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Detection and Classification of Breast cancer from Ultrasound Images using NASNet Model

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Abstract: Breast cancer is still a major global health challenge that requires precise diagnosis techniques in order to plan appropriate therapy. Because traditional methods are frequently imprecise, research into machine learning algorithms is necessary to increase detection rates. Breast cancer affects women worldwide and has an increasing recurrence rate, major complications, and rates of death. Benign and malignant are the two main types for cancers. This work looks into the detection and classification of breast cancer in ultrasound images using the NASNet model, a convolutional neural network well-known for its image analysis powers. Specifically, the NASNet Mobile model is trained on ultrasound images of breast cancer by using annotated data for supervised learning. The model delivers outstanding performance measures, such as an Accuracy of 94.6%, Precision of 97%, and F1-score of 96%, through intensive training and validation. Its 97% Recall rate demonstrates how well it works to reduce false negatives, which is important for early detection. Enhancing diagnostic accuracy and improving patient outcomes, the clinical practice of healthcare providers can be greatly benefitted by the successful use of the NASNet Mobile model in breast cancer ultrasound imaging. Potential directions for future research could include enhancing the model for wider clinical application and launching a new phase of precision medicine in the treatment of breast cancer.

Keywords: Convolutional Neural Networks, Deep Learning, Breast cancer, NASNet, Machine Learning.

1. INTRODUCTION

In response to the escalating global burden of breast cancer and other cancer related fatalities, the International Atomic Energy Agency (IAEA) and the International Cancer Research Centre (ICRC) have forged a collaborative partnership with the World Health Organization (WHO) [13]. This alliance is driven by a shared commitment to mitigate breast cancer related fatalities through concerted efforts aimed at bolstering health immunity and enhancing early stage detection coupled with top notch treatment modalities. There exists a growing sense of urgency within the WHO and the broader cancer community to confront the challenges posed by breast cancer and the burgeoning overall cancer crisis, which continues to strain individuals, communities, and healthcare systems alike [2]. Currently, cancer is a global hazard that is expected to influence one in five people. In order to protect the health and welfare of people everywhere, it is imperative that aggressive worldwide action be taken to reduce the prevalence of breast cancer and other cancers [3]. Breast cancer affects women worldwide and has an increasing recurrence rate, major complications, and rates of death. Benign and malignant are the two main types for cancers. Because benign malignancies only affect the targeted region and never propagate to other parts of the body, they are less harmful for people to live [4][5]. The malignant neoplasm sometimes referred to as a cancer oustumor, is an extremely deadly form of cancer since it has the potential to growth and negatively impact other physically components. In order to enhance patient outcomes, early and proper finding of invasive ductal carcinoma is essential. Breast carcinoma remains a significant public illness [6]. Promising opportunities exist for transforming medical image diagnosis and analysis accuracy due to recent advancements in artificial intelligence, namely in deep learning. With the ability to recognize complex patterns straight from raw data, Convolutional Neural Networks (CNNs) have become highly effective tools for automating imagine categorization tasks [7]. NASNet (Neural Architecture Search Network) is one of these architectures that stands out for feature extraction as well as efficacy. Numerous research are currently using machine learning and deep learning to speed up diagnosis, lower the risk of death, and increase patient longevity.

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Hospitals create and retain enormous amounts of data every day. Nevertheless, there is minimal patient data exchange because of issues with integrity, confidentiality, privacy, ethics, and the law [8]. In particular, convolutional networks from deep learning techniques have fast become the best approach for evaluating medical images. Arranged a range of datasets related to breast cancer using a novel, state-of-the-art machine learning technique [9]. The SEER dataset is subjected to a thorough analysis that takes into account a number of significant patient-related characteristics. Federated learning is a revolutionary approach that is being used to address research restrictions on a bigger scale while maintaining data integrity and privacy protection. By turning on the community firewall, medical data is subjected to a high level of protection [16]. Therefore, clinicians would benefit from being able to automatically identify lesions and evaluate either they are malignant or benign, and this may result in a large rise in life ratios. To extract features from input, neural networks use a multi-layered framework that starts with basic abstractions and progresses to more complex ones [17].

In this paper, Context regarding the significance of breast cancer detection and its related contribution is given in Sections 1 and 2. The proposed meta learning algorithm is described in Section 3. Results are shown in Section 4, proving its efficacy. Finally in Section 5 concludes this paper by showing the importance of sophisticated algorithms for enhancing breast cancer detection and treatment outcomes is highlighted.

2. RELATED WORK

Since breast carcinoma is the main reason of fatalities due to cancer across women on earth, initially recognition is vital to increasing the lives of patients. Using deep learning models, breast cancer can be identified and recognized in histopathology and mammography images [18]. Several experiments in this sector have yielded promising results, including attention-based models, multi-task learning, and convolutional neural networks with tiny SE blocks. Moreover, breast cancer can be accurately classified using deep residual networks. To identify and categorize images relevant to cancer from histology, pathology, and mammography, several DL models are employed [19]. Convolutional neural networks (CNNs), multitask learning, and attention based frequency models are commonly employed in research to achieve good results. Furthermore, models built on deep residual networks show great promise for improving the accuracy of image classification.

Aastha Joshi et al (2022) [1] look at the utilization of transfer learning (TL) methods for the real-time diagnosis of cancers of the breast in ultrasound images. They make use of 693 ultrasound images from the BUSI dataset, using the Inception-V3 and MobileNet-V2 models for extracting features and fine-tuning. By using conventional TL approaches over a range of network topologies, their goal is to decrease network parameters and improve knowledge of network efficiency. The results suggest that Inception-V3 outperforms MobileNet-V2, which performs second-best with an accuracy rate of 82.54%, and has the capability to boost the detection of breast cancer. Inception-V3 achieves the highest accuracy rate at 83.84%.

