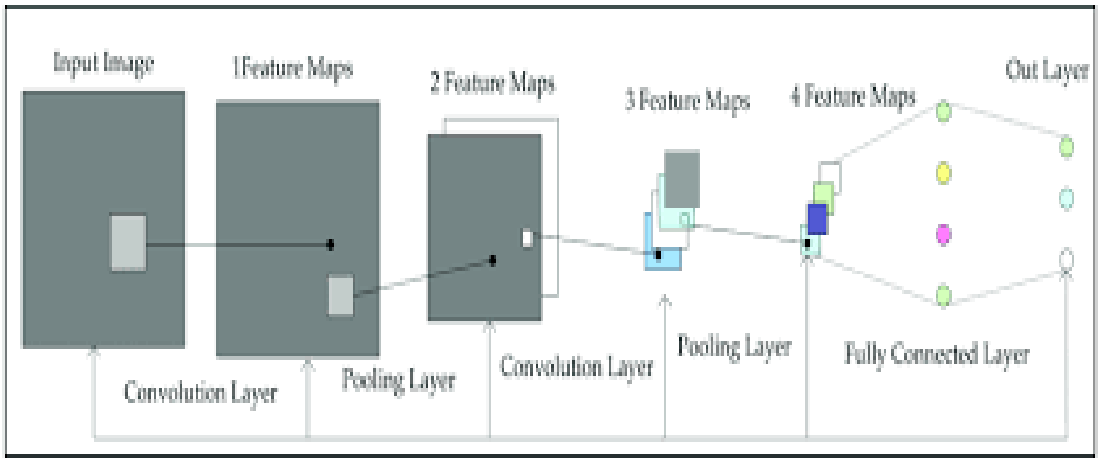


Fig 1: DenseNet Architecture Table 1 : DenseNet121

Model Code Result :

Epoch	Accuracy	Loss
1	0.67	0.60
2	0.69	0.58
3	0.66	0.58
4	0.65	0.61
5	0.65	0.61
6	0.67	0.59
7	0.69	0.58
8	0.68	0.58
9	0.66	0.59
10	0.67	0.59

