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Expert Opinion Article

A Deep Learning Framework for breast cancer prediction using Image Processing and Cloud-based Analysis

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Abstract: Women from all over the world are affected by breast cancer as a general problem of health. Early diagnosis and proper detection will go a long way in improving breast cancer survival rates as well as patient outcomes. In this study, we propose a novel deep learning-based framework for the prediction of breast cancer using cloud-based analysis and different image processing techniques. To maximize their potential, the UNet and ResNet50 architectures were combined in the framework for image segmentation and feature extraction respectively. Using a large dataset of breast cancer images, it learns to diagnose correctly as well as locate malignant spots. The system also has real-time predictions and is scalable with efficient cloud-based image processing. The suggested approach has the potential to enhance quick recognition and diagnosis of breast cancer, which could enhance patient outcomes and decrease healthcare expenditures. The findings show that the suggested technique has great levels of accuracy (91.15%), precision (89.94 %), sensitivity (90.84%), F1- score (92 %), and area under the curve (95%).

Keywords: Cloud Computing, Deep Convolutional Neural Network (DCNN), Discrete Cosine Transform (DCT), AlexNet, ResNet, UNet.

1. Introduction

Breast cancer has surpassed all other female cancers in terms of mortality rate in the last few decades [1]. About 15% of female deaths are caused by breast cancer. By 2040, the World Health Organization predicts, there will have been 2.7 million additional instances of breast cancer globally. The COVID-19 epidemic has put a strain on medical resources in many underdeveloped nations. Although there is strong evidence that detecting breast cancer early and treating it promptly improves survival rates, doing so is infamously difficult [2]. The risk of developing breast cancer depends on many factors, including a woman's age, her family's history of the disease, her exposure to estrogen throughout her life, the density of her breasts, and any genetic predisposition she may have, such as a mutation in the breast cancer gene. Enhanced, more precise methods of breast cancer screening are always welcome [3]. In women, breast cancer ranks high among the top causes of death [4]. Cloud computing has matured to the point where it can successfully replace on-premises server farms. Cloud computing is a service that stores data on a network of remote servers and makes it accessible to users whenever they need to access, modify, or delete it. Cloud computing services facilitate IT personnel's access to cloud service providers' products by providing a browser-based dashboard. Integrating patient records with other cloud-based data is made easier with the use of cloud computing, which in turn makes it more practical to update patientinformation. As a result of cloud computing's plethora of resources, it might be possible to store even the most massive biological picture or audio information online. The potential of cloud computing to boost service availability while decreasing downtime is crucial in the healthcare sector [5].

1.1. *Deep Learning (DL) in Medical Imaging*

Deep Learning (DL) has emerged as the dominant technique in the field of machine learning (ML). Dynamically learning representations of information, DL does so by mapping the incoming data onto more abstract representations [6]. In the realm of image pattern recognition, Deep Convolutional Neural Networks (DCNNs) are the highest effective kind of DL network. Backpropagation might be used to automatically train a DCNN to extract relevant features from training examples. Therefore, DCNN does not need the creation of features before training. DCNN features are projected to surpass hand-engineered features because of their superior level of selectivity and invariance if they are adequately trained using a large training set that is generally representative of the population of interest. A human expert would need a lot more time to detect and remember each one of hundreds of millions of occurrences than DL can do since it simplifies the learning process. DL has the potential to be more robust to variations in characteristics across discriminable classes, provided that the training data set is sufficiently large and diverse [7].

1.2. *Deep Learning Architecture for Breast Cancer Prediction*

Recently, deep-learning algorithms have shown exceptional performance, prompting some researchers to propose using this technique for the detection of breast cancer (BC) [8]. This DL-based Computer-Aided Design (CAD) method can automatically categorize breast lumps as cancerous or benign, eliminating the need for time-consuming manual processes such as lesion segmentation, feature calculation, and selection. ANN, autoencoders, DBN, and CNN are only a few of the DL-based BC diagnostic approaches that are included in this article's overview [9].

1.2.1. Discrete Cosine Transform (DCT)

A common method for lossy images and signal reduction is the DCT. After passing through the DCT, each chunk of raw picture data is converted into a collection of coefficients that stand for a certain frequency range. The redundant components may be characterized by a small number of bits, and the spectrum of all the DCT coefficient blocks in a single image is almost entirely centered in the upper left blocks [10]. DCT's energy compaction feature means that the majority of the image's information is condensed into a small number of DCT coefficients, making it useful for a wide range of image compression tasks [11]. Information is encoded in the form of DCT coefficients in this study, and the 3D discrete cosine transform is applied to the hyperspectral picture (consisting of the optimal selection of bands) [12]. The Forward Discrete Cosine Transform (FDCT) is carried out by partitioning each picture into 8x8 blocks, i.e., a discrete signal at each block. It is discovered, however, that this block-wise DCT procedure might result in unintended qualities such as blocking artifacts [13]. The author only considers a single block whose height (H) and width (W) are the same as those of the original input picture. The amplitudes of the basis signals, also known as the "DCT coefficients," are the outputs of an FDCT given an input H×W signal. Accordingly, the values of the DCT coefficients may be thought of as the relative quantity of the 2D spatial frequencies included in the original input signal, which is a picture. Most of the signal energy is condensed into a small number of converted DCT coefficients at low spatial frequencies, which is one of FDCT's most notable characteristics. For the discrete cosine transform, the proportion of large coefficients is minimal compared to the proportion of tiny coefficients. It is common for a natural image's low-frequency content to account for the bulk of the image's information. The picture is enhanced by the high frequencies that convey the abrupt changes that occur at those times [14].

