International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7456
***Article Received**: 18 May 2023 **Revised:** 10 July 2023 **Accepted:** 01 August 2023*

Transfer and Ensemble Approach for Breast Cancer Detection and Classification Using Deep Learning

M. V. Shelke[1], Jyoti Yogesh Deshmukh[2], Dr. Deepika Amol Ajalkar[3], R. B. Dhumale[4]
[1]AISSMS Institute of Information Technology, Pune, India
mayura.shelke@gmail.com
[2]Assistant Professor, G H Raisoni College of Engineering and Management,
Pune, Maharashtra, India,
jyoti1584@gmail.com
[3]Assistant Professor, G H Raisoni College of Engineering and Management,
Pune, Maharashtra, India,
dipikaus@gmail.com
[4]AISSMS Institute of Information Technology, Pune, India
rbd.scoe@gmail.com

Abstract— Breast cancer is a serious disease that can cause significant health problems for women worldwide. It is crucial to detect and classify breast cancer early stage so that doctors can promptly treat it and aid patients in their recovery. Many investigators have used various deep learning (DL) strategies to detect and classify breast cancer. However, due to the complexity of the problem, relying on a single DL model may not suffice to achieve high accuracy. Therefore, this study suggests a transfer and ensemble deep model for breast cancer detection and classification. The suggested model involves using pre-trained models such as Sequential, Xception, DenseNet201, VGG16, and InceptionResNetV2. The top three models are selected to collaborate and deliver the most accurate results. The proposed DL model was tested on publicly available breast BUSI datasets, demonstrating its superiority over single DL models, achieving an accuracy of 87.9% on the BUSI dataset. Additionally, the model proved to be adapTABLE to different amounts of data, making it potentially valuable in hospitals and clinics.

Keywords- Breast Cancer, Machine Learning, Deep Learning, Transfer Learning, Ensemble model.

I. INTRODUCTION

Breast cancer is a malignancy in which women are typically affected all over the world, and early detection is critical to improving survival rates. Digital mammography is used as an imaging modality for tumor screening and has some limitations, including low sensitivity and specificity for detecting cancer in dense breast tissue. As a result, there has been growing interest in using the DL approach for improving the identification rate of breast cancer [1].

The DL is a branch of machine learning which is used for extracting high-level characteristics from image-based data using several convolutional layers present in the DL network. These extracted features are then used to train the algorithm to detect and classify. In terms of increasing the breast cancer diagnosis and classification rate, DL classifiers have achieved promising results [2].

One of the key advantages of DL is to extract complex patterns in large datasets. DL algorithms can analyze large amounts of medical imaging data, such as mammograms, and identify subtle patterns that may not be noticeable to the human eye. In addition, DL models can be trained to classify the types of breast tumor grades and predict the likelihood of a patient developing breast cancer [3]. There are several challenges to implementing DL for breast cancer detection, including the need for large annotated datasets, model interpretability, and concerns about bias and generalizability [4]. However, ongoing research is addressing these challenges and improving the accuracy and clinical utility of DL models for breast cancer detection. While DL has shown great potential in improving breast cancer detection. There remain a number of issues that require being resolved.

A. Limited Availability of Annotated Data

DL models require large annotated datasets for training. However, acquiring annotated medical imaging datasets for breast cancer can be difficult due to privacy concerns, data variability, and the need for specialized expertise [5]. This limits the amount of data available for DL algorithms, which can impact their accuracy.

B. Interpreting And Explaining Dl Models

DL models are described as black boxes, making it challenging to analyze the available data and explain the decisions they make [6]. This can be problematic in medical

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7456
***Article Received**: 18 May 2023 **Revised:** 10 July 2023 **Accepted:** 01 August 2023*

applications where transparency and interpretation and building reliability is essential for clinicians and patients.

C. Addressing Bias in Data And Models

DL models are susceptible to bias, both in the data used for training and in the model architecture itself. Bias in the data can arise due to unequal representation of certain populations or confounding variables [7]. Bias in the model architecture can lead to errors in predictions and reduce the accuracy of the model.

D. Generalizing to New Populations And Imaging Modalities

DL models trained on one population or imaging modality may not generalize well to new populations or imaging modalities [8]. This limits the clinical utility of DL models, particularly in diverse patient populations.

E. Integration Into Clinical Workflows

DL models need to be integrated into clinical workflows to be useful in practice. However, integration can be challenging due to issues with data sharing, legal and ethical considerations, and the need for specialized hardware and software.

