EfficientNet-based Cloud Network Infrastructure for Improved Early Detection ofBreast Cancer

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Abstract:

Background: This paper introduces a novel strategy for improving breast cancer diagnosis by integrating the strengths of machine learning algorithms with cloud computing. Improving patient outcomes is the primary motivation for this study, which focuses on improving the accuracy of the EfficientNet approach for diagnosing breast cancer.

Methods: The study demonstrates the significance of DCT-based feature extraction in the field of breast cancer diagnosis. The paper also gives a detailed explanation of the critical collection of hyperparameters by combining the Marine Predators Algorithm and the Genetic Algorithm (MPA+GA). This is a technique that is needed to make machine learning models work as well as possible. The study also presents the design and parameter specifics of the EfficientNet model used for breast cancer classification.

Results: Results show that the suggested Efficient Net method is more accurate than the IMPA-ResNet50 model, which is only 98.32% accurate. Other models, such as HHO-ResNet50, GSA-ResNet50, MPA- ResNet50, RMSProp-VGG 16, and WOA-ResNet50, are only 87% to 95.95% accurate.

Conclusion: The proposed EfficientNet model, optimized with DCT-based feature extraction and MPA+GA, outperforms existing models, achieving superior accuracy in breast cancer diagnosis. This study marks a significant advancement in leveraging machine learning and cloud computing for medical imaging.

Keywords: Machine Learning, Marine Predators Algorithm, Genetic Algorithm, EfficientNet, Breast cancer detection.

1. Introduction

Over a million women are diagnosed with breast cancerevery year, making it an important public health concern around the world. Cancer that starts in the breast tissue cells is called breast cancer. There would be a projected 2.3 million new cases of breast cancer among women globally in 2020, as per the statement made by the WHO (world health organization), and 685,000 deaths from the disease (Momenimovahed & Salehiniya, 2019). Male breast cancer accounts for less than 1% of all instances, yet it is still a serious disease when it does occur (Maskeliūnas et al., 2019). The ability to detect breast cancer at an early stage is crucial for enhancing patient outcomes and decreasing mortality rates. When breast cancer is detected early, it is more likely to be treated successfully, with a greater chance of survival and less aggressive treatment required (Obaid et al., 2018). Mammography, medical breast exams, self-examinations, as well as cellular breast imaging are just a few of the tools used for the early identification of cancer of the breast, even though computerized segmentation of medical image techniques can aid with making objective decisions and help improve human-computer interaction (Kaushal et al., 2021).

The most used method of breast cancer screening is mammography. Long before indications develop, early detection of breast cancer is possible with a low-dose X-ray. If you are a woman over the age of 50 or a younger woman with a strong family history of breast cancer, you should get a mammogram. Clinical breast exams are physical exams performed by a healthcare professional to check for lumps or other abnormalities in the breast tissue. They are recommended for younger women as part of a routine check-up and for women over 40 in combination with mammography. Women perform self-breast examinations to detect abnormalities such as lumps. Doing breast self-examinations may help women become aware of their breast tissue and uncover any abnormalities that might need to be investigated further; however, they are not recommended as a general screening method (Lahoura et al., 2021). These techniques can make more detailed images of tissue from the breast, which can help find cancers earlier. Women should get screened for breast cancer, but they also need to know the warning signs. These include A modification to the size or form of the breasts. Inversion or discharge of the nipple. Skin changes occur such as redness or dimpling.

It is necessary to make sure that breast cancer is diagnosed at an early stage to increase the patients' chances for full recovery and decrease the mortality rates. Women should discuss with their doctors when and how often they should be screened based on their age, family history, and other risk factors.

However, conventional breast cancer detection methods, such as mammography, are not flawless. With the development of cloud computing and the rise in internet-connected devices, there has been an opportunity for more accurate and time-efficient breast cancer diagnostics (Kaushal et al., 2022).

Cloud computing and machine learning (ML) algorithms' developments have made it possible to develop breast cancer detection systems with higher accuracy (Bhat et al., 2015). Additionally, the provided system utilizes cloud computing-based infrastructure in storing and processing large amounts of medical data featuring patient histories, mammograms, and biopsy reports. These algorithms search patterns and anomalies from the data that leads to early detection of a stage of the breast cancer. The study analyses performance of various ML algorithms including Neural networks, logistic regression, and decision trees (Delen et al., 2005). Besides, this research also assesses scalability and efficiency of proposed system for processing speed, data storage capacity, network bandwidth among others. The findings of this research could have a huge impact on breast cancer screening, which could contribute to the development of improved and more effective screening techniques. In the case of cloud-based networking infrastructure and machine learning algorithms, it can boost the accuracy and dependability of breast cancer detection process thus saving lives and cutting back healthcare expenditure.

1.1 Machine Learning for Early Breast Cancer Detection

Given their ability to learn intelligently, it's possible that ML algorithms might be optimal for prediction. In this article, several machine learning ability-based techniques for detecting breast cancer in women are **B**

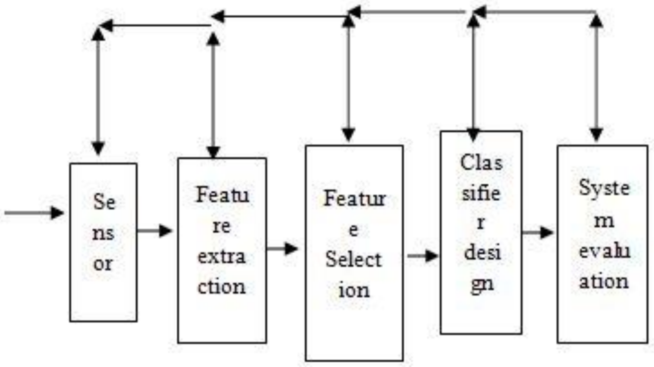

Figure 1. Classification system for cancer detection.

Nonetheless, barriers remain to the widespread use of machine learning for breast cancer screening (Gayathri et al., 2013). Both the lack of transparency and the inability to easily explain the workings of algorithms pose problems in the current state of the field. When applied to the profession of breast cancer detection, Machine learning possesses the capacity to significantly enhance diagnostic accuracy and facilitate earlier detection (Kornelia Polyak, 2011). Research and development efforts should be maintainedso that the limitations of these technologies can be removed, and their full potential realized.