1.2.2. AlexNet

The AlexNet is a well-known deep convolutional neural network structure. In a major step forward for the field of machine learning, AlexNet achieved excellent classification accuracy on the ImageNet dataset. After that, individuals began to invest more time and energy into studying deep learning models. In recent years, various deep CNNs, as well as training and optimization methods, have been developed [15Color images in common formats may be inputted into the original data source with only the cropped image in the following format: 227* 227* 3 pixels, where 227 is the input image's height and width and 3 is the information source's three-channel RGB mode [16]. Five convolutional layers and three full-connection layers make up AlexNet's eight-layer architecture; maximum pooling is executed after the third convolutional layer [17]. AlexNet is a neural network that deviates from the norm by substituting the ReLU activation function for the more common sigmoid and tanh activation functions. ReLU status as a non-saturated activation feature allows it to not only boost the training speed of the model but also to more effectively deal with the problems of the disappearance of gradients and gradient explosion that crop up throughout the process [18]. Fig. **1** represents the architecture of AlexNet [19].

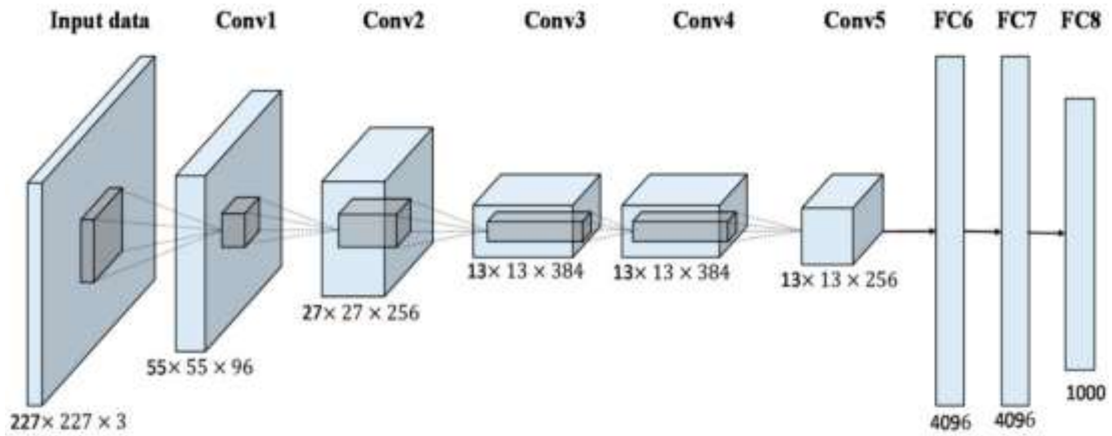

Fig. 1. AlexNet Architecture.

1.2.3. ResNet

The ResNet architecture is widely used for image categorization. Notable progress was made with its introduction, and it is still used as a baseline in articles presenting new designs or as a referent architecture for various analyses [20]. In all, the ResNet-32 consists of 30 Convolutional layers (Conv_Ly), a MaxPool, and an entirely linked layer with SoftMax layers, for a total of 32 layers. The Deep Learning Model known as a ResNet builds a network through stacked residual connections [21]. The ResNet model outperforms competing architectural models despite maintaining its efficiency even as the design grows more sophisticated. Despite having 32 fewer layers than previous ResNet models, the ResNet-32 model demonstrates performance on par with that of other versions of ResNet architectures. Because ResNet's residual blocks produce two distinct pathways, an architecture with r residual blocks would have **2r** paths to take when processing input. As a result, the model's performance is unrelated to the number of design layers. Working on fewer layers would also result in faster computations and training networks are made more capable [22]. Fig. **2** shows the ResNet 32 model's layered structure [23].

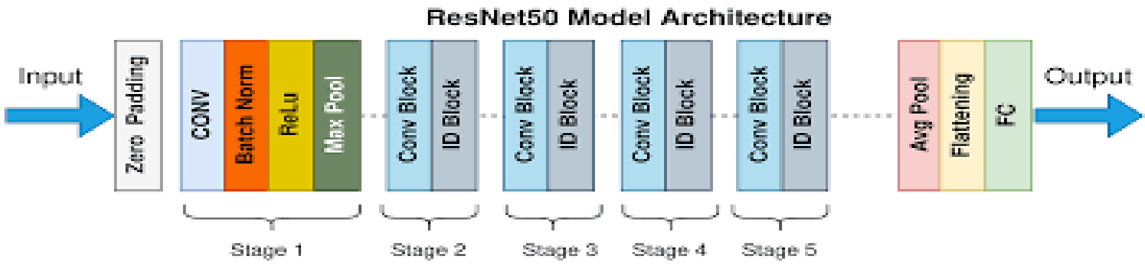

Fig. 2. ResNet Model Architecture.

1.2.4. UNet

The UNet model is well-known for its design, which consists of downsampling and upsampling as the two primary pathways [24]. Each iteration of the downsampling route comprises two rectified linear unit (ReLU)--activated convolutional layers that are 3 by 3, with the same amount of feature channels. After that, a 2-step pooling process with a 2-by-2 maximum size is performed. The number of feature channels starts at 64 and doubles with each successive downsampling step, reaching a maximum of 1024 channels at the end [25]. The upsampling procedure is a copy of the downsampling procedure, with the addition of a 2x2 up- Conv_Ly and a concatenation layer containing the feature map from the upsampling procedure. The following two layers are likewise ReLU-activated 3x3 convolutions. Each gradually decreasing size results in a decrease in the number of channels for features in these convolution layers, from 1024 to 64. Each of the 64 characteristics in the final feature map is categorized into one of the three target categories utilizing a SoftMax activation function, which is used in the final layer. There are no pre-trained weights utilized in the proposed network's training, and its 26 layers can handle 31 million parameters [26]. Fig. **3** presents the architectural structure of the UNet model [27].