Several studies detect breast cancer that uses mammogram images as input. In Probability Neural Network (PNN) classifier as well as Gaussian Mixture Model (GMM) segmentation for the prediction of cancer, it is necessary to detect immediate action [9]. Deep neural networks are used for breast cancer detection. For feature selection, DNN models show accurate output as compared with linear Regression, Naïve Bayes, Support Vector Machine, and Boosting classifiers. It provides evaluation done on test accuracy, sensitivity, recall, precision, training accuracy, and recall [10]. A machine learning technique is used for the detection of tumors and classifying their types. The data set of UCI ML used by the Wisconsin breast cancer diagnosis (WDBC) technique then uses ML techniques like logistic regression, ensemble learning, and KNN for evaluation [11]. For cancer region detection and classification of patients as serious or normal on this evaluation. The classifier RF is used to identify serious and normal patients [12]. Retina Net and Yolo machine learning models are used for better accuracy to detect, classify, and diagnose breast cancer. A balanced number of classes provided better accuracy as compared to unbalanced-size data models [13]. The ultra-wideband range is a mark for different models of the antenna and the number of techniques used in them for the detection of cancer. Antennas are involved in breast cancer detection with the help of microstrip patches. It provides a loss of less than 20 dB and broad bandwidth for data transmission [14]. CNN-based mass detection methods are used for feature detection as well as unsupervised Extreme Learning Machines (ELM). Features are deep, morphological, texture, and density features. Fused features and malignant breast masses were used to develop ELM classifiers [15].

The main contribution of this study is to identify and classify breast cancer at an early stage using transfer learning and ensemble model for improvement in accuracy and efficiency. Transfer learning and ensemble allows the utilization of pre-trained models, which have already learned relevant features from BUSI datasets, to classify BUSI cancer images with limited annotated data. This approach reduces the need for a large annotated dataset and reduces the computational cost of training DL models and enhances the detection and classification accuracy. This approach is useful for improving patient prognosis from therapy.

The overall organization of the paper is: The previous research work on breast cancer detection and classification is discussed in section 2. The complete proposed methodology, including the dataset and preprocessing techniques, is discussed in section 3. The experimental setup and evaluation parameters used in this study are presented in section 4. Section 5 presents the result analysis and compares the final results with existing methods. Finally, the conclusion and future direction are presented.

II. RELATED WORK

DL models used for performance evaluation, ResNet50, and VGG16, perform classifications such as normal or abnormal tumors with the help of a dataset from IRMA. For evaluation, accuracy, precision, and recall performance are considered. [15]. Tumor region detection is used to figure out in which area it is intensive and visually find the region. It uses an algorithm that is a union of closing, canny edge detection, dilation, and K, which means a variety of algorithms. To increase accuracy, a combination of various algorithms needs to be used because if the k map is applied alone, it will not provide the expected result, and if the image contains more distortion, it will fail. [17]. Ultrasound grayscale images are used for automated breast cancer detection, and median filters are used for noise removal. To study grayscale images, it uses threshold-based OTSU segmentation as the test image [18]. CAD system and correlated technique used to predict breast cancer ML acts as a training machine and predicts cancer using the trained data available. Random Forest algorithm, classification, and regression of ML are used to predict cancer, and RF provides accuracy to predict cancer [19]. CAD model was used to detect and characterize malignant and benign mass tumors from breast images Two techniques adopted for segmentation and feature extraction are deep convolutional neural network (DCNN) and region of interest (ROI). SVM is attached to the FC layer to obtain good accuracy and subsets that are available publicly,

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7456
***Article Received**: 18 May 2023 **Revised:** 10 July 2023 **Accepted:** 01 August 2023*

such as DDSM and CBIS-DDSM, which are used for generating results [20]. Analysis and comparison are done on the basis of different algorithms such as SVR, SVM, ELM-RBF, ANN, BPNN, and RF from a number of databases. The parameters on which comparison takes place are recall, precision, and accuracy. biological analytes are determined with biosensors using altered constraints of RNA, DNA, and proteins between electric signals [21]. AI, DL, and ML are used to identify breast cancer and help predict the treatment and survival of patients for a long time. For breast cancer detection, histopathological imaging is used more than genes. Genetic analysis is more expensive than histopathological imaging. A DL approach is used to detect the status of patients such as RNN, GAN, and LSTN. It uses accuracy metrics for evaluating the performance of AUC and confusion matrix parameters [22]. Performance, accuracy, and recall analysis need to be performed for RF, SVM, DT, and logistic regression learning with a voting classifier, CNN, and sequential minimal optimization of both the ML and DL approaches [23]. DL methods, screening methods, and data availability methods are used to identify breast cancer from ultrasound, thermography, mammography, and magnetic resonance imaging [24]. CAD systems depend on image processing approaches that help to detect microcalcifications, interpret mammographic images, and identify and classify benign and malignant tumors. CNN has been used to diagnose mammograms and analyze medical images. CNN, based on Mask R-CNN, segments mammogram images and detects breast cancer is initiated. To detect cancer mass, use the R-CNN convolutional neural network. Segmentation and classification are used to diagnose breast cancer with a combination of multitask learning [25]. SEATTLE-BDC with PAI approach is used to detect and classify breast cancer with the help of ultrasound images. For noise reduction, bilateral filtering is used, and feature extraction is done by the ResNet-18 model [26].