Uysal et al. (2022) [3] Provide a categorization using several classes strategy for breast ultrasound instances, utilizing the BUSI Pictures dataset again. The investigation's goal is to contrast the efficacy of ResNet50, ResNeXt, and 7 Chapter 3'sc. In this paper, a CNN architecture called VGG-16 is studied, and data is enhanced using conventional methods. The final three levels of VGG-16 now have three nodes. Whereas the ResNet model introduced three nodes, the ResNet50 design added two. As a result, the F1-Score, recall, accuracy, and area under the curve were assessed in the study. ResNet performed 85.83% more accurately than the other method. To further confirm the models' resilience, they might also be examined on additional datasets that are comparable.

Davoudi, et al. (2021) [10] Evolving convolutional neural network parameters through the genetic algorithm for the breast cancer classification problem. This paper offer, Effective treatment for breast cancer, which is the primary cause of cancer death among women, depends on early identification. Physicians use computer-aided diagnosis (CAD) systems; convolutional neural networks (CNNs) are frequently used because of CNNs' capacity to process complicated images. But accuracy depends on improving CNN parameters, particularly weights. This paper suggests using a genetic algorithm (GA) to optimize CNN weights. After testing on the BreakHis dataset and training the CNN with mini-batch gradient descent, Adam, and GA optimizers, we show that GA obtains a classification accuracy of 85%, which is comparable to Adam's.

Loizidou K, et al.'s (2023) [11] work offers a comprehensive examination of computer-assisted mammography-based breast cancer diagnosis and categorization. Preprocessing images, feature extraction, and classification algorithms including deep learning and machine learning techniques are all covered. Future research directions are explored, along with problems in CAD system development and performance evaluation criteria. The overall goal of the review is to increase reliability and effectiveness of mammography image-based breast cancer diagnosis.

Wang, X et al. (2022) [12] Intelligent hybrid deep learning model for breast cancer detection. The study presents a hybrid deep learning model that uses whole slide images (WSIs) from the PCam Kaggle dataset to automatically diagnose breast cancer (IDC +, -). Automated identification of breast cancer is essential because manual detection is laborious and prone to mistakes. With an accuracy of 86.21%, precision of 85.50%, sensitivity of 85.60%, specificity of 84.71%, and F1-score of 88%, the suggested model out performs other models in terms of pathologist mistakes and misclassification. Furthermore, the model demonstrates its efficacy in classifying breast cancer with an AUC of 0.89.

Geert Litjens et al.'s (2021) [14] More than 300 papers were covered in the 2017 study, the most of which focused on medical image processing. This report aims to demonstrate the extent to which DL methods have transformed the domain of medical image identifying. The authors identify specific contributions that address or circumvent these limitations and draw attention to the challenges in successfully implementing deep learning in medical field. The articles explain on the potential and difficulties of using deep learning to tasks including medical image segmentation, detection, classification, and registration. The study adds light on the most recent techniques and system architectures used in medical image analysis, emphasizing how deep learning may enhance patient care, diagnosis, and treatment planning. It also covers the difficulties of obtaining data, annotating it, making it interpretable, and clinically validating deep learning models for use in medical applications.

Yousefikamal, P, (2019) [15], Breast tumor classification and segmentation using convolutional neural networks, The research suggests two components of a diagnostic paradigm for breast cancer: tumor segmentation and picture classification. Pictures are classified as normal or abnormal by convolutional neural networks, and mammography pictures are preprocessed and segmented using a level-set approach that is improved by spatial fuzzy c-means clustering. With 78% accuracy and 69% AUC, the experimental validation on the MIAS dataset demonstrates great accuracy in picture classification and enhanced segmentation accuracy over previous approaches. By precisely outlining tumor locations and properly identifying anomalies, the proposed framework promises an efficient way to diagnose breast cancer.

Ali, M. D. et al.'s (2023) [21] Breast cancer classification through meta-learning ensemble technique using convolution neural networks. This work uses multiple CNNs and meta-learning to create a breast cancer classification model on the BUSI dataset. The complexity of images makes traditional methods difficult to use. More sophisticated methods are used, such as data augmentation, transfer learning, and meta-learning. With pre-trained models, transfer learning improves feature extraction, data augmentation increases dataset variety, and meta-learning maximizes learning for fast adaption to new data. Consolidating CNN outputs leads to increased accuracy through Meta ensemble learning. With an accuracy of 90%, precision of 86.4%, recall of 95.9%, and F1-score of 90.9%, a comparison of performance with cutting edge methods demonstrates efficacy, as demonstrated by evaluation.

Using data from Kaggle, the study aimed to establish a deep learning algorithm for the categorizing of breast carcinoma. The purpose of this dataset curation was to recognize cases of breast cancer. Convolutional neural networks, one type of deep learning approach, was used to evaluate medical images for exactly diagnosis, which may help medical practitioners make treatment decisions [20]. Based on these results, it is highly likely that deep learning models may be used for precise breast cancer identification and categorized. Breast cancer treatment has been the subject of numerous studies and recommendations. There is an exclusive approach to recognizing or tackling each theory or research question [22]. Meanwhile, some studies use methodologies that rely on processed images and system utilization, others track changes in the contour of the breast. The algorithms used to identify the sickness now have higher accuracy thanks to a few research projects [24]. Finding out if breast cancer is present or not is the main goal of this study. These studies did not distinguish between the eight subtypes of breast cancer.