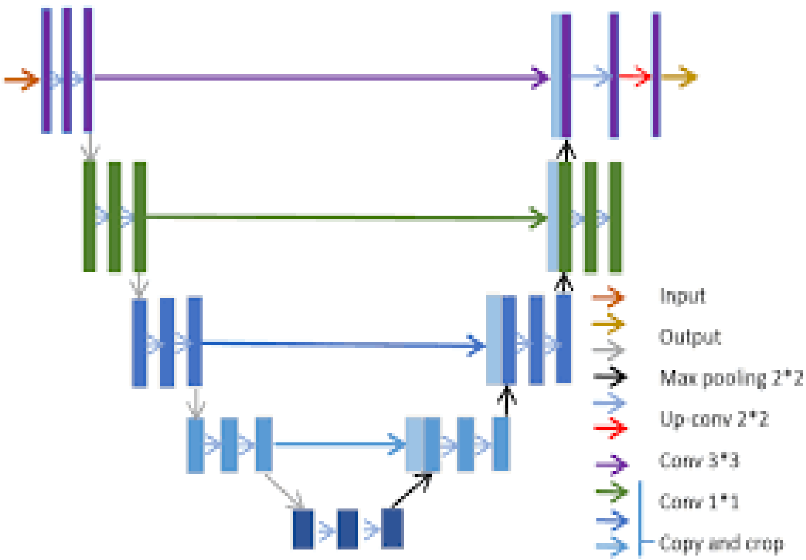

Fig. 3. UNet Model Architecture.

2. Related Works

A review of the literature reveals that many authors have attempted this method and published their results.

Michael et al. (2022) provided a procedure that a CAD program can optimize on its own.The majority of the 185 available characteristics are not utilized while training an ML model. Five AI classifiers were used to establish whether tumors were malignant or not. The experimental use of a DL classifier with 10-fold cross-validation led to the discovery of Bayesian optimization through a tree-structured Parzen estimator. The LightGBM classifier outperforms the other three classifiers in every metric: F1-score (99.80%), accuracy (99.86%), recall (99.50%), and precision (100.0%) [28].

Chowdhury et al. (2022) reported a method using CNNs and Transfer Learning for better breast cancer detection. The team debated using a pre-trained model to save time over manually assigning weights. This study specifically evaluates the ResNet101-based Transfer Learning Model and how well it performs on the ImageNet database. The suggested method improved accuracy to 99.58%. Extensive experimentation and hyperparameter adjustment were used to improve classification performance. Crucial in the fight against the illness, the suggested framework is intended to aid in the early detection of breast cancer [29].

Cassidy et al. (2022) explored the potential of a cloud-based and mobile-based system for the automatic identification of diabetic foot ulcers. The solution uses a unified mobile cross-platform architecture to make it easier to distribute TypeScript mobile applications on several devices. Diabetic foot ulcers were detected by training a DCNN on a cloud-based platform to which photos of patients' feet were uploaded through the mobile application. Medical efficacy and usability were the objectives of the system's evaluation by researchers from Salford Royal NHS Foundation Trust and Lancashire Teaching Hospitals NHS Foundation Trust [30].

Fagbuagun et al. (2022) showed that compared to prior systems, the proposed model is 1% more accurate, 1% more sensitive, and 1% more specific. Due to confounding factors including data set length and data pre-processing techniques, the current model for early identification of breast cancer still has space for development. Furthermore, it was shown that deployment strategies for Deep Learning (DL) models continue to influence the precision with which breast cancer is diagnosed [31].

Lilhore et al. (2022) used cloud-based IoT statistical analysis with fuzzy cluster-focused augmentation and optimum Support Vector Machine (SVM) classification to identify breast cancer infections earlier and improve medical therapy. With a focus on filtering in dynamic zones, the proposed technique uses fuzzy clustering to efficiently segment images. Fuzzy C-mean clustering and optimum support vector machine analysis are also used to characterize the region's traits and qualities throughout this transitional period [32].

Bhende et al. (2022) developed a breast mass identification model that required minimum distribution (RMD) based on deep pathological information mining. A shortage of samples limits the accuracy and applicability of the breast mass detection tool, which would assist doctors in identifying patients. Consequently, sample scarcity is actively addressed by selecting samples, deciding on features, and mining for cross-modal correlations. Experiments on two standard mammography image datasets reveal that the RMD model improves identification accuracy and that all three components (R, M, D) are beneficial. The RMD model's most notable feature is its multi-stage, layer-by-layer feature selection [33].

Ogundokun et al. (2022) suggested an IoT-based medical diagnostic approach for early detection of breast cancer. A comparison was made between the ANN and CNN with hyperparameter adjustment and the SVM, Multilayer Perceptron, and other conventional classifiers for malignant vs. benign categorization. Improving the classification performance of MLP and SVM was achieved via the use of a particle swarm optimization (PSO) feature selection approach, while the hyperparameters of the CNN and ANN models were optimized using a grid-based search. One such dataset is the Wisconsin Diagnostic Breast Cancer (WDBC) dataset. There was a 98.5% success rate with CNN and a 99.2% success rate with ANN in the proposed model's classification tests [34].

Peta et al. (2022) suggested a deep and efficient classification approach for breast cancer called the Student Psychology Whale Optimization-based Deep maxout network with optimization (SPWO-DMN). To successfully learn intrinsic properties from the data, a Deep max-out network is a great tool to use. An improved fitness measure-based update to the deep learning model's weighting function yields improved performance by learning to provide consistently low error rates across repeated runs. However, the suggested model achieves remarkable testing accuracy (0.931), testing sensitivity (0.953), and testing specificity (0.915) with a modest 100-node dataset [35].

Yu et al. (2021) devised a method using Extreme Learning Machine (ELM) to power a cloud-based breast cancer detection prediction. Because of the potential advantages of always-on system access, cloud computing might be useful in the healthcare industry. The suggested model also benefits from the cloud's availability of resources that contribute to its improved categorization accuracy. ELM's primary strength is that, unlike other gradient-based learning algorithms, it doesn't need the user to fine-tune the algorithm's settings (such as weights and biases). The research team suggested a cloud-based architecture for breast cancer analysis, wherein information would be gathered at rural healthcare facilities close to communities and communicated to specialists for further inquiry and additional patient guidance [36].