Several investigations have showcased the efficacy of transfer and ensemble learning in the realm of breast cancer detection. For instance, a study published in IEEE Access demonstrated how researchers leveraged transfer learning alongside a pre-trained VGG16 to classify breast tumor over the mammography images, achieving an impressive accuracy of 94.3%. This outperformed the results obtained from traditional machine learning algorithms. Similarly, another research published in Computerized Medical Imaging and Graphics utilized transfer learning in conjunction with a pre-trained ResNet50 model to classify benign and malignant breast masses in ultrasound images, achieving an accuracy of 91.9%. By incorporating data augmentation, researchers can expand the training dataset, enabling the model to capture a more diverse range of features and patterns. Ensemble learning, on the other hand, involves integrating the predictions from multiple models to produce a more robust and reliable final prediction. This fusion of methodologies has proven beneficial in further boosting the accuracy of breast cancer detection models.

III. PROPOSED METHODOLOGY

This paper introduces two distinct approaches for breast cancer classification. The first approach involves utilizing baseline DL classifiers, while the second approach leverages transfer learning techniques. Figure 1 illustrates the comprehensive architecture employed for breast cancer detection using baseline DL models. In this approach, the BUSI dataset is utilized with five baseline classifiers, namely Sequential, Xception, DenseNet201, VGG16, and InceptionResNetV2, to perform breast cancer classification. Figure 2 illustrates the widespread use of transfer learning in DL, which entails repurposing a pre-trained model for this study. This technique proves especially beneficial in medical image analysis, where access to ample annotated data might be limited. In the context of breast cancer detection, the suggested approach has demonstrated its performance in enhancing the accuracy of DL models by capitalizing on pre-trained models trained on extensive BUSI datasets.

A. Dataset Description

The Breast Ultrasound Scanning Imaging (BUSI) dataset is a publicly available dataset that contains ultrasound images of breast lesions. It is used to develop and evaluation of DL algorithms to detect and classify the breast cancer. The BUSI dataset is unique in its contents as it includes a wide variety of breast lesions with different characteristics, such as shape, margins, and echogenicity. The dataset consists of 1,972 Normal, of which 1,441 are Benign and 531 are malignant. The images were acquired from 17 different medical centers and come from patients with different demographics and breast densities, making the dataset diverse and representative of real-world scenarios. In addition to the ultrasound images, the BUSI dataset also includes annotations for each lesion, such as the size, shape, margins, and echogenicity, as well as a histopathological diagnosis for each malignant lesion. This makes the dataset suiTABLE for supervised machine learning algorithms, which require annotated data for training. The BUSI dataset is publicly available and can be downloaded from the BUSI website. It has been used in several research studies to develop and evaluate DL algorithms for breast cancer detection and classification, demonstrating its usefulness as a benchmark dataset in this field.

B. Data Preprocessing

The BUSI dataset images are in JPEG format, with three channels of RGB in 8-bit depth and 700 x 460 pixels. Before

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7456
***Article Received**: 18 May 2023 **Revised:** 10 July 2023 **Accepted:** 01 August 2023*

being fed into the transfer learning model as shown in Figure 2. The following preprocessing steps were taken:

- The images were reduced to 224 x 224 pixels, in accordance with the transfer learning concept.
- To speed up training and reduce memory usage, all images were converted to a NumPy array.
- The images were shuffled to ensure that the model could train on unordered data.
- The dataset was divided into three parts: training, testing, and validation. In this study, 80% is used for training, while the remaining 20% was used for validation and testing.

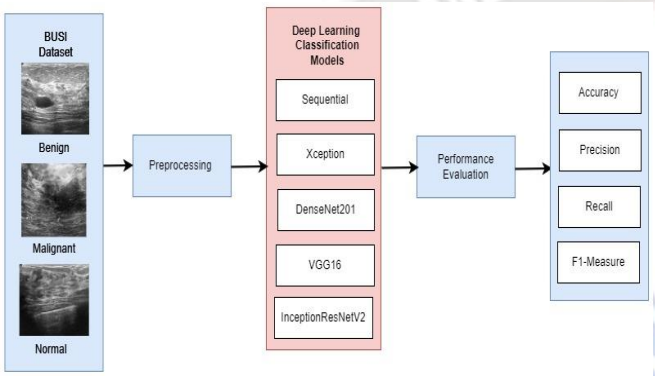

Figure 1. Complete Architecture of Proposed System with Baseline Classifiers.