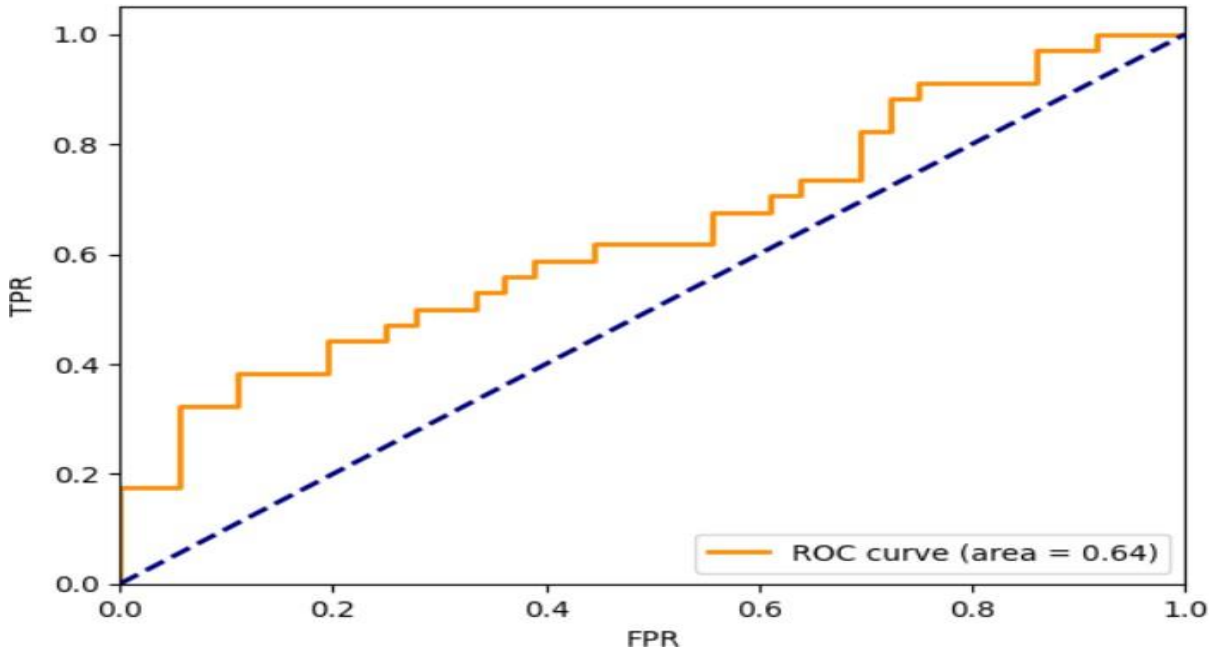


Fig. 2 - DenseNet121 ROC Curve

b.) MobileNetV2

MobileNetV2 is a convolutional neural network architecture designed for mobile and edge devices with resource constraints. It is an evolution of the original MobileNet architecture, and it was introduced by Google researchers in the paper titled "MobileNetV2: Inverted Residuals and Linear Bottlenecks."

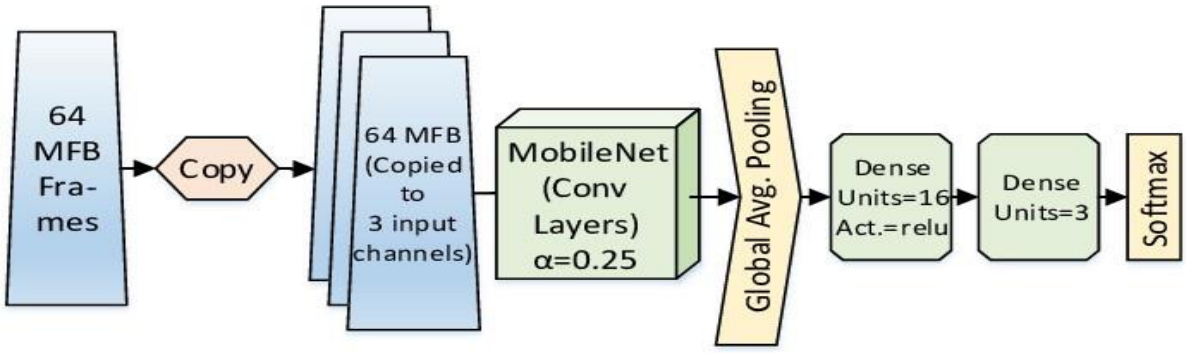


Fig 3:Network Architecture Of MobileNet

Here are some key features and concepts associated with MobileNetV2:

1.) Inverted Residuals with Linear Bottlenecks: MobileNetV2 introduces the concept of

inverted residuals, which includes a shortcut connection that skips one or more layers. Linear bottlenecks are used, where the input to each layer is passed through a linear (1x1) bottleneck layer before applying non-linear transformations.

2.) Depthwise Separable Convolution: Similar to the original MobileNet, MobileNetV2 uses depthwise separable convolutions to reduce the computational cost. Depthwise separable convolutions consist of a depthwise convolution followed by a pointwise (1x1) convolution. This allows for efficient filtering in spatial and channel dimensions separately.

3.) Linear Bottlenecks: MobileNetV2 uses linear bottlenecks to preserve information flow through the network. The linear layers help prevent the loss of information during the depthwise separable convolutions.

4.) Global Average Pooling (GAP): MobileNetV2 uses global average pooling instead of fully connected layers at the end of the network.

Table 2 : MobileNetV2 model code result

Epoch	Accuracy	Loss
1	0.65	0.61
2	0.63	0.61
3	0.68	0.60
4	0.65	0.62
5	0.67	0.60
6	0.66	0.60
7	0.64	0.62