1.2 Cloud-based Breast Cancer Detection using MachineLearning

Breast cancer is a common kind of cancer affecting women, and timely identification is vital for effective treatment. But traditional screening methods like mammograms can be expensive and time-consuming. Thankfully, today's technology allows us to improve breast cancer detection with the help of machine learning algorithms and a cloud-based network infrastructure (Ogundokun et al., 2022). Integrating all the components into a cloud-based architecture for early detection of breast cancer using ML algorithms would require a system that can handle processing an enormous amount of medical data with high precision and efficiency. This system would be used to analyze the patient's medical history, past imaging tests and try to identify any possible warning signs or abnormalities that could lead to breast cancer. Cloud data-based model for diagnosing breast cancer is represented in Figure 2 (Li et al., 2021).

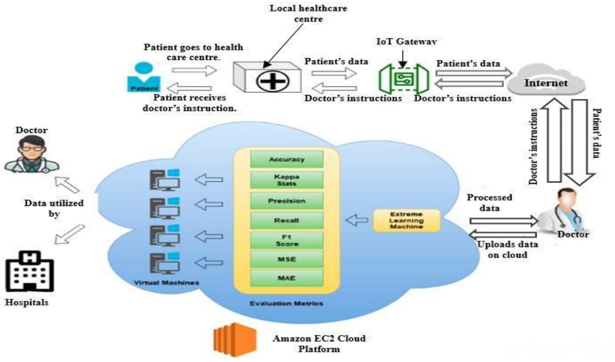

Figure 2. Diagnosis of Breast Cancer Based on Cloud.

An infrastructure that is cloud-based is the first component of this system which forms its backbone. For instance, large volumes of data are generated through medical imaging tests, and the cloud offers storage as well as computing power for such data. This enables healthcare providers to access and analyze this information from anywhere in the world provided they have an internet connection, thus facilitating easy sharing of data amongst health facilities and experts (Gary M. Clark, 1994). The second component is represented by ML algorithms used in data analysis. As a result, it helps to recognize patterns as well as anomalies that may show breast cancer using these algorithms which have been trained on big sets of medical imaging dataset. With the aid of artificial neural networks, deep learning aims at scrutinizing massive amounts of data for trends and predictions about risky areas that might be malignant. On the other hand, there is user interface which facilitates access to the system by health care providers. Data visualization among other tools can be added to the user interface to make it easy interpreting findings. Cloud based network architecture for early detection of breast cancer using ML algorithms has potential to enhance efficiency, accuracy, and availability of breast cancer screening. Henceforth such advanced technologies may help healthcare providers identify potential cases of breast cancer early enough thereby improving patient outcomes and perhaps even saving lives (Douglas G. Altman, 2007). The motivation behind this work stems from the pressing need to enhance breast cancer detection and diagnosis through the integration of innovative technologies. The integration of diverse data sources and the implementation of modern machine learning techniques, particularly the highly efficient EfficientNet model, represent a significant leap forward in the pursuit of early breast cancer detection. In essence, this work presents a promising solution, enabled by cloud computing and state-of-the-art machine learning, to elevate breast cancer detection to new heights, potentially saving countless lives.

The following is the outline for this paper: Section 2 provides a summary of the secondary sources used in this paper, while Section 3 explains the research context, Problem formulation is covered in Section 4, datasets are described in Section 5, research technique is covered in Section 6, and findings and discussion are presented in Section 7. The conclusion of this paper is presented in Section 8.