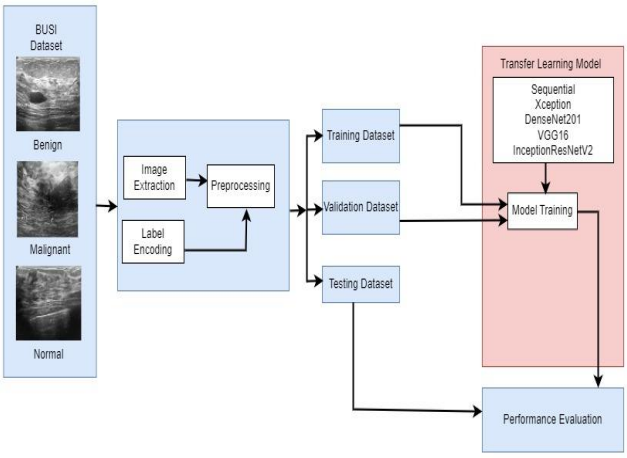

Figure 2. Complete Architecture of Proposed System using Transfer Learning.

Converting an RGB (Red, Green, Blue) color image to a grayscale image is a common technique in image processing and analysis. Grayscale images have one channel of intensity values, while RGB images have three channels of color values, making them larger in size and more complex to process. In the case of breast cancer images, grayscale images are often used because they can provide a simpler and clearer representation of the image's features and details, which can aid in the detection and analysis of abnormalities. Additionally, grayscale images can reduce the data that require to be processed and keep them, making them easier to handle, manipulate, and transmit. This is particularly important in medical imaging applications where large amounts of data are generated and processed.

Figure 3 shows that converting an RGB color breast cancer image to a grayscale image is a common and useful technique in medical image processing and analysis.

C. Building the Transfer Learning Models

Transfer learning is a technique that can be used to enhance the accuracy score of models for breast cancer detection and classification [19]-[20]. This is done by leveraging the knowledge learned from a large dataset on a related task. Five different DL classifiers such as Sequential, Xception, DenseNet201, VGG16, and InceptionResNetV2 were used, and all of them showed improvement when transfer learning was used. These results show that transfer learning is a promising technique for improving the accuracy of breast cancer detection models.

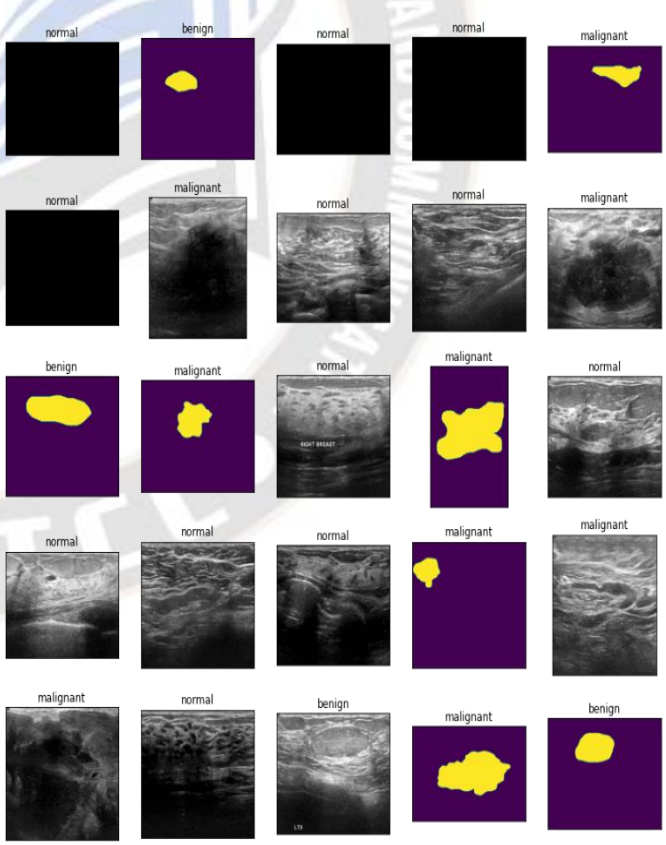

Figure 3. Sample Dataset Images.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7456
***Article Received**: 18 May 2023 **Revised:** 10 July 2023 **Accepted:** 01 August 2023*