Mehmood et al. (2021) indicated that mammography is mostly used to diagnose breast cancer. Mammograms could detect Ductal carcinoma in situ (DCIS) and d lobular carcinoma in situ (LCIS) with the use of contrast-limited adaptive equalization of histograms performed during preprocessing. To further distinguish the tumor regions, threshold detection-like segmentation is used for the images. Images go through morphological processes including erosion and dilation, after which their texture properties are analyzed, and Harlick texture features or form attributes are extracted from the annotated regions. Normal and abnormal patterns are separated using an SVM classifier. SVM is utilized to gain an accurate classification of prior patterns, and the flexible neuro-fuzzy inference method is employed to account for the overlapping characteristics of the patterns inside the images [37].

Lahoura et al. (2021) proposed unifies three areas of study: ELM is initially utilized in the recognition of breast cancer. Second, the gain ratio feature selection technique is used to filter out superfluous details. Finally, the author presents an ELM cloud-based system for remote breast cancer diagnostics. The effectiveness of the cloud-based ELM is evaluated in light of current medical diagnostic tools Cloud-based ELM performed better on the Wisconsin Diagnostic Breast Cancer (WBCD) dataset. Comparing standalone and cloud settings, ELM performed better. Important experimental results include an F1-score of 0.8129, recall of 0.9130, precision of 0.9054, and accuracy of 0.9868 [38].

Klyushin et al. (2021) evaluated 130 people: 68 breast cancer patients, 33 fibroadenomatosis patients, and 29 healthy persons with an average of 52 buccal epithelial nuclei. 20,256 pictures of buccal epithelial interphase nuclei (6752 without filter, yellow filter, and violet filter) make up the dataset. Each photo has three color channels (RGB) and a grayscale channel (halftones). Cloud data storage, cloud-based categorization, and the use of Internet of Things technologies for patient communication all contribute to improved diagnostic precision and patient convenience [39].

Ray et al. (2020) suggested Apache Spark-based BC analysis and prediction on the same dataset. For large data sets like healthcare data, this big data approach is powerful. The dataset's key characteristics were selected using PCA. The author tested the top 6 and 10 features. Cincinnati's EECS department's Hadoop cluster hosts the experiments. The author also compared the performance of Decision Tree and Random Forest Classifier machine learning methods. Our study benchmarks Decision Tree performance with top 10 features. Random forest Classifier outperforms the Decision Tree method for the top 6 and top 10 attributes. The top 10 features yield 97.52 % accuracy for Random Forest. The correct qualities boost BC prediction accuracy, according to our findings [40].

Saba et al. (2019) proposed a blueprint with a cloud-based cancer diagnostics decision support system. The proposed approach employs shape-based properties in its search for tumor cells. To further identify cells as malignant or benign, these features are used by Naive Bayesian or ANN classification systems. Additionally, the suggested framework considered the assessment of the affected cells, which might assist in ranking crucial medical procedures for patients throughout the diagnostic process [41].

Khan et al. (2019) showed that worldwide, Cancer of the breast is the second leading killer among women ages 20-59. Death rates from breast cancer might be lowered via earlier detection and treatment. The author combines ML and artificial intelligence-based methodologies in e-health care service to develop a method for early diagnosis and a class of malignant cells using the Internet of Medical Things (IoMT) in breast cancer. The proposed technique for identifying malignant cells relies on the extraction of form and texture features for identification, and a trio of widely used classification algorithms for classification. The proposed method uses Evolutionary Algorithms (EA) to choose optimal attributes to reduce computer complexity and speed up the process of classification for cloud-based e-healthcare services [42].

Memon et al. (2019) applied a feature selection strategy that uses backtracking to enhance the breast cancer dataset. To find the most accurate prediction model, the classification algorithm is taught and evaluated using a training/testing split technique. F1 score, execution time, specificity, sensitivity, and classification accuracy are additional ways to evaluate a classifier's performance. Here, we tested the proposed approach using the "Wisconsin Diagnostic Breast Cancer" dataset. The effectiveness of the SVM classifier is supported by experimental findings that show how the ideal subset of features is selected utilizing the recursive feature selection technique. Classification accuracy, sensitivity, specificity, and Matthews' correlation are all 99% for the linear SVM kernel [43].

Akram et al. (2017) presented a comprehensive overview of breast anatomy, risk factors, epidemiology, pathogenesis, stages, diagnostic investigations, and treatment options including surgery, hormone replacement therapy, radiation therapy, chemotherapy, targeted therapies, hormone therapy, stem cell therapy, complementary therapies, gene therapy, and more [44].

3. Background study

Early identification and accurate staging are essential for the effective treatment of breast cancer, a very frequent malignant tumor in females. The development of automated detection systems is warranted due to the time and effort needed for human identification, the occurrence of pathological mistakes and inappropriate categorization, and the overall need. The author of this research introduces a convolutional neural network (CNN) - gated recurrent unit (GRU) hybrid DL model that can automatically identify invasive ductal carcinoma (IDC) (+, -) in breast pictures taken from entire slides. There were many metrics used to evaluate the model's performance, including precision, accuracy, sensitivity, specificity, AUC, and F1-Score. A total of 86.21% accuracy, 85.50% precision, 84.71% specificity, 88.10% F1-score, and 0.89% area under the curve were all attained by the suggested hybrid model, indicating excellent performance. Fixing the pathologist's error and miss classification problem was made easier using the hybrid model compared to competing ML/DL techniques. It was more resilient and effective [45].