2. Related Works

In a recent study by Munappa et al., (2023) a novel deep-layered ensemble structure was introduced to address the challenges in the field. The suggested model draws from a total of nine models, including one each of the following architectures: EfficientNetB3, ResNet50, and DenseNet121; single, double, and triple completely linked layers. The stacking ensemble consists of three of these diverse models. Using the lymph node WSIs from the CAMELYON 17 challenge dataset, A comparison and analysis of the efficacy of these models were conducted with the deep-stacked ensemble. This study shows that the deep-stacked ensemble performs better than the individual models. The trade-off between recall and accuracy was also studied since recall is more important in this prediction job. Senan et al., (2021) developed a computer-aided design for analyzing histopathology images for breast cancer diagnosis. Traditional methods used for feature extraction in CAD systems are imprecise and time-consuming. To determine if breast cancer is benign or malignant, this study suggested utilizing a convolutional neural network (AlexNet) to extract deep characteristics from the BreakHis dataset. This study involved 4 experiments based on different factors, and each experiment contained 1407 images. It was observed that the proposed system attained the following results: 95% accuracy, 97% sensitivity, 90% specificity, and 99.36% AUC. This study aimed at demonstrating the potential of ML algorithms, particularly CNN, in improving the accuracy of breast cancer diagnosis and consequently the outcomes of patients. The paper introduces a machine learning model that Bhise et al., (2021) built using CNN classifier and Recursive Feature Elimination as a feature selection technique. To examine Naive Bayes, K-Nearest Neighbors (KNN), Support Vector Machines (SVM), classification models, and Logistic Regression were assessed by the researchers. For instance, Performance measures such as accuracy and precision were used to measure its performance on the BreaKHis 400X Dataset. Based on these findings, it can be assumed that this CNN works better than earlier versions on more difficult datasets. Non-linear activation functions such as ReLU which predicts the occurrence probability of an outcome were also adopted. Mehmood et al., (2201) carried out experiments for mammograms analysis for breast cancer detection using image processing techniques and ML algorithms. Therefore, they ran their experiment simulating it in MathWorks' MATLAB 2019 b system using their imported data from Mammographic Image Analysis Society dataset. The SVM classifier and flexible neuro-fuzzy inference method were used in classifying normal and abnormal patterns in this study. The findings from this research showed that cubic support vector machine (CSVM) based approach yielded high accuracies of 98.95% for the normal and 98.01% for the abnormal mammograms respectively. According to Wang et al., (2021) the authors recommend random center cropping (RCC), data augmentation and improved CNN architecture. RCC is better than other methods of image cropping that works only for large, low-resolution photos because it increases dataset size while keeping image quality and key area intact. Reduced sampling size makes the network better for low-resolution images. Attention and feature fusion strategies increase CNN's semantic understanding of extracted visual characteristics. The experimental results show that compared to baseline CNN architectures, the techniques greatly improve performance, with the best-performing method reaching an accuracy of 97.96% ± 0.03% and an Area Under the Curve (AUC) of 99.68% ± 0.01% in Rectified Patch Camelyon (RPCam) datasets. Baccouche et al., (2021) presented You-Only-Look-Once (YOLO)-based end-to-end technology to identify and classify precancerous breast lesions in complete mammograms. Preprocessing raw images finds breast abnormalities and labels them as mass or calcification. The model was validated using 2907 images from the Curated Breast Imaging Subset of the Digital Database for Screening Mammography (CBIS-DDSM) and 235 images from the INbreast databases. The 487 mammograms in a private dataset were also utilized. Finally, the study advocated for the use of fusion models to provide improved detection and classification. The best results on CBIS-DDSM, INbreast, and the individual private dataset detected 95.7% of mass lesions and 98.1% of calcification lesions. According to Falconi et al., (2020) Mammography screening is the gold standard since it may identify and diagnose breast problems at an early stage. Mass lesion malignancy classification and identification are tough for AI. Prior work in mammography classification used NASNet and Mobile Net in transfer learning to train a breast abnormalities malignancy classifier. VGG, ResNet, Xception, and ResNext are included. Overfitting is prevalent in deep learning model training. This attempt also addresses this problem. The CBIS-DDSM dataset shows that fine-tuning improves the VGG16 classifier the best, with an AUC of 0.844. In screening mammograms, Shen et al., (2019) construct a deep learning system to detect breast cancer. Using "end-to-end" training, the approach accommodates datasets with varied clinical annotation levels. Lesion annotations need image-level tagging for subsequent steps. This reduces the requirement for sparse lesion annotations. The top model has an AUC of 0.88 on one dataset and 0.95 on another, proving the method's superiority over previous methods. The average of the four models raised AUC to 0.91 and 0.98. The classifier's transferability between mammography systems suggests improved breast cancer screening tools. Agarwal et al., (2019) explored domain adaptability transfer learning for breast cancer detection. Training a CNN on a huge public dataset of digitized mammograms (CBIS-DDSM) begins. After that, INbreast, a smaller digital mammography database, tests the model. In CBIS-DDSM, InceptionV3 categorizes mass and non-mass regions better than VGG16, ResNet50, and the latter. An InceptionV3 domain adaptation study benefits digitized CBIS-DDSM and INbreast datasets. Five-fold cross-validation with receiver-operator characteristic curves is used to evaluate the accuracy of mass detection. ImageNet fared worse than CBIS-DDSM in transfer learning, with a TPR of 0.98 ± 0.02 at 1.67 FPI compared to 0.91 ± 0.07 at 2.1 FPI. The INbreast database mass detection literature lags the proposed TPR and FPI methods. In mammography images, Ragab et al., (2019) used deep learning and segmentation to differentiate benign and malignant breast tumors. CAD employs manual ROI determination and threshold-based region segmentation. Feature extraction uses the binary classification trained AlexNet Deep Convolutional Neural Network (DCNN) architecture. SVM classifiers are added to the last fully linked layer for accuracy. High accuracy is attained by training on large datasets; however, biomedical datasets include few patients, hence data augmentation methods like rotation are needed. DCNN accuracy for manually cut ROI is 71.01%. The highest AUC is 0.88. CBIS-DDSM data increases SVM accuracy to 87.2% and DCNN accuracy to 73.6%, with an AUC of 0.94, exceeding similar studies. Breast cancer detection may improve with this study. Sharma et al., (2018) discussed the significant problem of breast cancer, which has become the most dangerous threat among women worldwide. Detection of breast cancer is hampered by the requirement to differentiate benign from malignant tumors; this is an area where artificial intelligence (AI) techniques can be useful. According to this study, AI techniques can increase accuracy to 91%. Several artificial intelligence methods were used by the authors to determine if a tumor is benign or malignant. These methods included Decision Tree Classifier (DT), K-Nearest Neighbors (K-NN), and Support Vector Machine (SVM). It was found out that the SVM classifier is providing results that are more accurate than other demonstrating 96 % accuracy when trained on larger datasets. The development of big data in healthcare was presented by Khourdifi et al., (2018). Then, the researchers used a dataset on breast cancer to test four machine learning methods (RF, NB, SVM, and K-NN). All this research was done to compare different breast cancer prediction algorithms. The results from the experiments showed that SVM had the highest accuracy at 97.9%. The study's outcomes could be of assistance to healthcare providers in choosing the most effective machine learning algorithm for breast cancer prediction. Chaurasia et al., (2017) used the Wisconsin breast cancer dataset to evaluate different classification techniques and their performance. This research was performed to apply data mining methods for building an accurate breast cancer model. Sequential Minimal Optimization (SMO) was used in the Weka environment. Two other techniques were used for the testing. The result showed that SMO outperforms both with a prediction accuracy of 96.2%. In another study, Houssein et al., (2022) also emphasized this technique's importance when it comes to prediction accuracy in breast cancer diagnosis models. Breast cancer constitutes a significant public health concern and detecting it early can save lives. Improved detection of cancer is one area where CNNs have shown potential. This research utilizes a hybrid CNN and an improved optimization algorithm in diagnosing breast cancer. The marine predator's algorithm is used, which is improved with an opposition-based learning strategy to find the best hyperparameters for CNN architecture. The proposed method employs transfer learning using a pre-trained CNN model called ResNet50, resulting in the architecture IMPA-ResNet50. The model is evaluated ontwo mammographic datasets and compared with other approaches. The results showed that IMPA-ResNet50 achieved high accuracy, sensitivity, and specificity rates of 98.32%, 98.56% and 98.68% respectively, on the CBIS-DDSM dataset and 98.88%, 97.61% and 98.40% respectively, on the MIAS dataset. In comparison to alternative approaches, the proposed model exhibits remarkable accuracy, sensitivity, and specificity. Four additional optimization techniques are compared to IMPA, and IMPA-ResNet50 is shown to be the most effective. Overall, the method developed in this study ofcombining a convolutional neural network and an optimization algorithm improves the precision with which breast cancer can be detected and classified.

3. Background study

Breast cancer is a major health issue, and its detection inearly stages is critical to reducing mortality rates. CNNs haveshown promise in improved cancer detection. In this study, a hybrid CNN and improved optimization algorithm are proposed for breast cancer diagnosis. The marine predator's algorithm is used which is improved with an opposition-based learning strategy to find the best hyperparameters for the CNN architecture. The proposed method employs transfer learning using a pre-trained CNN model called ResNet50, resulting in the architecture IMPA-ResNet50. The model is evaluated on two mammographic datasets and compared with other approaches. The results showed that IMPA-ResNet50 achieved high accuracy, sensitivity, and specificity rates of 98.32 %, 98.56 %, and 98.68 %, respectively, on the CBIS-- DDSM dataset and 98.88 %, 97.61 %, and 98.40 %, respectively, on the MIAS dataset. Using other approaches, the proposed model is better. It has a high accuracy which makes it outperform the other approaches as well as sensitivity and specificity rates. In terms of performance, the IMPA algorithm is compared to four other optimization algorithms and IMPA-ResNet50 shows better results.