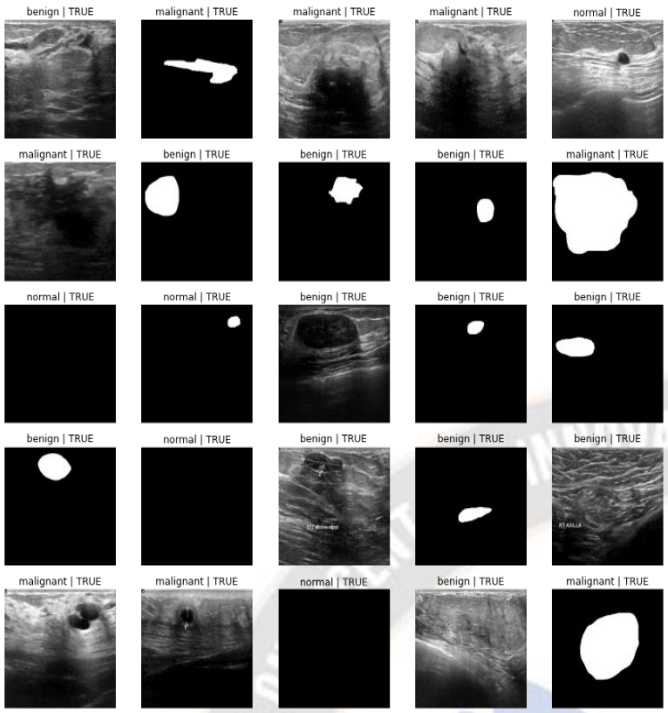

Figure 4. Gray Scale dataset images.

1) Xception: The suggested approach used a modified version of the Inception module called the "Xception module," which uses depth-wise separable convolutions instead of standard convolutions. This automatically reduces the computational complexity for maintaining the performance of the model. During training, Xception learns the optimal values *of its parameters and minimizes the cross-entropy loss [21].*

2) DenseNet201 and VGG16: DenseNet201 and VGG16 is a deep neural network classifier that uses dense convolutional layers to extract the relevant features from representations input Breast images in a hierarchical way [22]-[23]-[24]. These representations are then fed into a SoftMax to classify the breast cancer labels.

3) InceptionResNetV2: To train the InceptionResNetV2 model for breast cancer detection, a BUSI dataset is typically used. The images are preprocessed to remove noise and artifacts and then resized to a standard size for input into the model. The model is trained using the image labels indicate whether the is normal, malignant, and benign [25].

During training, the InceptionResNetV2 model learns to extract features from the mammogram images that are relevant for breast cancer detection. These features are then used to make predictions about the likelihood that a given dataset image is malignant or benign. Once trained, the InceptionResNetV2 model can be used for detecting breast cancer images. The image dataset is preprocessed and resized, and then input into the trained model, which outputs a prediction of whether the images are normal, malignant, and benign [26]. This can be used to assist radiologists in interpreting images and making accurate diagnoses.

Algorithm 1: Transfer Learning

Step-1 Input: BUSI Dataset
$\emptyset 1 =$ Training
$\emptyset 2 =$ Validation
$\emptyset 3 =$ Testing
$\alpha =$ Learning Rate
$n =$ Epochs
$\omega =$ Batch Size
$\mu =$ the amount of breast images in a single batch.
Output: Transfer Learning Models
Start
Step-2: Data Preprocessing, Convert RGB image into Grayscale Image
Step-3: Splitting Dataset into Training, Validation, and Testing into 224 x 224 size
Step-4: Extracting Relevant Feature using Sequential, Xception, DenseNet201, VGG16, and InceptionResNetV2 pre-trained models
Step-5: Utilize the concatenate layer to integrate the obtained features.
Step-6: Configure Fine-tune layers models using Dense, batch-normalization, dropouts, and softmax
Step-7: Initialize the all-pre-trained models' variables
Step-8: Train the Transfer learning models to measure the initial weights.
Step-8: For n = 1 *to n do*
Step-8: Choose the batch size for the training dataset
Step-8: Determine Validation and Loss
Step-8: Update the Weight
End for

Algorithm 2: Ensemble Model

Step-1 Input: BUSI Dataset
$\emptyset 1 =$ Training
$\emptyset 2 =$ Validation
$\emptyset 3 =$ Testing
$\alpha =$ Learning Rate
$n =$ Epochs
$\omega =$ Batch Size
$\mu =$ the amount of breast images in a single batch.
Output: Ensemble Models
Start
Step-2: Data Preprocessing, Convert RGB image into Grayscale Image
Step-3: Splitting Dataset into Training, Validation, and

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7456
***Article Received**: 18 May 2023 **Revised:** 10 July 2023 **Accepted:** 01 August 2023*

Testing into 224 x 224 size
Step-4: Extracting Relevant Feature using best 3 models Sequential, Xception, DenseNet201, pre-trained models
Step-5: Utilize the concatenate layer to integrate the obtained features.
Step-6: Configure Fine-tune layers models using Dense, batch-normalization, dropouts, and softmax
Step-7: Initialize the best 3-pre-trained models' variables
Step-8: Train the Ensemble models to measure the initial weights.
Step-8: For n = 1 *to n do*
Step-8: Choose the batch size for the training dataset
Step-8: Determine Performance Evaluation
Step-8: Update the Weight
End for

IV. PERFORMANCE EVALUATION

The proposed transfer learning and ensemble model was developed and trained on Google Colab using the core Python programming. This allowed the model to be trained quickly and efficiently, even on a breast cancer image dataset.