3. MATERIAL AND METHODS

Medical imaging improves the prediction of breast cancer when advanced deep learning is used in conjunction with random forest methods. These techniques identify patterns suggestive of the presence of cancer by extracting information from photos. This method allows for precise diagnosis by combining the interpretability of decision trees with the complexity of deep learning. Constant improvement guarantees flexibility in response to changing medical environments, resulting in improved patient outcomes and more efficient medical practices. The process of classifying breast cancer begins with preprocessing images, where density, quality, contrast, and noise reduction are optimized. Deep learning features are extracted from organized images using simple preparations of CNN models using ImageNet. Classification results are then sent into a meta-learner, which combines fundamental CNN predictions. The BUSI dataset is used for training random forest base classifier and meta-learner, making it possible to distinguish between malignant and benign breast cancer. This meta-model, which is based on the BUSI dataset, improves diagnostic accuracy by skillfully classifying images of breast cancer that are not publicly displayed as benign or malignant.

A. Proposed Model

The first step in the categorization of breast cancer entails improving image quality using pre-processing techniques like improvement in contrast and noise reduction. After pre-trained on the ImageNet dataset, basic convolutional neural networks are utilized to generate deep features necessary for classification, which enables them to identify complex patterns in the images. A random forest classifier is used as the foundation model and a meta-learner is used to aggregate the predictions from these CNNs. Images of patients with malignant and benign breast cancer are included in the BUSI dataset, which is utilized to train both the meta-learner and base classifier. The goal of this thorough approach is to guarantee precise categorization, which will enable early breast cancer diagnosis and treatment. The classification algorithms can learn the characteristics that differentiate benign from malignant tumors by using this dataset as training data. Images of breast cancer that have not yet been seen are classified as benign or malignant using the meta-model that was developed using the BUSI dataset. Making Use of the combined knowledge from the training set, this method predicts new images with accuracy. 10,000 photos of breast cancer, equally divided into benign and malignant categories with 5000 images in each, make up the novel dataset used in this study. A fair and accurate assessment of the classification models' performance is made possible by the balanced dataset, which guarantees that an equal amount of samples from each class are used in their training. The integration of pre-processing methods, deep learning feature extraction, and meta-learning results in a strong classification system that can reliably identify benign and malignant tumors in unseen photos, therefore contributing to the detection of breast cancer. The overall architecture of proposed model is shown in the Fig 1.

Grayscale pictures known as ultrasounds show how sound waves are reflected off inside body components. These pictures are frequently used in medical imaging to see soft tissues, like the breast, and they are very helpful in finding anomalies like cancers. Convolutional neural networks are used in breast cancer detection models to identify patterns in ultrasound pictures by learning to extract pertinent characteristics from the images and forecast outcomes based on those features. This is how a CNN model uses ultrasound images. Ultrasound picture input is commonly represented as two dimensional arrays of pixel values, where each pixel denotes a distinct place within the image. The intensity of the reflected sound waves is represented by the pixel values, and it varies based on the density and tissue type being scanned. Pre-processing to increase the quality of the ultrasound images and the CNN's capacity to extract significant features, pre-processing measures may be applied before the images are fed into the CNN model.

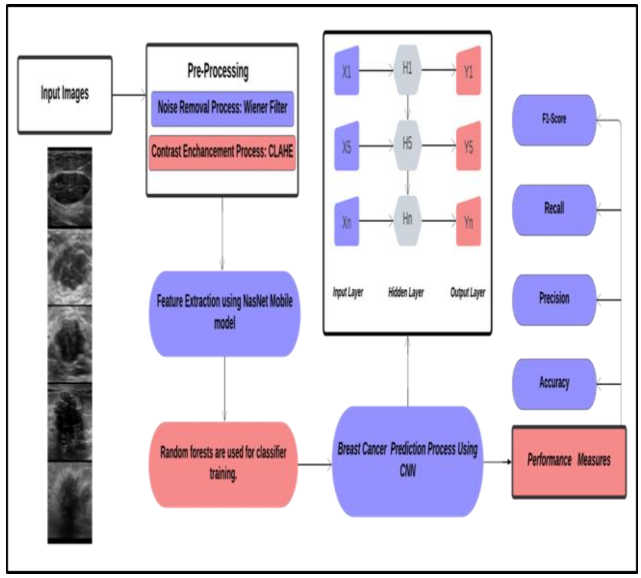


Figure 1: An Architecture Diagram

Pre-processing techniques that may be used to standardize the photos include noise reduction, contrast enhancement, shrinking, and normalization. Convolutional Layers one of the several layers in the CNN model, convolutional layers are in charge of extracting spatial feature hierarchies from the input pictures. Convolutional layers in ultrasound pictures use a range of filters to extract features that indicate various tissue structures, including edges, textures, and patterns.

Pooling Layers a common technique to decrease the spatial dimensions of feature maps without sacrificing significant features is to place pooling layers between convolutional layers. Feature maps are essentially down sampled when a method like max pooling chooses the maximum value from a portion of the input. Completely Connected Layers following multiple convolution and pooling layers, the recovered features are flattened and sent to completely connected layers, which use the learnt features to do classification. Typically, these layers are made up of highly linked neurons that understand the connections between the target labels (such as benign or malignant) and the attributes. The output layer is the last layer in the CNN model and is responsible for producing the predictions. When it comes to breast cancer detection, the output layer might be made up of a single neuron with a sigmoid activation function that generates a probability score that represents the likelihood that breast cancer is present. The CNN model is prepared using classified ultrasound images in order to reduce a reduction functional that measures the variation between the expected and real tags; this process is called optimization, and iteratively changes the model's parameters using optimization techniques such as Adam and stochastic gradient descent (SGD) to improve the model's predictive accuracy. The CNN model's execution is assessed after training on an alternate dataset, and metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC) are frequently used to gauge the model's efficaciousness in this regard.