4. Problem formulation

Breast cancer is the top frequent cancer in females and the principal cause of cancer demise globally; early detection is crucial for successful treatment. However, conventional mammography-based screening approaches, especially in low-resource settings, have limits in accuracy and cost-effectiveness. To solve this problem, a hybrid cloud architecture based on deep features has been suggested. This would boost screening precision while cutting expenses.The system takes photos as input, processes them via data reprocessing and image enhancement, and then divides them into training and testing sets. The images used in the tests are segmented with the help of the watershed method, and then the ROI is extracted and improved with the use of Error Level Analysis (ELA). Discrete Cosine Transform (DCT) and AlexNet methods are used for feature extraction and selection, while the UNet model substitutes the encoder ResNet 50 in system training. System production is forecasted, and the results are processed in the cloud infrastructure in response to user demands. The final objective is to develop an accurate ROI identification system that can be integrated into an existing cloud-based framework for automatic image processing.

5. Research objectives

- Developing a hybrid deep feature extraction method that can successfully extract high-level properties from mammography photos is crucial for assisting in the early detection of breast cancer.
- Developing a hybrid deep feature extraction cloud architecture is essential for real-time breast cancer detection.
- To explore the most recent breast cancer imaging deep learning models for feature extraction.
- To increase the accuracy of breast cancer diagnosis, a hybrid deep feature extraction approach combining different DL models is being developed.
- To develop and deploy a cloud architecture for managing massive amounts of breast cancer imaging data.

6. Proposed Methodology

The process involves acquiring a dataset of images, pre-processing them, and dividing them into training and testing data. Testing data is accessed from the cloud for faster processing. Image segmentation is performed using the watershed algorithm, and regions of interest are extracted and enhanced. Features are extracted using DCT and AlexNet, and important featuresare selected. The model is trained using UNet architecture with ResNet 50. After training, the model predicts outputs for new data. In the end, the data is sent to a cloud service for processing, such as a website or database.

In the following, the author will discuss a possible approach using the Fig. **5** architectural design as an example.

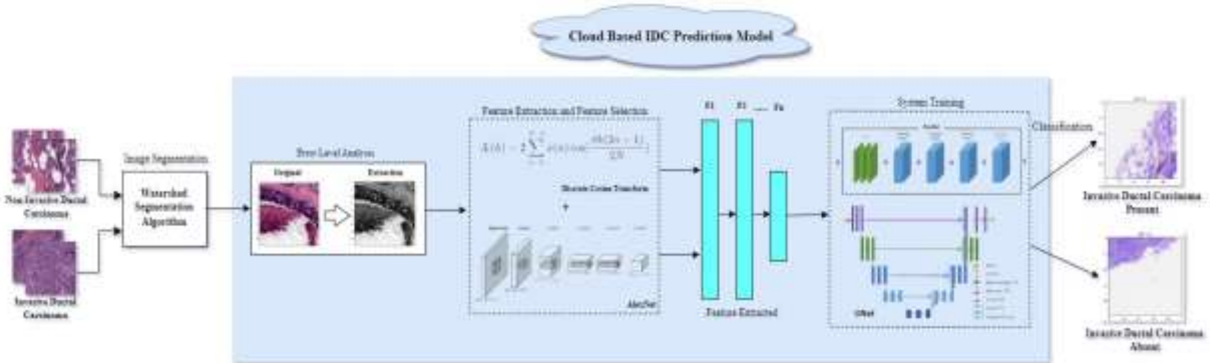

Fig. 5. Architectural Diagram of Proposed Methodology.

6.1. Proposed Algorithm

Cloud-Based Breast Cancer Classification Algorithm using Enhanced UNet and Image Enhancement
Step 1. Data Pre-processing: *I_preprocessed = DataPreprocessing (D)* ***Step 2. Image Enhancement:*** *I_enhanced = ImageEnhancement (I_preprocessed)* ***Step 3. Data Splitting:*** *D_train, D_test = SplitData (I_enhanced)* ***Step 4. Direct Cloud:*** *Cloud_output = CloudProcess (D_test)* ***Step 5. Image Segmentation using Watershed Segmentation Algorithm:*** *I_segmented = WatershedSegmentation (D_train)* ***Step 6. ROI Extraction and Enhancement using ELA:*** *ROIs = ROIFeatureExtraction (I_segmented)* *ROIs_enhanced = ELAEnhancement (ROIs)* ***Step 7. Feature Extraction from ROI using DCT and AlexNet:*** *features = DCT_AlexNet (ROIs_enhanced)* ***Step 8. Feature Selection:*** *selected_features = FeatureSelection (features)* ***Step 9. System Training using Enhanced UNet (Replace Encoder with ResNet50):*** *model = EnhancedUNet (ResNet50, D_train, selected_features)* ***Step 10. Output Prediction:*** *output = model. predict (D_test)* ***Step 11. Feed/Process into Cloud Framework based on Received Request:*** *result = CloudProcess (output)*

Let D represent the raw breast cancer data, I_preprocessed the data after preprocessing, I_enhanced the data after image enhancement, D_train the training data, D_test the testing data, I_segmented the image segmented utilizing the watershed segmentation algorithm, ROIs the region of interest extracted from the segmented images, ROIs_enhanced the region of interest enhanced with ELA, features the features extracted from the segmented images using DCT and AlexNet from the ROIs, selected_features be the selected features after feature selection, model be the trained UNet model with the encoder replaced by ResNet50.

7. Results and Discussions

7.1. *Performance Metrics*

The UNet + ResNet model's ability to accurately categorize IDC (+,-) tissue was evaluated using the following performance measures, which were considered and calculated.

- Positive IDC (+) samples were expected; hence this result is a true positive (TP).
- The term true negative (TN) is used to describe IDC (-) tissue samples that have tested negative.
- Negative IDC (-) samples that are incorrectly identified as positive IDC (+) constitute a false positive (FP).
- For an FN, it is expected that samples with a positive IDC (+) would be negative.