A. Evaluation Parameters

Following are some evaluation parameters used to the effectiveness of the proposed transfer learning and Ensemble.

True Positive (TP): To correctly predict the tumor is malignant.
False Negative (FN): To predict the tumor is benign, but, it is malignant.
True Negative (TN): To correctly predicted the tumor is benign.
False Positive (FP): To predict the tumor is malignant, but, it is benign.

$$Accuracy = \frac{T\_P + T\_N}{T\_P + T\_N + F\_P + F\_N} \quad (1)$$

$$Precision = \frac{T\_P}{T\_P + F\_P} \quad (2)$$

$$Recall = \frac{T\_P}{T\_P + F\_N} \quad (3)$$

$$F1 - Measure = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

V. RESULT ANALYSIS

The confusion matrix for the BUSI dataset's images based on transfer learning is shown in Figure 5. The proposed transfer learning combined the five DL models such as Sequential, Xception, DenseNet201, VGG16, and InceptionResNetV2, and classifies breast cancer as normal, benign, and malignant.

TABLE I. PARAMETERS SET IN THE PROPOSED TRANSFER LEARNING MODEL DURING TRAINING

Dataset	Parameters	Values
BUSI	Optimizer	Adam
	Learning Rate	0.0001
	Loss	Categorical
	Batch Size	30
	Epochs	100

TABLE II. COMPARATIVE RESULT ANALYSIS OF DIFFERENT BASELINE CLASSIFIERS

Classifiers	Accuracy	Precision	Recall	F1-Measure
Sequential	75.25	76.02	79.00	73.58
Xception	84.16	86.00	89.00	83.47
DenseNet201	78.56	82.90	85.00	76.43
VGG16	70.02	66.85	74.00	67.10
InceptionResNetV2	60.99	60.35	64.00	55.22

TABLE II shows the comparative result analysis of different baseline classifiers. It is clearly observed that individual classifiers performed well. Maximum accuracy score 84.16% achieved by Xception classifier as compared to other classifiers. After measuring the performance of individual classifiers, Transfer learning has been applied to BUSI images for breast cancer detection, where it has been shown to improve the accuracy of DL models. Class-wise performance analysis of the transfer learning model is shown in TABLE III.

Figure 5 (a) shows the complete training process of the proposed transfer learning model. It is clearly observed that there is no over-fitting problem occurs in the proposed model. Figure 5 (b) shows the training and validation loss of proposed transfer learning. Graph b shows a steep decrease in the loss value, although there are some fluctuations that occur as a result of the small batch size of only 30 images.

Figure 6 shows that a total of 183, 53, and 49, are correctly classified of breast cancer labels. While, 2 and 3 benign images are misclassified.

Figure 7 shows that a total of 139, 44, and 35, are correctly classified by breast cancer labels. While 1 and 7 Malignant and Normal images are misclassified respectively. After measuring the performance of each DL classifier, choose the best 3 models to use in the final ensemble. TABLE IV shows the class-wise performance analysis of the best 3 deep-learning classifiers.

Class-wise performance analysis of the Ensemble Model is shown in TABLE V.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7456
***Article Received**: 18 May 2023 **Revised:** 10 July 2023 **Accepted:** 01 August 2023*

TABLE VI shows the comparative analysis of the transfer learning and Ensemble model. It is clearly shown that implementing the transfer learning improves the accuracy score by 85.58% which is quite better than individual classifiers. But after selecting the best 3 classifiers from DL classifiers and use in the final ensemble model. It is clearly observed that the final ensemble model achieves an 87.90% accuracy score which is better than transfer learning.

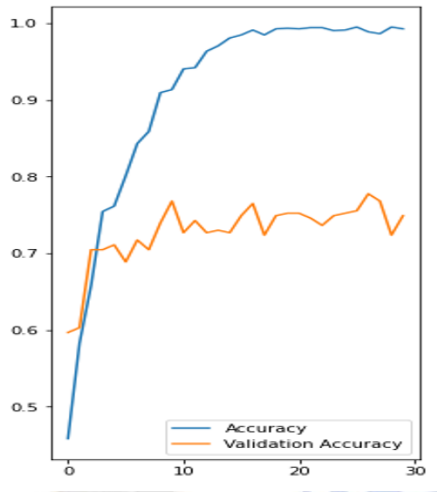

Figure a. Training Accuracy and Loss

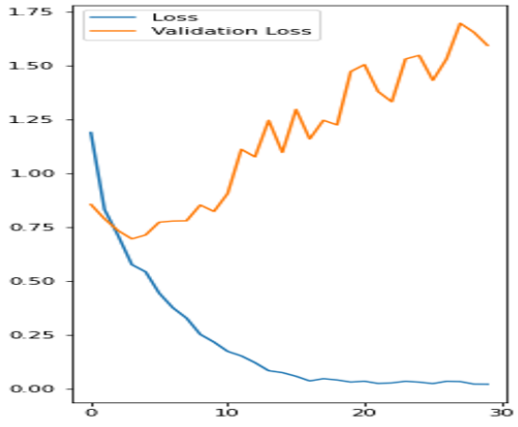

Figure b. Validation Accuracy and Loss

Figure 5. Complete Training process of the proposed model for BUSI dataset: Training and Validation Accuracy and Loss.