B. Dataset

An essential part of this project is the dataset, which shapes the potential of the model to generalize breast cancer at various stages. It will consist of a set of annotated medical pictures. To provide a thorough and reliable training procedure, the dataset will be meticulously selected to include a representative sample of both normal and cancer affected images. Standardization and augmentation are two examples of data pre-processing procedures that will be used to raise the standard and diversity of the entire collection. The source of the dataset is Kaggle, a BUSI dataset affiliate. Professionals in deep learning and data science congregate virtually. As of the most significant causes of death internationally for women, breast cancer is a malignancy that often affects women. Over the world, there will be 827,000 deaths and 3.1 million cases in 2022.About 80% of cases of breast cancer that are detected are categorized as ductal invasive carcinoma, making it the most frequent type of the disease. This classification, which begins in the milk ducts and spreads to nearby tissues, presents a major management and beneficial challenge for breast cancer. Early detection and targeted treatments are crucial in addressing this prevalent form of breast cancer. A proper treatment strategy and a higher patient survival rate are directly related to early and accurate diagnosis. The dataset includes three classifications of ultrasound images of breast cancer: normal, malignant, and benign. These images show that deep learning algorithms perform exceptionally well in tasks such as diagnosis, segmentation, and categorization, indicating their possibility of improvement the evaluates and treatment of breast cancer.

As part of the baseline data collection, women aged 25 to 75 had their breast ultrasound images taken. This data was collected in 2018. In total, there are 600 female patients. The set comprises 780 images, each with a majority dimension of 500 × 500 pixels. The images are PNG files. There are now three categories of images: benign, malignant, and normal. Researchers and medical practitioners can utilize the BUSI dataset as a resource to identify and diagnose breast cancer. The dataset consists of 780 images obtained from ultrasound scanning that demonstrate breast cancer, with an average dimension of 500 × 500 pixels. The visuals are divided into three groups: 133 images that are considered normal, 210 images that are considered malignant, and 487 images that are considered benign.

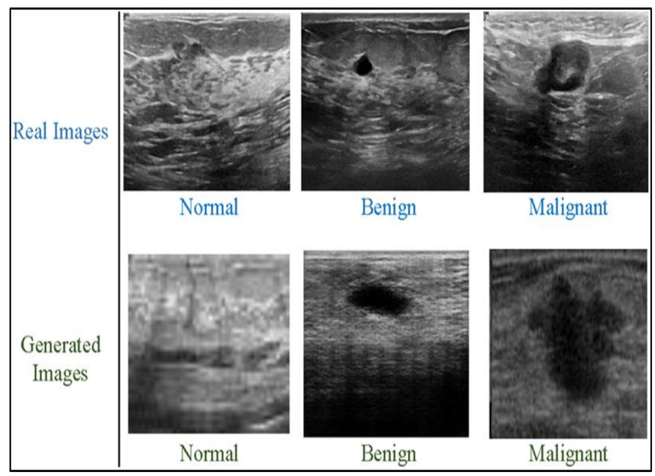


Figure 2: Pictures of benign and aggressive breast cancer.

Since the BUSI dataset contains a huge number of ultrasound images, both malignant and benign, with varying features, it is difficult to classify. The proposed technique not only improves the diagnosis accuracy and reliability, but also improves the performance of breast cancer categorization.

C. Pre-processing

There are various processes involved in pre-processing ultrasound pictures of breast tissue for contrast enhancement using CLAHE and noise removal using a Wiener filter. A thorough tutorial on carrying out these pre-processing actions may be found below: Load Ultrasound Images to begin, load the ultrasound pictures of the breast tissue into the image processing program of your choice (Python with OpenCV or MATLAB libraries, for example). Convert to Grayscale in the event that the ultrasound pictures are colored, turn them into grayscale. Grayscale representation is adequate for additional processing because ultrasound images usually only include one channel of information intensity. A traditional method for signal processing that is used to reduce noise in signals and pictures is the Wiener filter. By lessening the impact of additive noise and maintaining significant aspects of the original signal, it seeks to improve the signal's quality. When the statistical characteristics of the signal and noise are known or can be inferred, the Wiener filter which functions in the spatial domain is especially useful. The original signal's mean square error is reduced when the Wiener filter is applied, which is how it operates. The signal's frequency components are given a weight according to their signal-to-noise ratio in order to achieve this. Detail preservation in images is achieved by assigning greater weight to signal components in areas where signal strength outweighs noise. Filtering is used more aggressively to suppress noise in locations where noise is predominant. Contrast limited adaptive histogram equalization is a technique that can be used to enhance the intensity of an image while lowering the amount of amplified noise. When there are areas of the image with different contrast levels or when using typical histogram equalization techniques could cause the noise to be over amplification, it works especially well. Contrast limited Adaptive Histogram Equalization (CLAHE): CLAHE works locally on specific areas of the image, as opposed to classic histogram equalization, which applies a global alteration to the entire picture. A distinct histogram equalization transformation is calculated for every tile when the image is divided into patches or tiles. Contrast limiting a contrast limiting mechanism is applied by CLAHE to avoid over amplification of noise in areas with low contrast. In order to guarantee that the contrast enhancement is kept within a predetermined range, it clips each tile's histogram to a maximum value that has been set. Histogram equalization is applied to each tile, and then CLAHE employs interpolation techniques to blend the improved tiles together smoothly while preventing apparent artifacts at tile boundaries. Create non-overlapping patches or tiles in the image. For every tile, calculate the pixel intensity histogram. For each tile, apply histogram equalization, mapping pixel intensities to a new range in order to improve contrast. By cropping the histogram to a predetermined maximum value, you can apply contrast limiting. Reconstruct the final image by interpolating the results to merge the improved tiles. In many image processing applications, including digital photography, satellite imaging, and medical imaging, retaining visual details while boosting contrast is essential. These applications frequently use CLAHE. When dealing with photos impacted by noise or poor lighting, or in situations where there is uneven illumination or fluctuating contrast levels, it is extremely helpful.