This research provides an efficient way for improving breast cancer detection/identification accuracy using hybrid CNNs and an optimization algorithm (Houssein et al., 2022).

4. Problem formulation

In many areas, breast cancer screening and diagnosis are limited especially in low-income countries. Therefore, there is a growing interest in utilizing machine learning algorithms via cloud-based network infrastructures designed to detect breast cancer at an early stage. However, there are several challenges to the implementation of this approach, including the need for large, high-quality datasets for training algorithms, the need for transparent and explainable algorithms that can be easily integrated into clinical practice, and the need for secure and reliable cloud-based infrastructure for storing and processing sensitive patient data. This research therefore aims to assess the practicality of such cloud-based network infrastructure for early detection of breast cancer through ML algorithms and identify challenges as well as opportunities of applying it in the clinical practice.

5. Dataset description

The CBIS-DDSM dataset is a public mammography dataset available on Kaggle that consists of 2,620 mammography exams performed on 1,003 patients, available on this link "https://www.kaggle.com/datasets/awsaf49/cbis-ddsm-breast-cancer-image-dataset". The data contains images of both benign and malignant breast lesions, alongside clinical details such as patient age and lesion type. The images are available in raw as well as processed formats that have been used in different applications like breast cancer diagnostics and lesion identification. This dataset is already a popular choice for researchers who want to design and evaluate ML algorithms aimed at detecting and classifying breast cancers. This dataset is often used in research on the development and performance evaluation of machine learning algorithms that are used for detecting and classifying breast cancers.

Figure 3 illustrates some photos from the dataset:

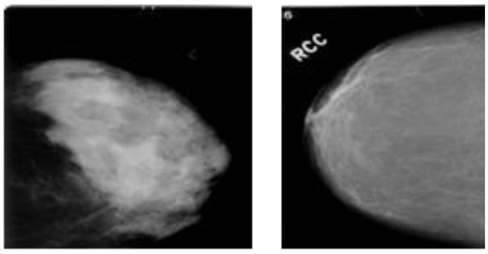

Figure 3. Some samples from the CBIS-DDSM dataset.

The CBIS-DDSM dataset is summarized in Table 1. It uses DDSM (Digital Database for Screening Mammography), an open database for breast cancer research.

Table 1. Overview of the CBIS-DDSM dataset.

Attributes	Description
Dataset Name	CBIS-DDSM (Curated Breast Imaging Subset of DDSM)
Dataset Origin	Sourced from the publicly available DDSM breast cancer dataset.
Data Type	Medical imaging dataset containing mammograms
Imaging Modality	Digital mammography
Purpose	Used for breast cancer detection and classification research
Number of Images	Approximately (10239) images
Image Resolution	Varies; typically, high-resolution mammograms

Image Format	DICOM (Digital Imaging and Communications in Medicine)
Annotation Labels	Typically contains labels for breast lesions, calcifications, masses, and other breast abnormalities.
Annotation Format	Annotations are often provided as XML files.
Availability	Publicly available for research purposes

6. Research Methodology

6.1 Techniques Used

6.1.1 Discrete Cosine Transform (DCT)

The DCT (Discrete Cosine Transform) is a mathematical process that is used for feature extraction in computer vision and image processing. By transforming the signal into a set of cosine functions with different frequencies, we can identify the most important features in images.

Mathematically, DCT can be expressed as follows:

$$X_k = \frac{2}{N \times C_k \times sum(x_n \times (\frac{cos(\pi \times k \times (2n+1)}{2N}))} \quad (1)$$

where,

N = number of samples in the signal

x_n = value of the signal at time n

X_k = kth coefficient of the DCT

C_k = normalization constant

The image is divided into a grid and the DCT is applied to each block in that grid. The resulting coefficients serve as features for classification. Mostly, the choice of relevant features is usually made based on their magnitude or variance. In mammography, DCT can be employed to extract characteristics from mammograms or other images of breast cancer to be used by a machine learning model when training for breast cancer detection (Agarwal et al., 2019).

6.1.2 Marine Predators Algorithm (MPA)

This study uses the Marine Predators Algorithm (MPA) as an optimization algorithm to improve hyperparameter values for breast cancer detection using ML algorithms (Kaladevi et al., 2023). Breast cancer diagnosis using orca predation optimization algorithm. Journal of Intelligent & Fuzzy Systems, 45(3), 3855-3873). Additionally, the MPA is a biological inspired algorithm that simulates the hunting behavior of aquatic predators (Faramarzi et al., 2020). With regard to machine learning, MPA is used for finding the best hyperparameters values of ML algorithms which are important for attaining optimal performance. The MPA's general architecture is depicted in Figure 4 (Houssein et al., 2022).

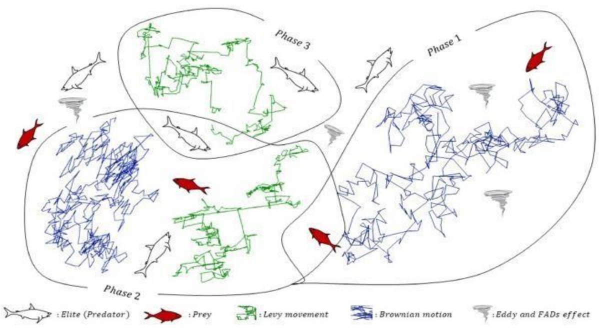

Figure 4. General architecture of the MPA.

The present study uses the MPA to improve an existing ML model for breast cancer recognition. The MPA is employed to optimize the hyperparameters of the model for optimal performance in breast cancer detection. These include adjusting its learning rate, varying the number of layers and nodes in each layer (Mohamed et al., 2022). By making the model perform better, using MPA helps in ensuring that it is optimized for performance and hence more effective for early breast cancer detection (Alafeef et al., 2020). Generally, this part is very important because it highlights how MPA can generate values for hyperparameters used in breast cancer detection which in turn can have a significant impact on patient outcomes.