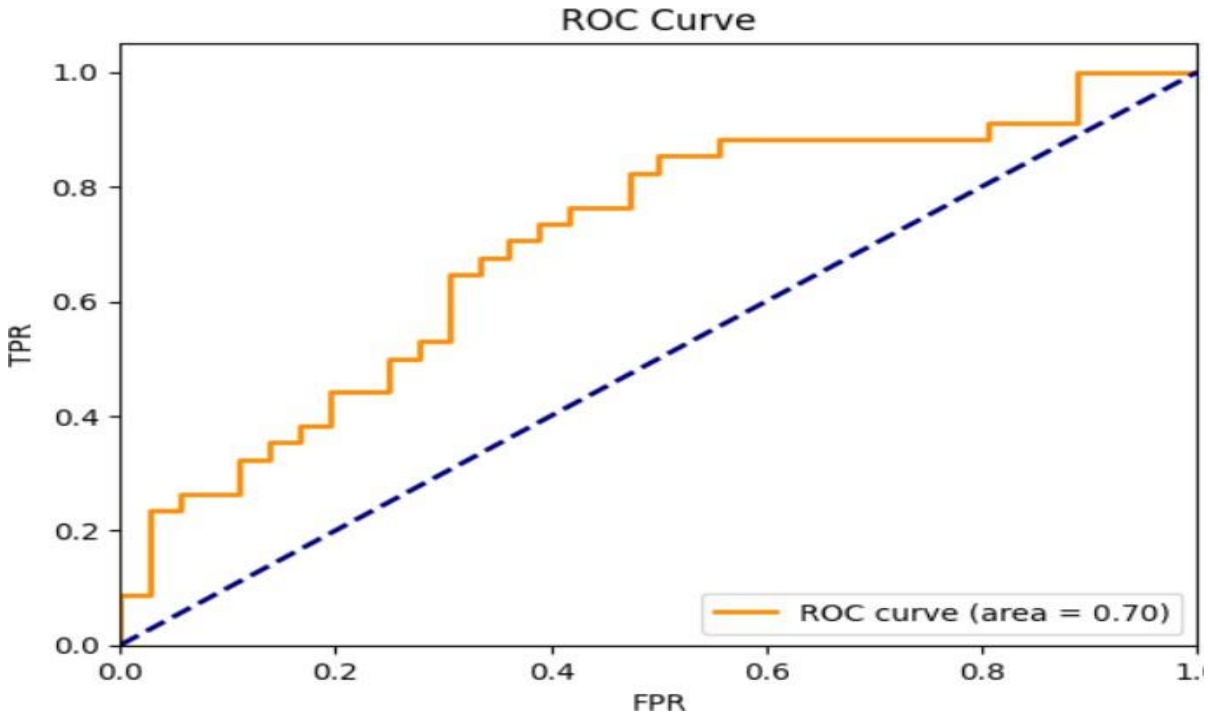


Fig 4: MobileNetV2 ROC Curve

ResNet50

ResNet-50 is a deep learning model introduced by Microsoft Research in 2015. It is part of the ResNet family and has 50 layers, making it deeper than the original ResNet model (ResNet-18). ResNet-50 is widely used for various computer vision tasks, including image classification, object detection, and feature extraction.

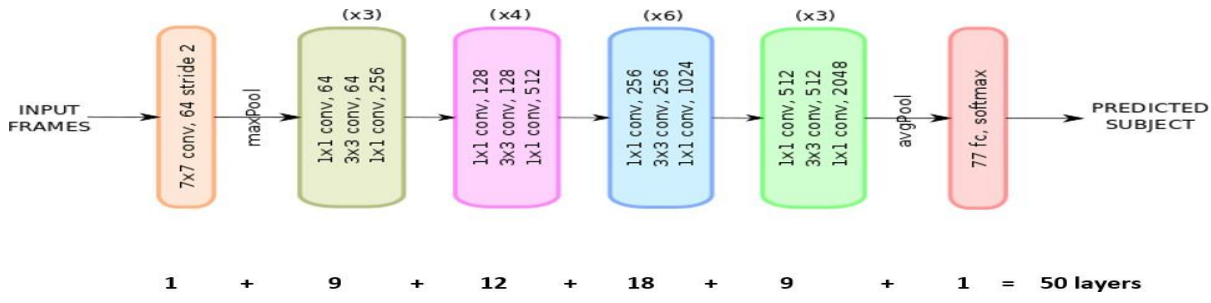


Fig 5: ResNet-50

Layer structure Here are the key characteristics of the ResNet-50 model:

1.) Architecture: ResNet-50 consists of 50 layers, divided into convolutional layers, pooling layers, fully connected layers, and shortcut connections (skip connections). The skip connections help in mitigating the vanishing gradient problem, making it easier to train very

deep networks.