D. Random Forest as a Classifier

Random Forest is a trendy machine learning technique made as a classifier for problems related to breast cancer determination and detection. The process of classifying breast cancer using random forests is as follows: The process of selecting important characteristics from the breast cancer data is necessary prior to training the random forest classifier. Imaging features (such as tumor size and shape), biomarkers (such as gene expression levels), and clinical data (such as patient age and family history) may all be included in these features. A successful classifier requires careful feature selection, which can be accomplished using methods like principal component analysis (PCA) or domain knowledge obtaining the Equivalent Training Data, The learning and assessment sets of the dataset are separated after the features have been chosen. With the help of the learning set and the assessment set, the random forest-based classifier is trained and its performance assessed. For the model to avoid becoming biased, the dataset needs to be well-balanced and represent both benign and malignant instances. Building Multiple Decision Trees for the Random Forest Classifier: The random forest algorithm builds multiple decision trees for the training stage. Each decision tree is trained using a different collection of parameters and training data each time. This unpredictability improves generalization and reduces overfitting. A subset of the training data is used to form each tree in the forest during preparation, and splits are made based on the features (such entropy or Gini impurity) that produce the largest reduction in impurity. Combining Predictions following the training of every decision tree, predictions are generated for every test sample by combining the predictions of every tree separately. When classifying data, the test sample is allocated to the class among the trees that receives the greatest number of votes, or the most frequently predicted class. Assessment Once the random forest classifier has generated predictions on the testing set, its performance is tested a variety of measurements, such as accuracy, F1-score, recall, precision, and the region under the receiver's operating characteristic curve(AUC-ROC). The capacity of the classifier to accurately identify cases as benign or malignant is revealed by these metrics.

Fine-tuning: Change hyperparameters such as required samples per node, depth, and number of nodes to increase the effectiveness of the random forest classifier. Determining the ideal parameters is aided by grid or random search techniques. These classifiers are very adaptable and effective in accurately classifying breast cancer cases by utilizing imaging cues and patient data to produce accurate predictions. They are useful tools in medical diagnostics because of their versatility and dependability, which provide reliable insights into both benign and malignant situations.

1) NASNet Mobile

Neural Architecture Search Network, or NASNet Convolutional neural networks (CNNs) with mobile architectures are made for embedded and mobile devices. It is a byproduct of automated neural architecture search (NAS), in which algorithms look for the best architecture given specific restrictions and goals rather than having human specialists create the architecture. Because NASNet Mobile is designed with efficiency and speed in mind, it can be implemented on devices with constrained computational capabilities, such tablets, smartphones, and other edge devices. It makes this efficiency possible with a number of architectural elements, such as:Depth wise separable convolutions by dividing the spatial and channel-wise convolutions, these convolutions drastically cut down on the amount of parameters and calculations required to perform a given task, hence decreasing the computational burden associated with standard convolutions. Network architecture search NASNet Mobile is the outcome of automatically employing evolutionary or reinforcement learning techniques to find the best neural network design. Finding designs that are effective in using computational resources and perform well on a given task is the goal of this procedure. Effective architecture NASNet Mobile's architecture aims to create a good trade-off between accuracy and computational cost by carefully balancing model complexity with efficiency. Designed with mobility in mind NASNet Mobile takes into account limitations such low memory, processing power, and energy consumption in order to function well on mobile and embedded devices.

2) Convolutional Neural Network(CNN)

Convolutional Neural Networks (CNNs) have been a hot topic in breast cancer research since they can detect breast cancer earlier and lead to better treatment outcomes. CNNs are a subclass of deep learning models that are particularly good at deciphering complex patterns and characteristics from medical imaging data, such as MRI scans, ultrasound pictures, and mammograms. An outline of CNNs' application in breast cancer screening is provided below:

a) Image Pre-processing to improve image quality, eliminate noise, and standardize image properties, pre-processing techniques can be used prior to feeding images into CNNs. By using these pre-processing techniques, CNN is better able to identify and extract relevant characteristics from the images.

b) Preparing Training Data to train CNNs, sizable labeled datasets are needed. CNN models are trained in the context of breast cancer detection using datasets that include labeled images of both benign and malignant tumors. CNN architectures that are appropriate for applications involving the identification of breast cancer are created by researchers. Convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification are some of the layers that are commonly included in these systems. Many CNN designs have been investigated for breast cancer detection applications, including VGG, ResNet, NASNet, Inception, and DenseNet. All things considered, CNNs have demonstrated tremendous potential in the identification of breast cancer by using deep learning techniques to evaluate medical pictures and offer precise and prompt diagnoses. For CNN-based breast cancer detection systems to function better and be more accessible, research and development in this area must continue.