6.1.3 Genetic Algorithm (GA)

The Genetic Algorithm (GA) is a search-based optimization method that is inspired by the principles of natural selection and genetics. It finds the best solution to a problem through a continuous generation and evaluation of potential solutions (Alhijawi et al., 2024). The first step involves the production of a collection of possible outcomes also referred to as chromosomes (Immanuel & Chakraborty, 2019). The chromosomes are then evaluated by checking how well they solve the problem using a fitness function. In this case, only the fittest ones are chosen for replication in which they mate with another partner resulting into new offspring's (Kora & Yadlapalli, 2017). Crossover and mutation facilitate inheritance, and thus characteristics from parents are passed on to children. The new population of offspring is then calculated by using the fitness function (Youssef et al., 2016). GA algorithm works by mimicking the processof evolution, where the fittest individuals in a population survive and reproduce, passing on their favorable traits to their offspring. Figure 5 shows the working principle of the GA (Haldurai et al., 2016).

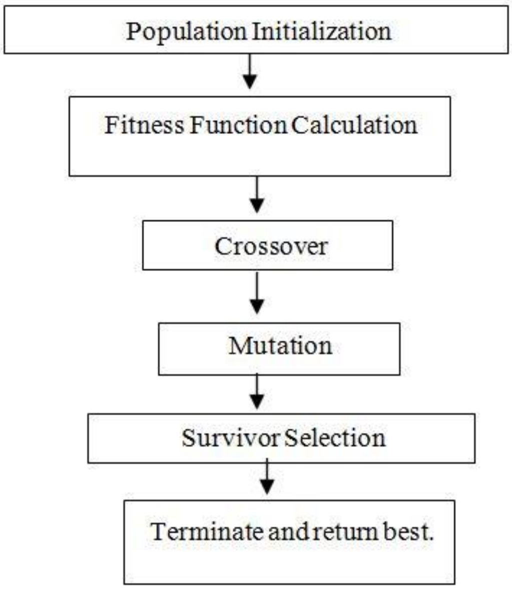

Figure 5. Working principle of Genetic Algorithm.

The hyperparameters are selected randomly, and theGA algorithm evaluates the performance of the model using these hyperparameters. The algorithm then selects the best- performing individuals (models) and applies crossover and mutation operations to generate a new population of potential solutions. This is done until a good solution is found or until a predetermined number of iterations have passed. By using GA to generate hyperparameter values, it is possible to find an optimal combination of hyperparameters that results in high classification accuracy, sensitivity, and specificity in detecting breast cancer (Guido et al., 2023).

GA is widely used in various fields, including engineering, economics, and computer science. Schedule optimization, resource allocation, and machine learning feature selection are just a few of the many optimization challenges that have benefited from its application. To sum up, GA is essential in creating hyperparameter values that might boost the ability of ML models for breast cancer detection and categorization, ultimately leading to better patient outcomes (Anaraki et al., 2019).

6.1.4 EfficientNet

In 2019, researchers announced EfficientNet, a neural network architecture that aims to provide state-of-the- art performance with fewer parameters and calculations. It uses a compound scaling technique to boost efficiency while decreasing computing overhead by simultaneously expanding the network's depth, width, and resolution. Some examples of computer vision tasks in which EfficientNet has shownstrength include image classification, object recognition, andsegmentation (Joshi et al., 2022). Transfer learning in deep learning often makes use of this architecture because it has already been trained on big datasets like ImageNet and can be fine-tuned for individual applications (Atila et al., 2021). In the context of classifying beginning and malignant breast cancer, EfficientNet can playa crucial role in achieving high accuracy and reducing false negatives.

Models in EfficientNet are pre-trained on hugedatasets before being fine-tuned for a certain purpose. This pre-training phase enables the model to acquire a wealth of features that can be utilized in the classification of breast cancer. The architecture of EfficientNet consists of multiple layers, including convolutional layers, depth-wise separable convolutional layers, and fully connected layers as shown in Figure 6 (Kaur et al., 2022).

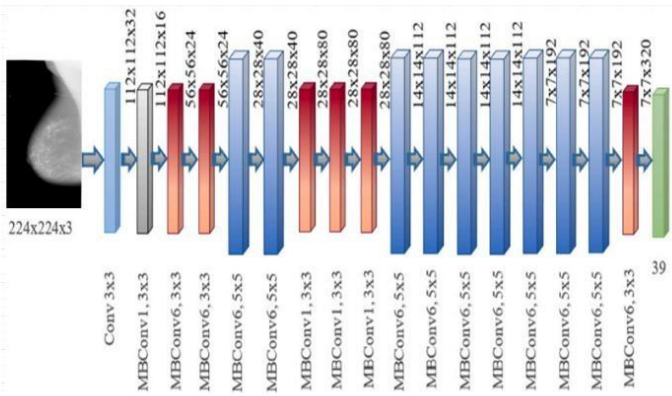

Figure 6. EfficientNet.

For example, EfficientNet has been shown to beat other state-of-the-art models in recognizing skin lesions and diabetic retinopathy identification, both of which are medical picture classification tasks. High accuracy in determining whether a mammography image is benign or malignant can be achieved with the use of EfficientNet in the framework of breast cancer classification. EfficientNet's primary function in identifying benign and malignant breast cancer is to supply a computationally efficient and accurate model that can aid in raising the bar for breast cancer detection and therapy.

6.1.5 Cloud computing

Computing services are provided over the internet, a model known as "cloud computing (David et al., 2022)." Without purchasing costly gear or setting up complex infrastructure, customers can gain instant access to data, applications, and computer resources. Data centers house the remote servers used in cloud computing, and users gain access to them over the Internet (Himabindu & Jyothi, 2017). Storage, computation, and program execution are just a few of the many computer services made available by these servers. The adaptability of cloud computing is demonstrated by its use with multiple service models (Wentao Liu, 2012).

Moreover, four different deployment strategies can be employed in cloud computing, which include Common clouds, public clouds, hybrid clouds, and private clouds as illustrated in Figure 7 (Shei & Muniyandi, 2023). Each of these types has its unique characteristics and advantages.

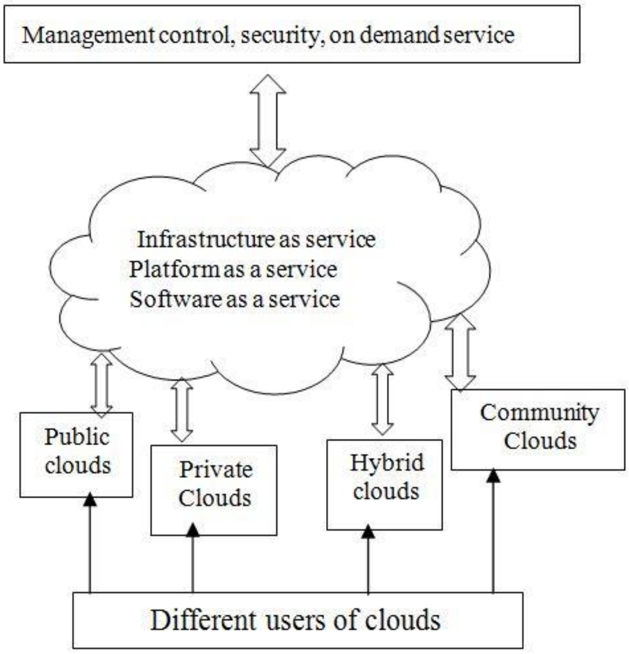

Figure 7. General Cloud computing model.