2.) Convolutional Layers: The ResNet-50 model starts with a 7x7 convolutional layer with a stride of 2, followed by a max-pooling layer. It then contains four stages, each with multiple convolutional blocks.

3.) Pooling Layers: ResNet-50 uses max-pooling layers to reduce the spatial dimensions of the feature maps.

4.) Activation Function*:* ReLU (Rectified Linear Unit) is used as the activation function after each convolutional layer.

5.) Global Average Pooling (GAP): Instead of using fully connected layers at the end, ResNet-ses global average pooling, which averages the values of each feature map to produce a fixed-size output. This helps reduce the number of parameters and prevents overfitting.

6.)Softmax Output*:* For image classification tasks, ResNet-50 uses a softmax activation function in the output layer to produce probabilities for each class.

7.) Pre-trained Weights: ResNet-50 is often pre-trained on large-scale image datasets such a ImageNet. The pre-trained weights can be used for transfer learning, where the model is finetuned on a smaller dataset or a different task.

Table 3: ResNet50 model code result

Epoch	Accuracy	Loss
1	0.74	0.50
2	0.76	0.50
3	0.74	0.50
4	0.75	0.50
5	0.75	0.51
6	0.75	0.50
7	0.75	0.50
8	0.72	0.51
9	0.72	0.52
10	0.75	0.52

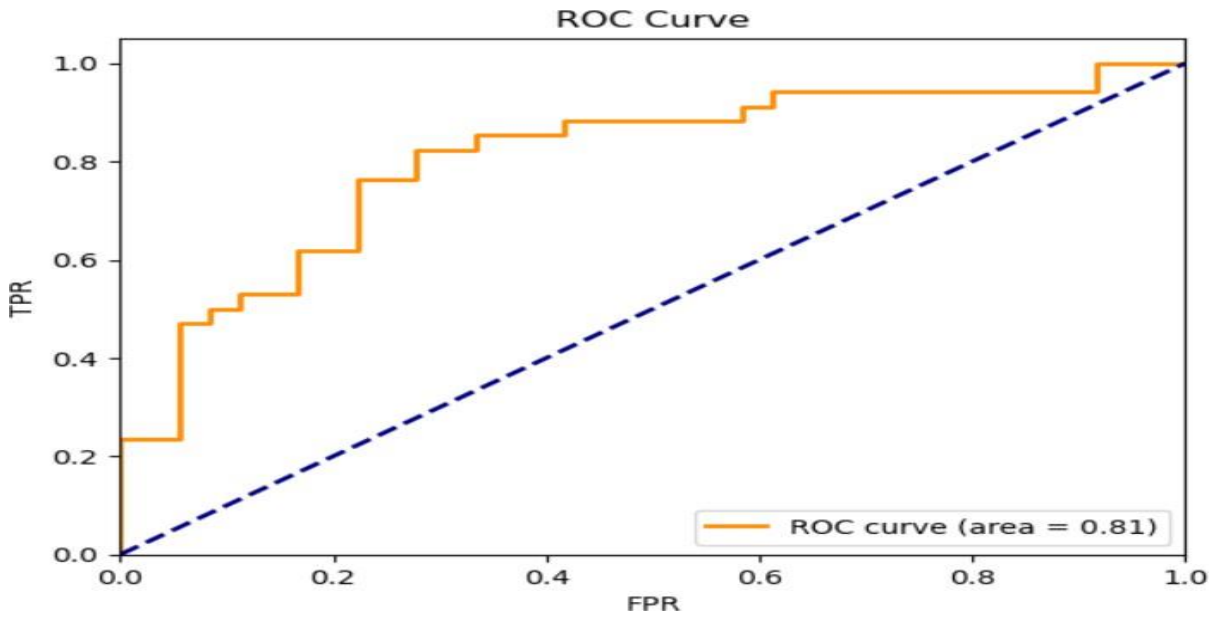


Fig 6: ResNet50 ROC Curve

c.) InceptionV3

Inception v3 is a deep convolutional neural network architecture that was introduced by Google researchers as part of the Inception family of models. It is the third iteration in the series, following the original Inception (GoogLeNet) and Inception v2 architectures. Inception v3 was designed with a focus on improving the efficiency and accuracy of image .