E. Feature Extraction

By utilizing the recently trained convolutional neural network (CNN), the NASNet Mobile model facilitates the extraction of relevant and discriminative features from input photos. NASNet Mobile is a mobile optimized deep learning architecture that can capture visual input in hierarchical representations. The general process of feature extraction with the NASNet Mobile model is as follows: Load Pre-Trained Model to start, load the NASNet Mobile model that has already been trained. Deep learning frameworks like TensorFlow and PyTorch provide pre-trained models. These models are capable of extracting generic characteristics that are helpful for a variety of picture identification tasks because they have been learned with extensive image datasets. Preparing the Input photos prepare the photos in accordance with the NASNet Mobile model's specifications. Using the already trained NASNet Mobile model, run the pre-processed images via the extraction of characteristics. When extracting features from a model, you usually employ the activations of one of the intermediate layers, referred to as the "bottleneck layer" or "feature extraction layer. The model has learned high-level abstract features represented by these activations. How to Get Feature Vectors? To obtain feature vectors for every input image, retrieve the activations from the selected layer. Comparable images are predicted to have comparable feature vectors, and these feature vectors act as representations of the input images in complex space of attributes. Feature Vector Representation: Based on the application, you can either utilize the raw feature vectors as input for tasks that come after (like classification) or you can process them first (like dimensionality reduction) before using them. Utilization of feature vectors the feature vectors that have been extracted can be applied to a variety of tasks that necessitate the comprehension of visual content, including object identification, image retrieval, and image classification. Utilizing pre-trained CNN models, such as NASNet -+ Mobile, for feature extraction has various benefits over starting from scratch. These include the ability to use learned representations from huge datasets, lower computing costs, and generalization to new tasks and domains.

F. Performance Metrics

The work presents a unique method of classifying breast cancer by combining the CNN NASNet Mobile model with the random forest algorithm. This combination works quite well and is a potential approach to the accurate classification of breast cancer. Future research may go into supplementary CNN models, varied medical imagery, and various techniques. With precision, recall, and F1 score acting as performance indicators, the proposed method notably attains an impressive accuracy of 94%. Formula for calculating Accuracy, Recall, F1- score and Precision.

1) Accuracy:

Accuracy is defined as the proportion of accurately identified occurrences both actual positives and true negatives across all examples in the dataset. Although accuracy is a crucial criterion, it might not be enough for datasets that are unbalanced, such those used in jobs involving medical diagnosis.

Accuracy is equal to (TP+TN) / (TP+TN+FP+FN) (1)

2) Precision:

According to its definition, precision is the percentage of accurately anticipated positive outcomes among all of the beneficial projections the model produces. Regarding the prognosis of breast cancer, precision measures how well the model identified malignant cases among all the cases it has classified as such. A low rate of false positives is indicated by a high precision in the model.

Precision is equal to (TP) / (TP+FP) (2)

3) Recall:

Recall is the fraction of real positive cases in the collection that are true positive forecasts, which is often referred to as sensitivity. Recall would show whether or not the model could accurately identify every case of malignancy in the dataset when it came to breast cancer prediction. A low percentage of false negatives is shown by a strong recall of the model.

Recall is equal to (TP) / (TP+FN) (3)

4) F1-score:

A statistic that assesses how well memory and accuracy are equal is called the F1-Score. It is computed using the integrated mean of precision and recall. When there is a disparity in the dataset's classes, it is especially helpful. An improved balance between recall and precision is indicated by a higher F1-Score.

F1 Score is equal to 2 * ((Precision + Recall) / (Precision * Recall)) (4)

4. Experimental Results

A. Training and Testing

For efficient evaluation, make sure the dataset is formatted and labelled correctly and is divided into distinct training and testing sets. In case training is required, handle missing values, choose pertinent features, and properly prepare the data. Establish a Random Forest classifier instance first, then modify its hyper parameters (such as the maximum tree depth and number of trees). Adapt the model based on the training set. Analyse the model's performance with testing sets, calculating metrics such as ROC curve, F1-score, recall, accuracy, and precision. Use techniques like random search and grid search to fine-tune the Random Forest classifier's hyper parameters for optimal performance. Utilize the model to forecast fresh, unobserved data whenever you're satisfied with its performance.

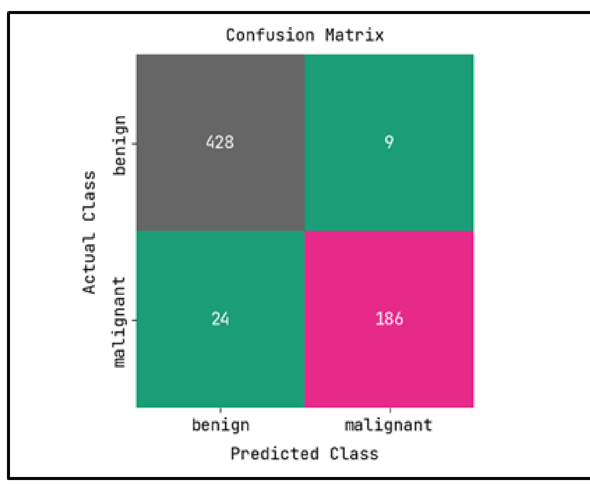


Fig 3: confusion Matrix

Prior to testing, prepare training images by performing pre-processing operations like scaling and normalization. Load a CNN model that has been trained to identify breast cancer and can determine whether cancer is present in ultrasound pictures. To get predictions for each image, apply the loaded CNN model to test photos. To assess the

performance of the model, compare the predicted labels with the ground truth using measures such as accuracy, ROC curve, F1-score, precision, and recall. Examine forecasts and performance indicators visually to see how well the CNN model is utilizing the dataset. In fig 3 that is frequently used to assess how well a classification model is performing is called a confusion matrix. It lets you see how well a machine learning algorithm is performing by comparing expected and actual classes.
Usually, a confusion matrix has four primary parts: The number of cases that were accurately anticipated to be positive (e.g., correctly recognized as having breast cancer) is known as the True +ve (TP) statistic. The True –ve (TN) is the no of instances that were correctly expected to be negative, i.e., correctly diagnosed as not having breast cancer. False Positive (FP): Also referred to as Type I error, this term describes the quantity of cases that were erroneously anticipated as positive (for example, diagnosed as having breast cancer when none exists). The number of cases that were erroneously projected as negative is known as a false n-ve (FN), also known as a Type II error. Confusion matrices are useful tools for analyzing how well a classification model performs, especially in situations where there may be imbalances between the classes or when different kinds of errors have disparate effects. They offer perceptions into the model's advantages and disadvantages, which aid in directing future model optimization and judgment.