Cloud computing has exploded in popularity in recent years due to its many useful features, such as its low initial investment, scalability, and adaptability. It enables businesses and organizations to easily increase or decrease their computer resources on demand, with no up-front costs (Yayik & Kutlu, 2014). In the context of breast cancer detection and classification, cloud computing can be used to store and process large amounts of medical imaging data. ML techniques and tools can be accessed and utilized to examine data for patterns that may signal the presence of breast cancer. If successful, this could improve patient outcomes by increasing the accuracy of breast cancer diagnosis. In this study, using machine learning techniques, a network architecture is set up in the cloud for breast cancer detection.

The network is housed on a platform for cloud computing, which facilitates the easy integration of different machine learning algorithms and the effective processing of massive volumes of data. Cloud computing provides the infrastructure for processing and analyzing massive amounts of data fast and effectively, making it an essential part of ML-based breast cancer diagnosis.

6.2 Proposed Methodology

The proposed methodology for breast cancer detectioninvolves collecting a reliable dataset and verifying it for any missing values. Subsequently, the emphasis transfers to data preprocessing, which includes cleansing, normalization, image processing, and noise reduction. The dataset is divided into test and training sets. Then, the Discrete Cosine Transform (DCT) is used to extract features from breast cancer images, and the Marine Predators Algorithm (MPA) and the Genetic Algorithm (GA) are used to generate crucial hyperparameters for the EfficientNet model. Fine-tuning is accomplished by using the produced hyperparameters to adjust the model after it has been trained using the training dataset. The testing dataset is evaluated for performance, andessential metrics are calculated. The trained model plays a central role in formulating predictions, particularly in the identification of breast cancer via mass and calcification. The model is finally deployed on a cloud infrastructure, where a suitable service provider is chosen, virtual machine instances are configured, necessary dependencies are installed, the model is uploaded, and its functionality is rigorously tested via an API endpoint to ensure operational success. The workflow of the proposed methodology is illustrated in Figure 8 given below:

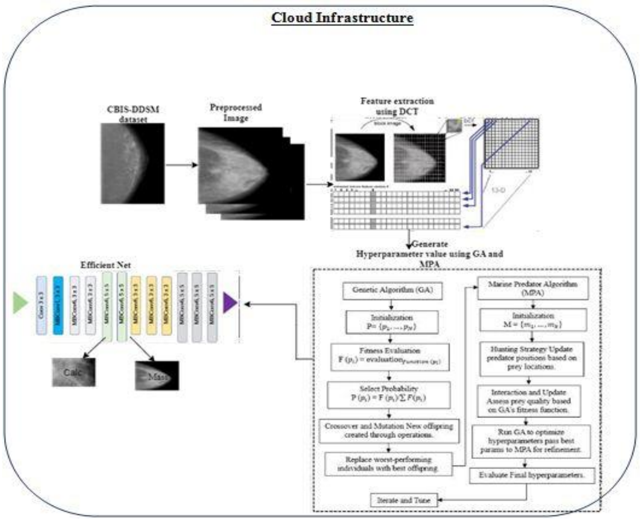

Figure 8. Flowchart of the proposed methodology.

6.2.1 Proposed Algorithm

The major steps of the proposed algorithm are as follows:

- **Step 1: Dataset Collection**
  - Let $\boldsymbol{D}$ denote the breast cancer dataset.
  - Verify the dataset for missing values or errors.
- **Step 2: Data Preprocessing**
  - Let $\boldsymbol{D'}$denotes the preprocessed dataset.
  - For each data point in $\boldsymbol{xi}$, in $\boldsymbol{D}$, do:
  - If $\boldsymbol{xi}$ is not missing or irrelevant:
  - Normalize: $\mathbf{y_i} = \frac{\mathbf{xi-\mu}}{\boldsymbol{\sigma}}$, where $\boldsymbol{\mu}$ is the mean and $\boldsymbol{\sigma}$ is the standard deviation.
  - Apply image processing techniques: $\mathbf{y_i} = \mathbf{process}\ (\mathbf{y_i})$
  - Apply noise reduction techniques: $\mathbf{y_i} = \mathbf{reduce_{noise(y_i)}}$
  - Add $\boldsymbol{y_i}$ to $\boldsymbol{D'}$.
- **Step 3: Splitting the Dataset**
  - Let $\boldsymbol{Dtrain}$ and $\boldsymbol{Dtest}$ denote the training and testing datasets, respectively.
  - Randomly select k data points from D' for training andthe rest for testing.
- **Step 4: Feature Extraction**
  - Let $\boldsymbol{F}$ denote the set of extracted features.
  - For each data point $\boldsymbol{yi}$ in $\boldsymbol{Dtrain}$ or $\boldsymbol{Dtest}$, do:
  - Apply Discrete Cosine Transform (DCT) to $\boldsymbol{yi}$: $\boldsymbol{fi} = \boldsymbol{DCT}(\boldsymbol{yi})$

  - Select the most relevant features from $\boldsymbol{fi}$
  - Add select features to $\boldsymbol{F}$
- **Step 5: Generate Hyperparameters**
  - Let $\boldsymbol{H}$ denote the set of generated hyperparameters using MPA and GA
- **Step 6: Training using Efficient Net**
  - Let $\boldsymbol{M}$ denote the Efficient Net
  - Train the model on $\boldsymbol{Dtrain}$ using hyperparameters $\boldsymbol{H}$.
  - Fine-tune the model using $\boldsymbol{H}$
- **Step 7: Testing the Data on the Trained Efficient Net Model**
  - Let **A**, **P**, **R** and **F1** denote accuracy, precision, recall, and F1 score.
  - For each data point yt in Dtest , do:
  - Predict the output: $\boldsymbol{oi}$ = predict ($\boldsymbol{M}$, $\boldsymbol{yi}$)
  - Calculate performance metrics: **A**, **P**, **R**, $\boldsymbol{F}$ = **evaluate (**$\boldsymbol{o_i}$, $\boldsymbol{y_i}$**)**
- **Step 8: Prediction**
  - For each data point $\boldsymbol{yi}$ in $\boldsymbol{Dtrain}$ or $\boldsymbol{Dtest}$, do:
  - Predict the output: $\boldsymbol{pi}$ = predict ($\boldsymbol{M}$, $\boldsymbol{yi}$)
  - Classify breast cancer detection: $\boldsymbol{mass_{result}}, \boldsymbol{calc_{result}} = \boldsymbol{classify}\ (\boldsymbol{p_i})$
- **Step 9: Deploy the Model on Cloud Infrastructure**
  - Let $\boldsymbol{C}$ be the chosen cloud service provider.
  - Let $\boldsymbol{VM}$ be the virtual machine instance.