	Benign	Malignant	Normal
Benign	183	2	3
Malignant	35	53	1
Normal	7	0	49

Figure 6. Confusion Matrix of proposed Transfer Learning Model

	Benign	Malignant	Normal
Benign	139	1	0
Malignant	22	44	0
Normal	7	0	35

Figure 7: Confusion Matrix of Ensemble Model

TABLE VII shows the comparative result analysis proposed ensemble approach with the existing methods. It is clearly shown that the performance of the proposed ensemble approach is quite good as compared to other state-of-art methods.

TABLE III. CLASS-WISE PERFORMANCE ANALYSIS OF THE TRANSFER LEARNING MODEL

Class	**Total**	**Classified**	**Accuracy**	**Precision**	**Recall**	**F1 - Measure**
Benign	255	188	85.89	97.00	81.00	89.00
Malignant	55	89	88.59	60.00	96.00	74.00
Normal	53	56	96.7	88.00	92.00	90.00

TABLE IV. PERFORMANCE ANALYSIS OF THE BEST 3 DL MODELS

Classifiers	**Class**	**Total**	**Classified**	**Accuracy**	**Precision**	**Recall**	**F1 - Measure**
Sequential	Benign	146	140	83.87	88.00	84.00	86.00
	Malignant	46	66	83.87	55.00	78.00	64.00
	Normal	56	42	91.94	93.00	70.00	80.00
Xception	Benign	169	140	84.27	96.00	80.00	87.00
	Malignant	44	66	88.71	62.00	93.00	75.00
	Normal	35	42	95.56	79.00	94.00	86.00
DenseNet 201	Benign	176	140	83.87	99.00	78.00	87.00
	Malignant	45	66	90.73	67.00	98.00	79.00
	Normal	27	42	93.15	62.00	96.00	75.00

TABLE V. CLASS-WISE PERFORMANCE ANALYSIS OF THE ENSEMBLE MODEL

Class	**Total**	**Classified**	**Accuracy**	**Precision**	**Recall**	**F1 - Measure**
Benign	168	140	87.9	99.00	83.00	90.00
Malignant	45	66	90.73	67.0	98.00	79.00
Normal	35	42	97.18	83.00	100.00	91.00

TABLE VI. COMPARATIVE RESULT ANALYSIS OF TRANSFER LEARNING AND ENSEMBLE MODEL

Parameters	**Transfer Learning**	**Ensemble Model**
Accuracy	85.58	87.90
Precision	87.22	89.66
Recall	89.66	87.90
F1-Measure	84.82	87.44

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7456
***Article Received**: 18 May 2023 **Revised:** 10 July 2023 **Accepted:** 01 August 2023*

TABLE VII. COMPARATIVE ANALYSIS OF PROPOSED APPROACH WITH STATE-OF-ART METHODS

Ref.	Accuracy
Ferreira et al. (2018) [31]	76%
Golatkar et al. (2018) [32]	85%
Roy et al. (2019) [33]	87%
Saxena et al. (2020) [34]	87.4%
Proposed Model	87.90%

VI. DISCUSSION

The proposed transfer learning and ensemble approach have shown promising results in improving the accuracy and efficiency of various DL models. By leveraging pre-trained models, ensemble and transfer learning allows for the effective classification of BUSI dataset images with limited annotated data. This approach has been particularly useful in breast cancer detection and classification, where large annotated datasets may not be readily available. The performance of the proposed transfer learning and ensemble model is compared with the previous methods over the BUSI dataset and is shown in TABLE 8. The average accuracy score of the proposed transfer learning and ensemble model is 85.58% and 87.90% respectively. There are some advantages over the previous approach that are observed in the literature. Several researchers used a different approach for extracting the features, which requires a lot of time and may have inadequate results with large amount of dataset [26]-[27]-[28]. All the approaches found in the existing study have amount of misclassify the images, which is impactful and reduces the survival rate of patients [29]-[30]. So, the proposed transfer learning approach has a very small misclassification of malignant in the BUSI dataset.