In table 1 A convolutional neural network (CNN) architecture called GoogLeNet was created with image categorization tasks in mind. Google researchers created it, and they presented it in the publication "Going Deeper with Convolutions". GoogLeNet's deep design combined with computational efficiency is one of its core characteristics. In this model they achieved accuracy level 87%, precision 86%, Recall 87%, F1-score 85%. AlexNet is composed of eight layers three is completely linked layers come after five convolutional layers. When it was first introduced, this depth was remarkable because it helped the system identify intricate details in pictures. Pooling regions overlapped as a result of AlexNet's use of max pooling layers with a stride of 2. In this model they achieved accuracy level 87%, precision 86%, Recall 87%, F1-score 85%. With the preservation of significant features, this method assisted in reducing spatial dimensions.

ResNet50 serves as an effective basis for image analysis. Researchers can develop image classification models to support breast cancer detection by transferring its pre-trained skills and then specializing on breast cancer data. Using this accuracy can be achieved on 88%. In those photographs, this model is very good at identifying simple forms, colors, and textures. NASNet searches a wide range of potential CNN architectures using reinforcement learning via NAS. It basically makes a controller model more capable of analyzing various network configurations and determining which ones are most effective for a given task (such as picture classification). By utilizing the NASNet model, we were able to attain a 94% accuracy level in our model. This makes it possible for NASNet to find strong and effective CNN designs that require less resources to attain high accuracy. The Fig. 4 shows the performance of various DL Models.

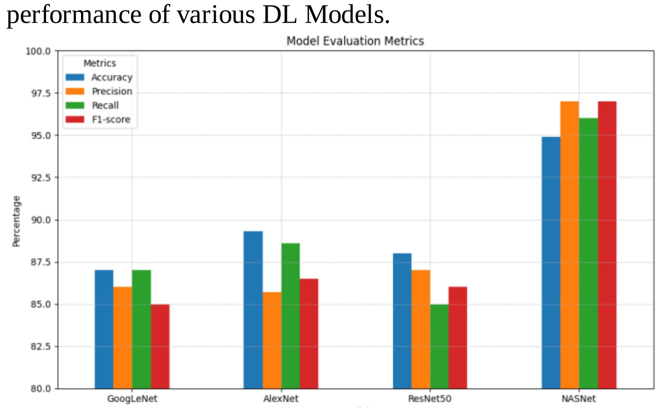
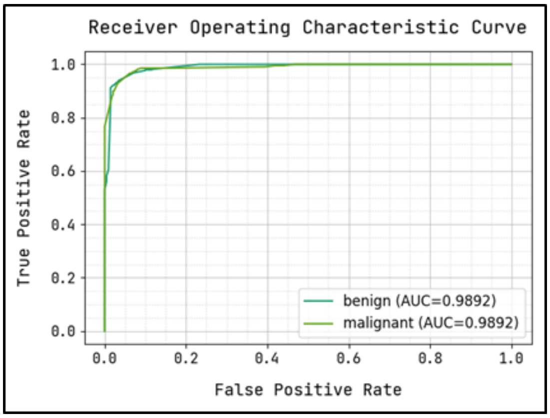


Fig 4: Graph represent the performance of various Deep learning models

TABLE I. PERFORMANCE ANALYSIS OF DL MODELS

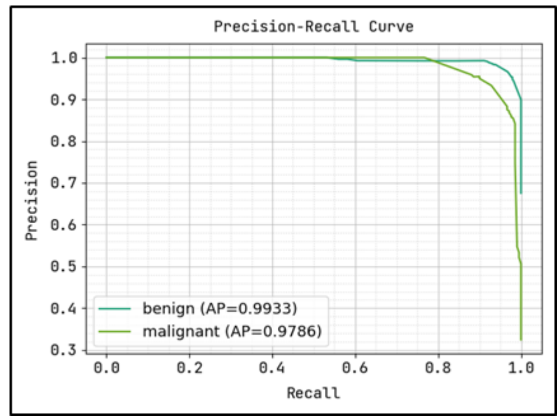
Model	Accuracy	Precision	Recall	F1-score
GoogLeNet	87%	86%	87%	85%
AlexNet	89.3%	85.7%	88.6%	86.5%
ResNet50	88%	87%	85%	86%
NASNet	94.6%	97%	96%	97%



a) ROC curve

The effectiveness of a model for binary categorization over a variety of thresholds is graphically represented by the ROC curve. It demonstrates how there is an offset between the true positive rate (sensitivity) and the false positive rate when the discriminating threshold is altered. The ratio of real positive instances (malignant tumors) that the model properly classifies as positive is known as the genuine positive rate, or sensitivity. The Fig. 5 shows the trained data of ROC curve and Precision Recall curve.