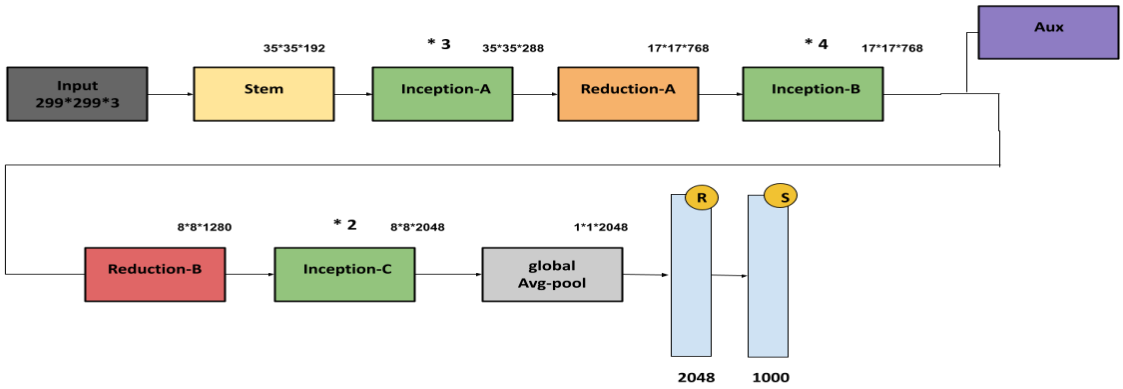


Fig 7: InceptionV3 Architecture

Here are some key features and concepts associated with Inception v3:

1.) Inception Modules: Inception v3 utilizes a series of Inception modules, which are building blocks that allow the network to capture information at different spatial scales. These modules use a combination of convolutions of different sizes (1x1, 3x3, 5x5) and pooling operations to capture features at various resolutions.

2.) Factorization into Smaller Convolutions: Inception v3 introduced the idea of factorizing large convolutions into a series of smaller convolutions. This helps in reducing the number of parameters and computational complexity while maintaining or improving representation power.

3.) Auxiliary Classifiers: The network includes auxiliary classifiers at intermediate layers during training. These auxiliary classifiers are added to the loss function and help with gradient flow during backpropagation. They act as regularization and can improve the training of deep networks.

4.) Batch Normalization: Inception v3 incorporates batch normalization, a technique that normalizes the input to a layer across the mini-batch. Batch normalization helps stabilize and accelerate the training process by reducing internal covariate shift**.**

5.) Global Average Pooling (GAP): Similar to MobileNetV2, Inception v3 uses global average pooling instead of fully connected layers at the end of the network. This reduces the number of parameters and helps in making the model more computationally efficient**.**

Table 4: InceptionV3

Epoch	Accuracy	Loss
1	0.70	0.56
2	0.73	0.56
3	0.69	0.58
4	0.67	0.58
5	0.69	0.58
6	0.69	57
7	0.72	56
8	0.68	59
9	0.68	58
10	0.68	57