To diagnose breast IDC cancer, the following performance measures are used: F1 score, accuracy (Acc), precision (Prec), sensitivity (Sens), specificity (Spec), and, most importantly, the area under the curve (AUC) and Matthew's correlation coefficient (MCC).

$$Acc(\%) = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Prec(\%) = \frac{TP}{TP + FP}$$

$$Sen(\%) = \frac{TP}{TP + FN}$$

$$Spec(\%) = \frac{TN}{TN + FP}$$

$$F1 - Score(\%) = \frac{2 * Sens * Prec}{Sens + Prec}$$

$$MCC(\%) = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

7.2. Experimental Results

Hybrid DL models, including CNN-GRU and the proposed UNet + ResNet50 model, were used to experiment. Results from these approaches were evaluated using the testing dataset.

7.2.1. *Performance Metrics Analysis*

A classifier's accuracy is a crucial metric to examine when determining how well it performs. In addition, the term "precision" (Prec) refers to the measurable degree of accuracy achieved by real-time prediction. The F1 score has been used interchangeably with the term "TPR", andit has been used to examine a wide variety of IDC situations in the academic literature. A breast cancer IDC's stability might be roughly gauged using the F1 score. Additionally, the ratio used to differentiate across classes is shown by AUC. The suggested model was evaluated and compared to CNN-GRU of the BC-IDC (+,) detection based on the performance measure. The results were better with the proposed model.

The suggested techniques Acc, Prec, Sens, Spec, F1, and AUC of the suggested technique were 99.51, 89.94, 90.84, 88.58, 92, and 95 percent, respectively. The complete study of performance assessment indicators used for forecasting is shown in Fig. **6.**

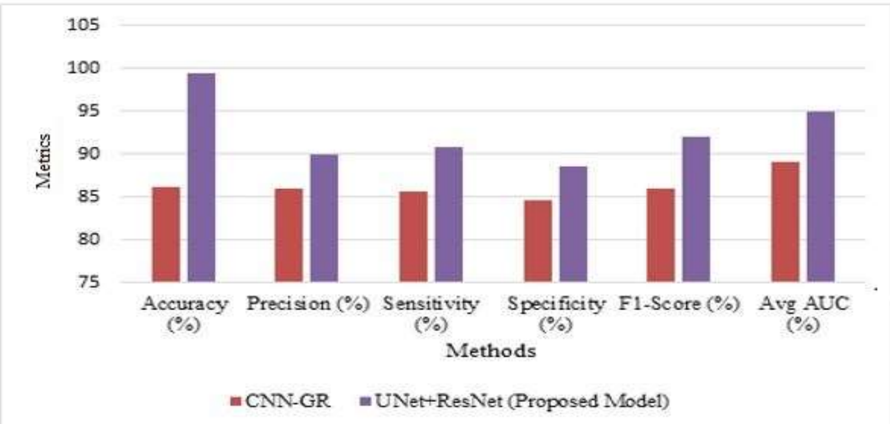

Fig. 6. Analysis of Performance Measures.

7.2.2. Confusion Matrix

The author used a confusion matrix to analyze how well the model classified data. The BC- IDC is properly categorized by the confusion matrix (plus, minus). On the same classification measure scale, CNN-GRU models and the UNet + ResNet50 are both examined and assessed. Fig.**7** shows the confusion matrix of CNN-GRU and Fig. **8** shows that the UNet + ResNet50 hybrid model successfully identifies BC-IDC (+,-), outperforming another model.

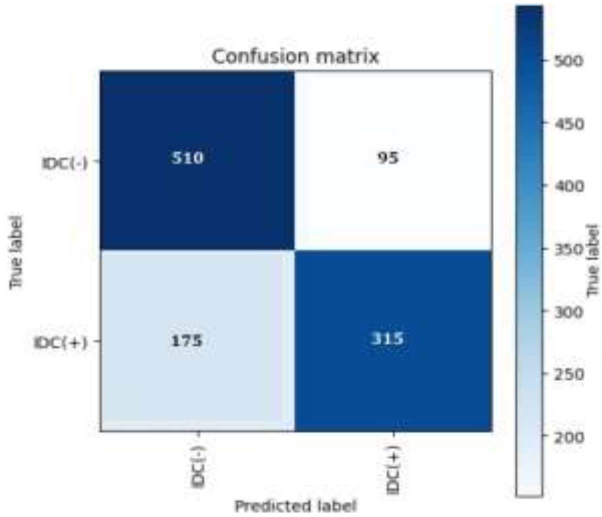

Fig. 7. Confusion Matrix of CNN_GR.

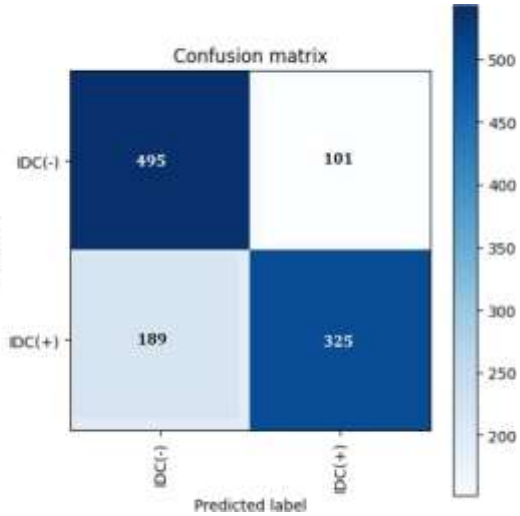

Fig. 8. Confusion Matrix of UNet+ResNet50.