It demonstrates that the model can correctly identify patients with breast cancer in terms of medicine. False Positive Rate: This is the rate of benign tumors that are actually grouped as negative cases but are incorrectly classified as positive by the model. In terms of medicine, it denotes the possibility of false positives for alarms or mistaken positive diagnoses for patients who do not have breast cancer.



b) Precision-Recall curve

Fig 5: Graph represent the ROC curve and Precision-Recall curve of the trained data

TABLE II: STATE OF ART COMPARISON OF EXISTING MODELS.

Reference	Method	Accuracy	Precision	F1-Score	Recall
Proposed model	NASNet Mobile	94.6	97.5	96.9	97.9
Yang, Ziqi, et al.(2020)[7]	TSDBN ResNeXt-18	90.2	95.2	93.2	91.4
Guo, Yanhui, et al.(2023)[8]	FRPC Transformer	90.5	90.5	90.5	90.5
Shia, et al.(2021)[9]	Linear SVM,ResNet-101	74.6	75	74	75.5
Rezazadeh et al.(2022)[5]	LightGBM-500	91	94	93	93
Xiaomei Wang et al.(2022)[12]	CNN-GRU	86	85	88	85
Davoudi et al.(2021)[10]	CNN-GA	85.4	94.7	80.1	69.4

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The Precision-Recall curve can be used to assist in choosing a threshold that is suitable for the classification task. You may give priority to recall (minimizing false negatives) or precision (minimizing false positives) depending on the particular application and requirements. In situations where datasets are unbalanced, the Precision-Recall curve offers important information into how well a breast cancer detection algorithm is performing. It assists researchers and doctors in understanding how well the model classifies cases of breast malignancy and in making decisions about the course of therapy and care of their patients.

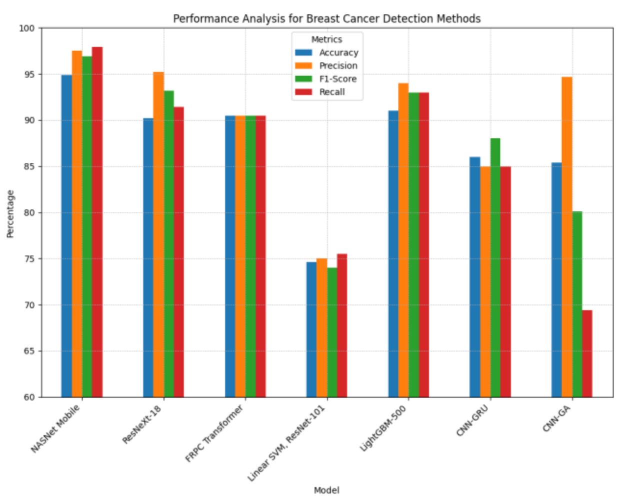

Fig 6: Performance Metrics for Breast Cancer Detection Methods

A number of research have looked into the use of NASNet and related neural architecture search (NAS) algorithms in medical imaging tasks, such as breast cancer diagnosis. Researchers want to improve the pre-trained NASNet model's ability to identify malignant regions or categorize breast lesions by tailoring it to the unique features of breast cancer imaging. To enhance performance on breast cancer detection tasks, these hybrid models may take advantage of NASNet's advantages in autonomously creating network structures and incorporate domain-specific knowledge. Using NASNet in multi-task learning frameworks for breast cancer detection: the model learns to classify tumor subtypes, identify malignant regions, and predict patient outcomes based on imaging data all at the same time. In table 2 the percentage of positive projections that proved to be accurate is measured by precision. With a precision of 97.5%, the suggested task has the maximum accuracy, meaning that 97.5% of the positive cases predicted are accurate. The precision values of previous research and references are lower, ranging from 83.2% to 87.4%. Recall quantifies the ratio of actual positive cases that the algorithm properly identifies. Additionally, the suggested work attains the greatest recall of 97.9%, which indicates that 97.9% of all real positive cases were accurately detected. Recall values for previous research and references range from 84.1% to 95.9%. By calculating the balanced average of the two criteria, the F1-Score offers a compromise among recall and precision. With its maximum F1-Score of 96.9%, the suggested task strikes a fair mix between recall and precision. The F1-Scores of previous research and references range from 82.9% to 90.9%. The overall correctness of the algorithm's predictions is represented by accuracy. With an accuracy value ranging from 85.8% to 90%, the suggested work outperforms previous work and references, achieving the greatest accuracy of 94.9%.

5. CONCLUSION

The severe need for improvements in healthcare technologies is highlighted by the fact that breast cancer is a serious worldwide health problem. Improvements in diagnosis and therapy are possible via the use of deep learning (DL) and machine learning (ML), which are adept at analyzing large volumes of medical imaging. To improve the dataset’s quality, we used advanced image enhancing methods such as the Wiener and CLAHE filters. By improving medical image quality, these techniques create data that is easier to interpret and more insightful for analysis. We prepared the groundwork for strong model development by carefully selecting training, validation, and testing datasets. Our suggested model showed remarkable performance metrics after going through rigorous training, validation, and testing procedures. Our model demonstrated its efficacy in accurately detecting breast cancer with values of 97.5% for Precision, 97.9% for Recall, 94.9% for Accuracy, and a remarkable 96.29% for F1-Score.Data can be used for training in 80% of cases and validation in 20% of cases. We will investigate further image augmentation techniques in the future and compare various CNN designs with new imagery to assess their effectiveness. Our mission is to develop more accurate and dependable diagnostic tools by consistently pushing the envelope of uniqueness in breast cancer detection. Our goal is to improve patient outcomes globally via continuous research and development. In future to increase overall performance, ensemble approaches aggregate predictions

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from several different individual models. The application of NASNet in ensemble frameworks for the detection of breast cancer, which combine predictions from CNN models with NASNet predictions to provide enhanced robustness or accuracy against variations in imaging data.

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