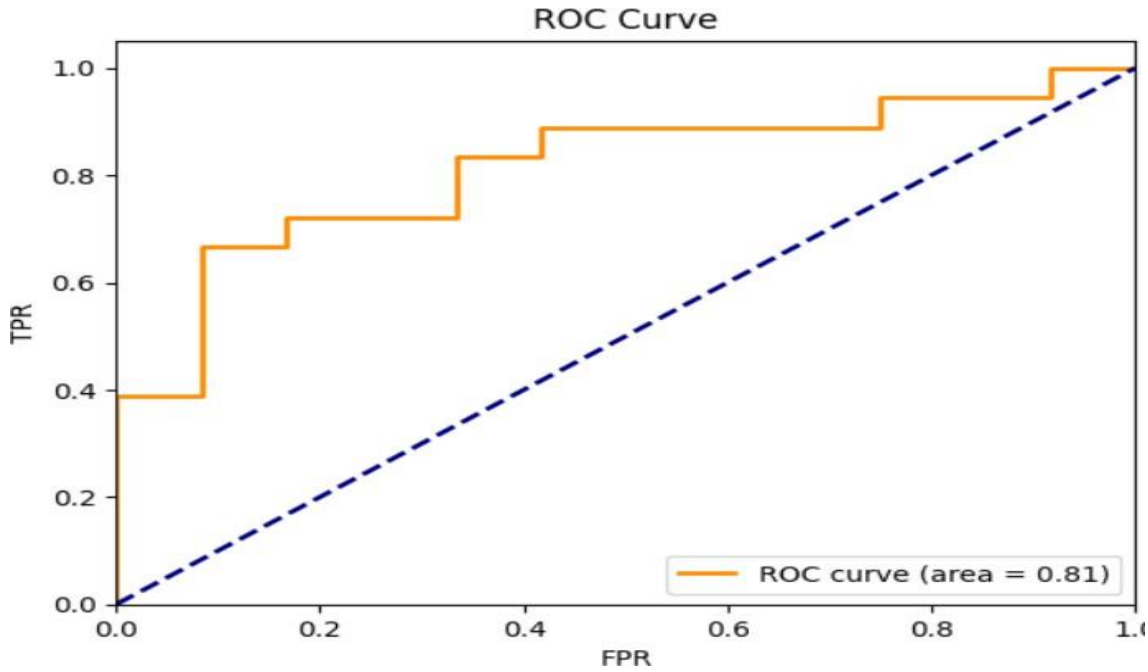


Fig.7 InceptionV3 ROC Curve

d.) Hybrid Models:

Table 5: ResNet50 + InceptionV3 hybrid model code result

Epoch	Accuracy	Loss
1	0.80	0.42
2	0.79	0.44
3	0.78	0.45
4	0.78	0.44
5	0.79	0.43
6	0.77	0.44
7	0.78	0.45
8	0.80	0.43
9	0.81	0.41
10	0.81	0.42

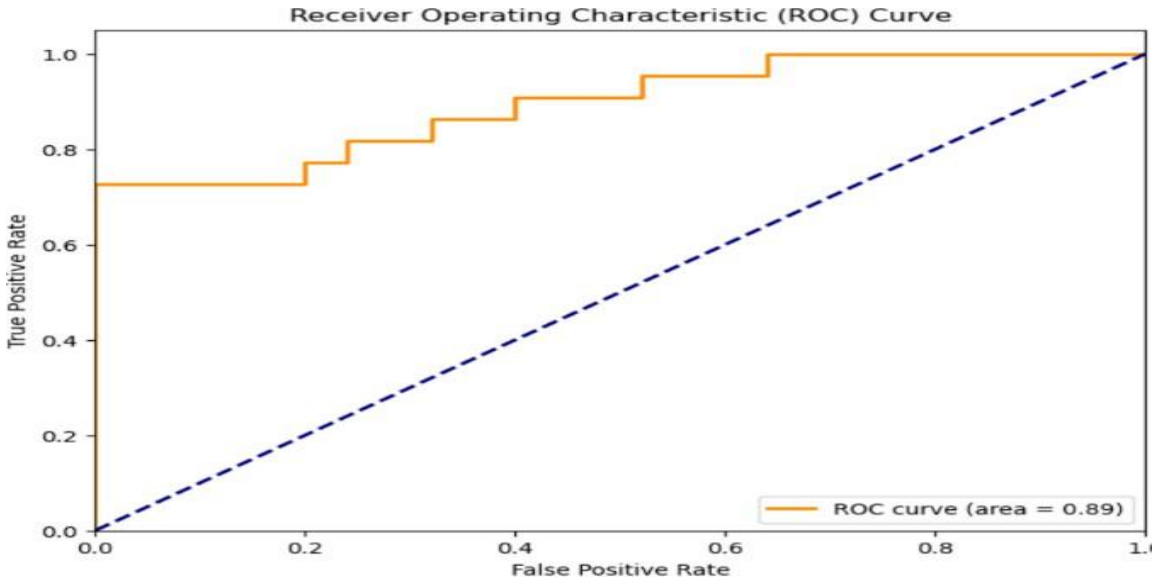


Fig 9: ResNet50 + InceptionV3 ROC Curve

Table 6: MobileNetV2 + DenseNet121 hybrid model code result

Epoch	Accuracy	Loss
1	0.69	0.58
2	0.66	0.60
3	0.67	0.60
4	0.68	0.59
5	0.66	0.60
6	0.68	0.58
7	0.66	0.60
8	0.66	0.60
9	0.65	0.62
10	0.66	0.60