- Create VM: $\boldsymbol{VM} = \boldsymbol{CREATE\_VM}(\boldsymbol{C})$
- Set up API: $\boldsymbol{API} = \boldsymbol{set\_API}\ (\boldsymbol{C}, \boldsymbol{VM})$
- Test API: $\boldsymbol{test}_{\boldsymbol{API}}(\boldsymbol{API})$

7. Results and Discussion

Table 2 provides a comprehensive overview of feature extraction using DCT for various medical cases. Each row corresponds to a distinct patient, identified by a Patient ID, and contains additional information regarding the patient's breast density, image view, abnormality ID, abnormality type, pathology, and subtlety. The table also provides the locations of the source picture and the ROI mask files. Lists of DCT feature values (labelled DCT feature 1, DCT feature 2, etc.) demonstrate the numerical outcomes of the feature extraction procedure. Computed from the medical pictures, these traits are crucial for further investigation and diagnosis. As an illustration, Patient 1 had a breast density of 2, was assessed using the Cranio-Caudal (CC) view, and had an anomaly ID of 101, which was determined to be a benign tumor. This patient's breasts were found to have a benign mass. The outcome of the pathology was negative, earning a score of 3 for subtlety. The related images and ROI masks are also included in this document. In addition, the patient’s DCT feature values are indicated: 0.123, 0.456, and 0.789 for features one through N respectively. The feature extraction process utilizing DCT is shown as per above; each row provides a detailed picture of the procedure as it was applied to a different patient.

Table 2. Illustrates Breast abnormality feature extraction using DCT.

Patient _id	Breast _dens	Image _vie	Abnormality id	Abnormality _type	Pathology	Subtlety	Image file path	ROI mask file path	DCT fea	DCT fea	..	DCT feat

	ity	w							ture 1	ture 2		ure N
1	2	CC	101	Mass	Benign	3	CBIS-DDSM/jpeg/1.3.6.1.4.1.9590.100.1.2.129308... 3	CBIS-DDSM/jpeg/1.3.6.1.4.1.9590.200.2.1.229308... 1	0.123	0.456	..	0.789
2	3	MLD	102	Calc	Malignant	2	CBIS-DDSM/jpeg/1.3.6.1.4.1.9590.100.1.2.153339... 7	CBIS-DDSM/jpeg/1.3.6.1.4.1.9590.200.2.1.229308... 2	0.234	0.567	..	0.890
N	1	CC	103	Mass	Benign	1	CBIS-DDSM/jpeg/1.3.6.1.4.1.9590.10	CBIS-DDSM/jpeg/1.3.6.1.4.1.9590.200.2.	0.345	0.678	..	0.901

							0.1.2.1789 94... 10	1.229308... 3				

A machine learning model’s training process has several hyperparameters that define its various aspects and their values are summarized in Table 3. Optimizing these hyperparameters is done by applying techniques like Marine Predators Algorithm (MPA) and Genetic Algorithm (GA) that play an important role in obtaining the highest possible performance of the model. The values of these hyperparameters are essential in setting expectations forthe model's output and behavior.

Table 3. Hyperparameter for Model Training.

Hyperparameter	**Value**
Test Size (train_test_split)	0.25
Random State (train_test_split)	42
Dropout Rate (EfficientNetBO)	0.4
IMG_SIZE	50
Batch Size (model1.fit)	75
Learning Rate (model1.compile)	0.001
Number of Epochs(model1.fit)	10
Number of Total Epochs (model1.fit)	specified in ‘epochs’ variable)

Here's a brief explanation of each hyperparameter and its value:

- **Test Size (train_test_split):** This is the percentage ofthe dataset that is used for testing, while the remainder is utilized for training. This instance reserves 25% of the data for testing.
- **Random State (train_test_split):** This is a seed valuethat guarantees the same random partitioning of the dataset each time the code is executed. This caseestablishes a random state of 42.
- **Dropout Rate (EfficientNetBO):** The neural network regularization method dropout prevents overfitting. Itoccasionally loses input units during training. The dropout rate is 0.4.
- **IMG_SIZE:** Input picture size is shown here. A 50x50pixel resolution is applied to the photos.
- **Batch Size (model1.fit):** The training iteration's batchsize indicates how many samples are handled at once.The optimal batch size is 75.
- **Learning Rate (model1.compile):** The hyperparameter learning rate determines the amount of the training steps used to update the model's weights. The rate of learning is set at 0.001.
- **Number of Epochs (model1.fit):** The training dataset is iterated through in one go throughout an epoch. Themodel is trained in this instance for 10 epochs.
- **Number of Total Epochs (model1.fit):** The number of training epochs sets the duration of the training process. The value is 100 here, but it could be a variable.

Table 4 details the number of layers, the type of output generated by each layer, and the weights and biases used in an EfficientNet model.

Table 4. EfficientNet Model Layers and Parameters.

Layer (type)	Output Shape	Param #

conv2d (Conv2d)	(None, 50, 50, 32)	896
max_pooling2d (MaxPooling2d)	(None, 25, 25, 32)	0
conv2d_1 (Conv2d)	(None, 25, 25, 64)	18496
max_pooling2d_1 (MaxPooling2d)	(None, 12, 12, 64)	0
conv2d_2 (Conv2d)	(None, 12, 12, 128)	73856
max_pooling2d_2 (MaxPooling2d)	(None, 5, 5, 128)	0
conv2d_3 (Conv2d)	(None, 5, 5, 128)	147584
max_pooling2d_3 (MaxPooling2d)	(None, 2, 2, 128)	0
flatten (Flatten)	(None, 512)	0
dense (Dense)	(None, 128)	65664

dense_1 (Dense)	(None, 2)	258
Total params: 306, 754 Trainable params: 306, 754		

Figure 9 illustrates the training and validation loss, providing insights into how the loss function evolves during the training process. Classification accuracy is an important metric for any machine learning model, and Figure 10 provides a visual depiction of the EfficientNet model's performance based on the validation data set and the training dataset.