7.2.3. FNR, FOR, FPR, and FDR Analysis

The suggested IDC breast cancer screening method could be further analyzed by a battery of important performance measures including false omission rate (FOR), false positive rate (FPR), false negative rate (FNR), and false detection rate (FDR). Fig. **9** displays that the UNet + ResNet50 model outperformed CNN-GRU, with an FPR of 0.001, FOR of 0.0014, FNR of 0.0002, and FDR of 0.0006.

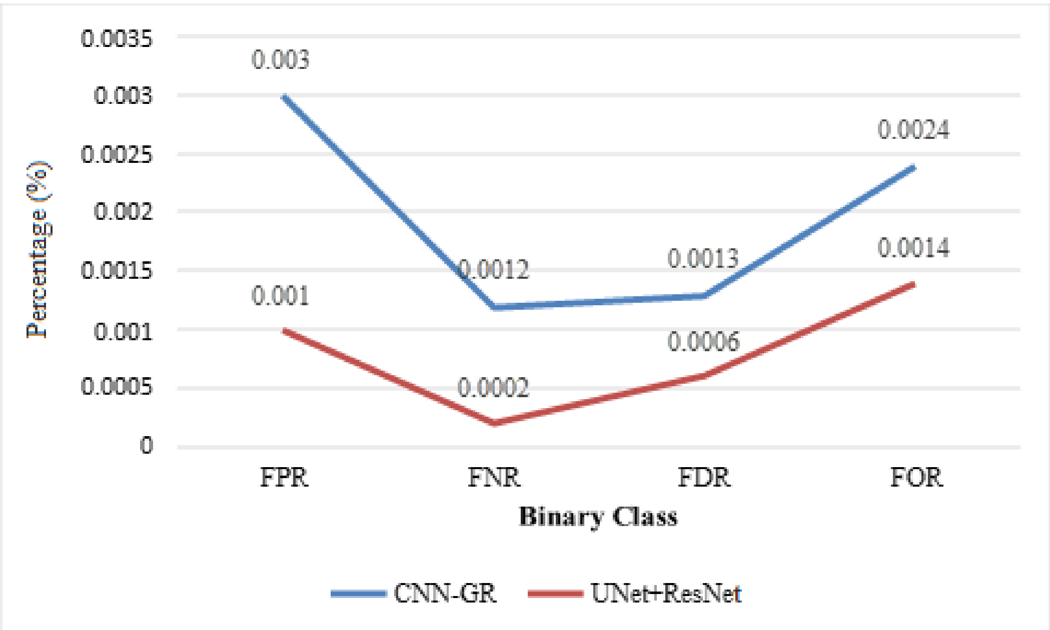

Fig. 9. Analysis of FNR, FOR, FPR, and FDR.

7.2.4. Assessing TNR, TPR, and MCC

A confusion matrix approach is used to determine the TNR, TPR, and MCC values to analyze the performance of the suggested hybrid model. Fig. **10** shows that the TPR, TNR, and MCC are 92.1%, 90.3%, and 89.9%, respectively. The results of the suggested UNet + ResNet50 model are superior to those of the previous hybrid model.

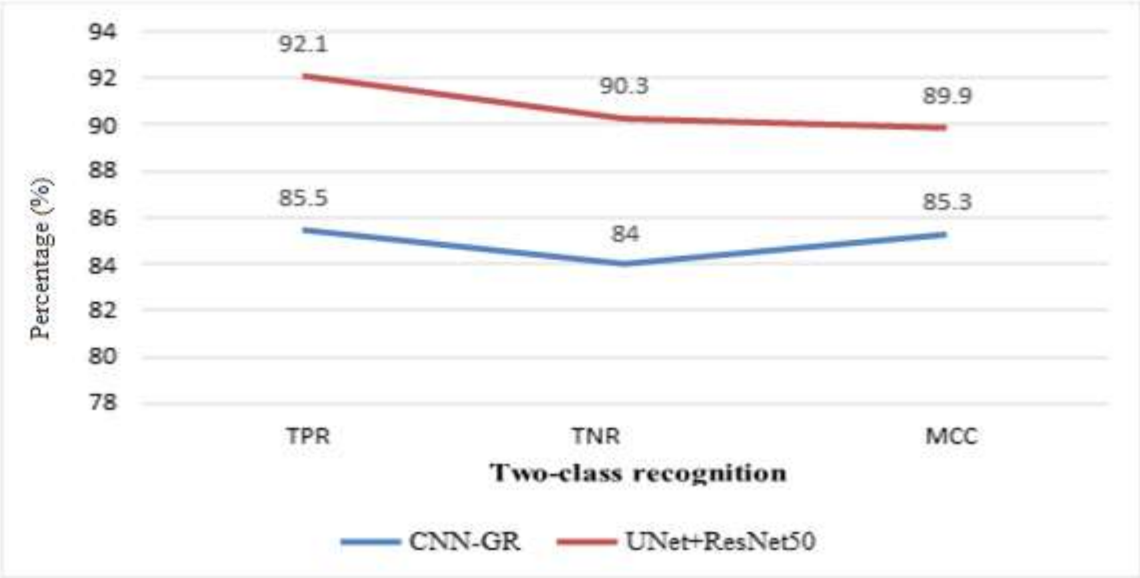

Fig. 10. TPR, TNR, and MCC.

7.2.5. Computational Time and Memory Usage

The algorithm's computational time and memory consumption are tracked every epoch while it is being trained. The provided Fig 11 shows the amount of time and memory used during each of the training epochs in seconds and megabytes, respectively. Fig. **11** shows that the computational time and memory usage are stable throughout the training epochs. The algorithm's scalability is demonstrated, suggesting it is ready for suitability for deployment in cloud environments with varying hardware configurations.