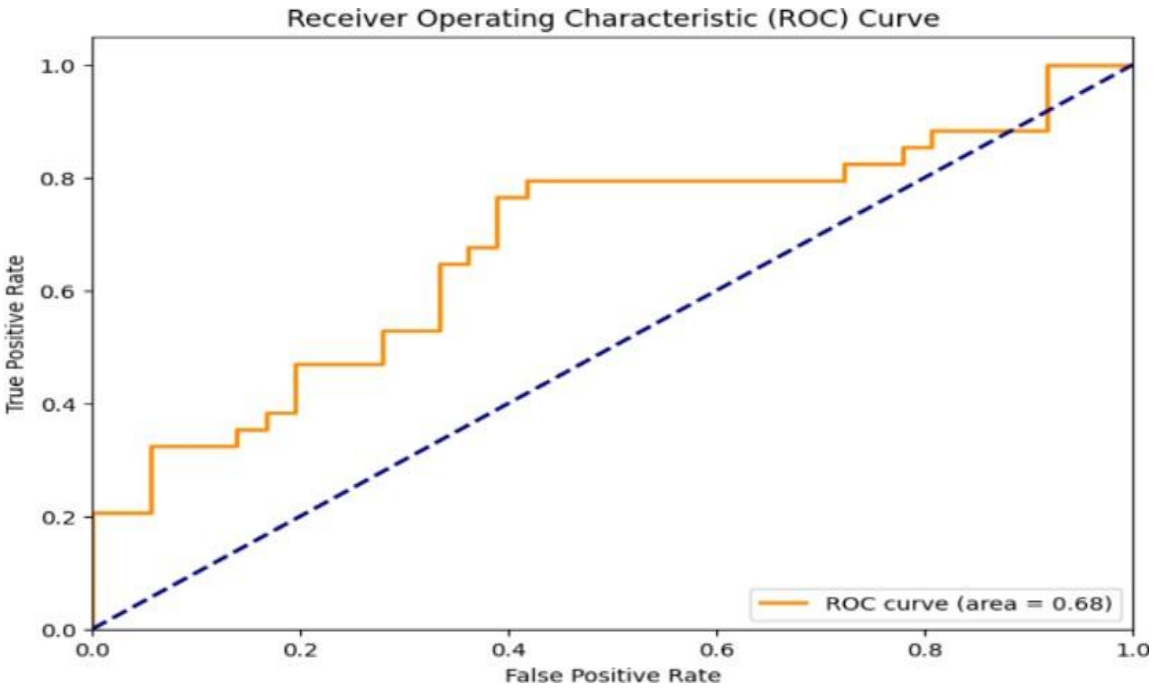


Fig 10 - MobileNetV2 + DenseNet121 ROC Curve

7.) FUTURE WORK

The emergence of DL techniques has revolutionized medical imaging, offering immense potential to enhance the diagnosis and treatment of various diseases. DL algorithms present several advantages compared to traditional ML methods. For instance, DL algorithms can be trained using robust hardware such as graphical processing units (GPU) and tensor processing units (TPU), greatly accelerating the training process.

This has enabled researchers to train large DL models with billions of parameters, yielding impressive results in diverse language tasks. However, to fully leverage the potential of DL in medical imaging, several challenges must be addressed. One of the primary challenges is the scarcity of data. DL algorithms require abundant, high-quality data for effective training. Yet, acquiring medical imaging data is often challenging, particularly for rare diseases or cases requiring long-term follow-up. Furthermore, data privacy regulations and concerns can further complicate the availability of medical imaging data. Another challenge lies in the quality of annotations.

DL algorithms typically demand substantial amounts of annotated data for effective training. However, annotating medical imaging data can be subjective and time-consuming, leading to issues with annotation quality and consistency. This can significantly impact the performance of deep learning algorithms, particularly when accurate annotations are vital for diagnosing or treating specific conditions. Additionally, imbalanced classes pose another challenge in medical imaging.