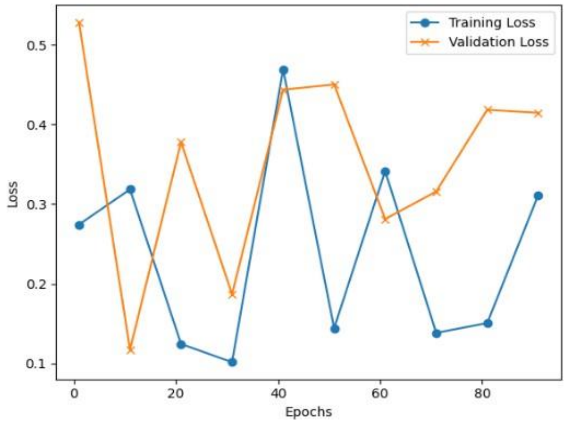

Figure 9. Training and Validation Loss.

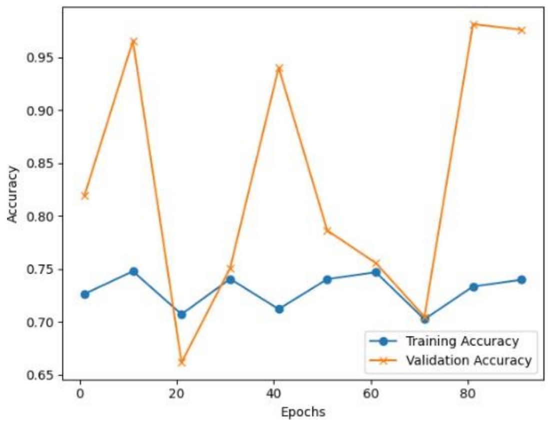

Figure 10. Training and Validation Accuracy.

7.1 Comparative study

In recent times, ML models have been created to aid in the earliest possible diagnosis of breast cancer. Breast cancer riskassessment is performed by these models by deep learning algorithm analysis of mammograms. In this context, the performance of five different classification models, namely MPA-ResNet50, HHO-ResNet50, RMSProp-VGG 16, GSA-

ResNet50, IMPA-ResNet50, and WOA-ResNet50, were compared based on various parameters, including theproposed EfficientNet method and their observed performance is illustrated in table 5 given below:

Table 5. Comparison table for various techniques.

Classification Model	Specificity (%)	Sensitivity (%)	F1-score (%)	Precision (%)	Accuracy (%)
MPA-ResNet50 (Houssein et al., 2022)	95.28	93.03	93.85	94.22	95.95
HHO-ResNet50 (Houssein et al., 2022)	94.84	93.12	94.5	94.12	94.55
RMSProp-VGG 16 (Falconi et al., 2020)	78.26	84.9	81.84	79	87
PA-ResNet50 (Houssein et al., 2022)	98.56	96.61	97.65	98.68	98.32
GSA-ResNet50	95	94.16	94	95	95.48

(Houssein et al., 2022)					
WOA-ResNet50 (Houssein et al., 2022)	94	93.1	94	94	94.13
EfficientNet (Proposed method)	99.61	98.31	98.79	99.84	99.91

Various authors have presented the specificity, sensitivity, F1-score, precision and accuracy of many categorization models in this table of comparisons. A comparison of categorization models performance indicators across research is shown in the table. A model's specificity, sensitivity, F1-score, precision, and accuracy are listed in each row. The study by Houssein et al. [31] employed multiple variations of the ResNet50 model, namely MPA- ResNet50, HHO-ResNet50, IMPA-ResNet50, GSA- ResNet50, and WOA-ResNet50. Notably, the proposed Efficient Net method demonstrated exceedingly high performance, obtaining a specificity of 99.61%, a sensitivity of 98.31%, an F1-score of 98.79%, a precision of 99.84%, and an outstanding accuracy of 99.91%. This shows that the Efficient Net method is superior to the other models compared in this analysis. Falconi et al. [24] used the RMSProp-VGG 16 model, which displayed great performance with a specificity of 78.26%, sensitivity of 84.9%, F1-score of 81.84%, precision of 79%, and accuracy of 87%. The table gives a complete summary of classification models' which defines different types through the distinction between them and shows that the suggested EfficientNet method has better results in comparison to others.

8. Conclusion

Overall, the results of this study show that integrating ML algorithms with cloud computing has the potential to greatly improve breast cancer diagnosis. Increasing the accuracy of breast cancer diagnoses and consequently bettering patient outcomes is a major goal of the proposed Efficient Net method due to the exceptional accuracy achieved by this approach. Earlier reduced mortality rates have resulted from the use of this infrastructure, which is highly scalable and efficient. This study is a major step forward in incorporating machine learning into medical imaging more broadly, whichhas exciting implications for the future of healthcare and the battle against breast cancer. This study has proven the importance of feature extraction with Discrete Cosine Transform (DCT) When it comes to diagnosing and learning more about breast cancer diagnosis. Additionally, Important hyperparameters are collected using a combination of MPA+ GA for use in training a machine learning model which.

The Learning Model is critical to the functioning of the model and was selectively chosen for it to be successful. It has layers and parameters' structure outlined in EfficientNet which was used for breast cancer classification. In conclusion, among other models, the proposed EfficientNet method achieved a better accuracy of 99.91%. The second place went to the IMPA-ResNet50 with an accuracy of 98.32%. IMPA-ResNet50 came second with an accuracy of 98.32%. The other models, HHO- ResNet50, GSA-ResNet50, MPA-ResNet50, RMSProp-VGG 16, and WOA-ResNet50, had accuracies ranging from 87% to 95.95%. The proposed EfficientNet method was the most precise model, with a remarkable accuracy of 99.91%. That it outperforms every other model speaks volumes about how useful this method is for spotting breast cancer in its earliest stages. Overall, the study's findings demonstrate that using cloud computing alongside machine learning algorithms improves breast cancer diagnosis by a substantial margin. The superior accuracy of the proposed EfficientNet method has great promise for increasing the precision of breast cancer diagnoses and bettering overall patient outcomes. Early detection and lower mortality rates can be attributed in part to the study's cloud-based infrastructure, which is both scalable and efficient. This research is an important step toward expanding the use of machine learning in medical imaging.

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