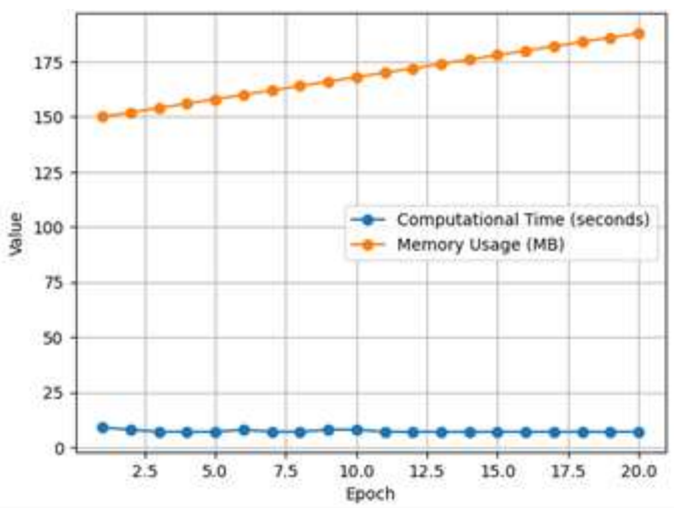

Fig. 11. Computational Time vs Memory Usage.

8. Comparison with other methods

Results from the proposed model are in line with those from DL approaches to breast cancer prediction that have been proposed more recently. Table 1 shows that the proposed model outdoes previous DL approaches in terms of learning success with low losses and having the smallest difference between validating and training levels of accuracy. There is conclusive evidence that the DL model performed well. The study, along with the precedent studies to which the results were compared, used precision as an indicator of success. However, the author employed assessment criteria including accuracy, precision, recall, and F1-score to convey the results of investigations more effectively. Fig. **12** represents the graphical representation of the comparison of the proposed method with other methods.

Table 1. Comparison with other methods.

Authors [References]	Technique	Accuracy
Wang et al. [45]	CNN-GRU	86.21%
Abunasser et al. [46]	Xception	97.60 %
Assegie et al. [47]	Adaptive Boosting (Adboost)	92.53 %
Robin et al. [48]	UNet	94.2 %
Tsehay et al. [49]	SVM	91.91%
Proposed Method	**UNet+ResNet50**	**99.51%**

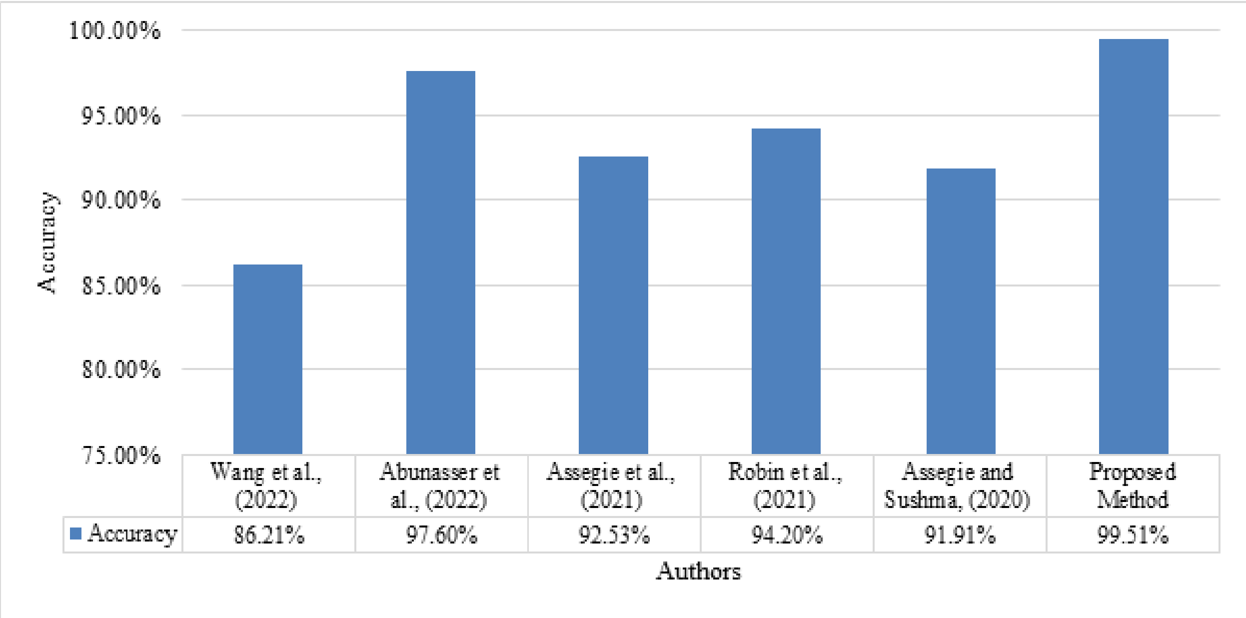

Fig. 12. Comparison with other methods.

9. Conclusion and Future Work

In conclusion, the development of a DL framework for breast cancer prediction using image processing and cloud-based analysis, specifically employing the UNet+ResNet50 architecture, represents a significant advancement in medical diagnostics. The proposed framework leverages the power of DL and combines it with sophisticated image processing techniques, thus offering a potentially promising solution for precise and efficient breast cancer detection. The UNet+ResNet50 architecture is capable of identifying breast cancer lesions from medical images by extracting complex features and leveraging contextual information. The model is trained using a large dataset and high computational resources, making it have higher accuracy in predicting whether one has breast cancer to enable early detection and timely intervention. Moreover, the framework incorporates cloud-based analysis which enhances its scalability and accessibility. Through leveraging the computational power and storage capacity of the cloud, this enables efficient processing of large datasets as well as facilitating collaboration amongst healthcare providers leading to better accuracy and diagnostic capabilities. Suggested method accuracy (91.15%), precision (89.94%), sensitivity (90.84%), F1-score (92%), and AUC (95%).

In the future, we will have to improve the performance of the framework by using more sophisticated methods of data augmentation, for example, rotation, scaling, and noise addition techniques that can make the model more robust and generalizable.

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