In numerous instances, the occurrence of certain states may be relatively low, which can result in imbalanced datasets that have a detrimental effect on the performance of DL algorithms. This situation can pose a significant challenge, especially for rare diseases or conditions with limited data availability. Another crucial concern in medical imaging is the interpretability of models. Although DL algorithms have showcased remarkable performance across various medical imaging tasks, the lack of interpretability in these models can hinder their adoption. Clinicians frequently necessitate explanations for the predictions made by these algorithms in order to make informed decisions, but the opacity of DL models can make this task arduous.

Data privacy is a paramount concern in medical imaging. Medical images encompass confidential patient information, stringent regulations dictate the utilization and dissemination of such data. The effective training of DL necessitates substantial access to extensive medical imaging data, thereby introducing challenges concerning data privacy

and security. Additionally, computational resources pose another challenge in the realm of medical imaging. DL algorithms mandate substantial computational resources for the effective training and of models. This predicament can prove particularly troublesome in medical imaging, given the size and intricacy of medical images, which can strain computing resources. DL algorithms can be vulnerable to adversarial attacks, where small perturbations to input data can cause significant changes in the model's output. This can be particularly problematic for medical imaging, where even small changes to an image can have substantial implications for diagnosis and treatment.

Several potential strategies can be employed to address these challenges effectively. One approach involves the development of transfer learning techniques, enabling DL models to be trained on smaller datasets by leveraging information from related tasks or domains. This approach holds particular promise in medical imaging, where data scarcity poses a significant obstacle. Another approach involves placing emphasis on the development of annotation tools and frameworks that enhance the quality and consistency of annotations. This becomes important in cases where annotations play a critical role in diagnosing or treating specific conditions. Furthermore, improved data sharing and collaboration between institutions can help alleviate both data scarcity and privacy concerns.

By pooling resources and sharing data, it becomes feasible to construct more extensive and diverse datasets that can be employed to train DL models with greater effectiveness. Additionally, enhancing the interpretability of DL models in medical imaging techniques stands as another critical area of research. The development of explainable AI techniques can provide clinicians with valuable insights into the underlying factors contributing to a model's predictions. Lastly, bolstering the robustness of DL models constitutes a crucial focal point. This entails exploring adversarial training techniques, as well as leveraging ensemble methods and other strategies to enhance the overall robustness and generalizability of DL models.

DL techniques have the potential to revolutionize medical imaging. However, to fully leverage this potential, it is crucial to address several challenges. These challenges encompass data scarcity, annotation quality, imbalanced classes, model interpretability, data privacy, computational resources, and algorithm robustness. By prioritizing strategies to tackle these challenges, it becomes possible to develop DL models that are more effective and reliable for various medical imaging applications.

8.) CONCLUSION

Detection of breast cancer using deep learning has shown promising results and great potential in improving the accuracy and efficiency of breast cancer diagnosis. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated their ability to learn meaningful patterns from MRI images and make accurate predictions for breast cancer detection. This is due to several factors such as :

Spatial hierarchies : CNNs leverage the spatial hierarchies in images. They can recognize local patterns in the initial layers and progressively learn more complex, abstract features in deeper layers.

Automation and Speed*:* Deep learning models can process large volumes of medical images quickly, providing a faster and more automated screening process. This is particularly crucial in the context of breast cancer detection, where early diagnosis is vital for effective treatment.

Research Advancements: Continuous research and development in the field have led to the improvement of CNN architectures and training techniques. Researchers and practitioners have been able to refine models to achieve better performance, making them more reliable for breast cancer detection.

ResNet50 and InceptionV3 presented in this study has achieved the highest value of accuracy individually and even when combined. The performance of all the four models, therefore ResNet50, InceptionV3, DenseNet121 and MobileNetV2 was evaluated using Receiver Operating Characteristic (ROC) Curve.

Earlier detection of Breast Cancer can improve the survival rate of patients. Fortunately, advancements in medical imaging techniques have made it possible to diagnose Breast Cancer at an early stage. The rapid development of Artificial Intelligence based techniques in Medical Image Analysis (MIA) have made it possible to fully utilize large datasets for improved BC diagnosis and precision medicine by automatically extracting the relevant features**.**

9.) BIBLIOGRAPHY

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