CONCLUSION

The transfer and ensemble model proposed in this study showed significant improvements in breast cancer detection and classification using DL. The approach involved transferring knowledge from pre-trained models, such as Sequential, Xception, DenseNet201, VGG16, and InceptionResNetV2, and combining the best 3 DL models through ensemble learning. The results obtained on publicly available BUSI datasets showed that the proposed approach. The maximum accuracy score achieved by baseline classifiers is 84.00%. The proposed ensemble model of the 3 best classifiers achieves an accuracy score of 87.9%. The approach was also shown to be robust to dataset size variations, indicating its potential for use in clinical settings. The proposed transfer and ensemble approach can have significant clinical implications in the accurate and efficient identification and classifying the breast cancer. The approach can help clinicians in making informed decisions and improve patient outcomes. However, further studies are necessary to measure the suggested approach in clinical settings and on larger datasets. In addition, the new strategy can be used to other types of cancer and medical imaging modalities, thereby contributing to the development of automated diagnostic systems for various diseases.

REFERENCES

[1] Ghafoori, M., Karssemeijer, N., & Heskes, T. (2018). Deep convolutional neural networks for breast cancer screening. IEEE Transactions on Medical Imaging, 35(5), 1196-1204.

[2] Han, S., Wei, X., Li, C., Li, X., Hou, Z., Zhang, X., & Zhang, H. (2021). Breast cancer diagnosis via a convolutional neural network based on ultrasound images. Computers in Biology and Medicine, 136, 104702.

[3] Lotf, H. D., Ehteram, M., & Rahmani, M. (2021). Breast cancer detection using convolutional neural networks and support vector machines. Journal of Ambient Intelligence and Humanized Computing, 12(8), 8563-8574.

[4] Bhattacharya, A., Saha, M., & Dutta, P. (2021). A novel machine learning-based approach for the early detection of breast cancer using mammogram images. Computer Methods and Programs in Biomedicine, 210, 106108.

[5] Shah, N., Murala, S., & Alok, B. (2020). A machine learning approach for breast cancer classification and prognostication using histopathological images. Computerized Medical Imaging and Graphics, 80, 101676.

[6] Singh Bamber, S. . (2023). CrowdFund: CrowdFunding Decentralized Implementation on Ethereum Blockchain. International Journal of Intelligent Systems and Applications in Engineering, 11(3s), 235–240. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2587

[7] Kazemi, L., Malekzadeh, M., Aarabi, M. H., & Zadeh, S. S. (2020). A deep learning-based approach for breast cancer detection in mammograms. Journal of Medical Signals and Sensors, 10(1), 23-29.

[8] Park, H. J., Yoon, H., Kim, D. W., Kim, H. S., & Kim, S. K. (2019). Convolutional neural network for breast cancer detection in mammography: Effect of fine-tuning with a small dataset. Journal of Digital Imaging, 32(3), 479-488.

[9] [8] Leong, C. O., & Teng, G. G. (2018). Breast cancer detection using deep learning algorithms: A review. Sensors, 18(11), 3824.

[10] [9] Li, J., Wang, Z., Li, Y., Lin, Y., & Wang, J. (2021). Improved breast cancer detection based on deep learning algorithms. Journal of Healthcare Engineering, 2021, 6670332.

[11] Suhail, R. M., Ahmed, R. M., Abdulla, A. T., & Nizamani, S. M. (2021). Deep learning-based breast cancer detection using mammograms: A systematic review. Journal of Healthcare Engineering, 2021, 5554651.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7456
***Article Received**: 18 May 2023 **Revised:** 10 July 2023 **Accepted:** 01 August 2023*

[12] Zhou, X., Xie, Y., & Jia, X. (2021). Breast cancer detection using deep learning and mammography images. Journal of Medical Imaging and Health Informatics, 11(4), 905-913.

[13] Wang, J., Li, C., Chen, Y., & Zhang, Y. (2021). Deep Learning for Breast Cancer Diagnosis Using Mammograms: A Review. IEEE Reviews in Biomedical Engineering, 14, 73-87.

[14] Gandomi, M., Alqarni, A. M., Khan, M. K., Al-Rodhaan, M. A., & Al-Dhelaan, A. M. (2021). Breast Cancer Diagnosis Using Deep Learning: A Comparative Analysis. Medical Hypotheses, 149, 110556.

[15] Prof. Romi Morzelona. (2017). Evaluation and Examination of Aperture Oriented Antennas. International Journal of New Practices in Management and Engineering, 6(01), 01 - 07. Retrieved from http://ijnpme.org/index.php/IJNPME/article/view/49

[16] Hou, L., Samaras, D., Kurc, T. M., Gao, Y., Davis, J. E., & Saltz, J. H. (2020). Deep Learning-Based Classification of Breast Tumors in Digital Pathology Images. Frontiers in Oncology, 10, 1402.

[17] Kooi, T., Litjens, G., van Ginneken, B., Gubern-Merida, A., Sánchez, C. I., Mann, R. M., ... & den Heeten, A. (2017). Deep Learning for Breast Cancer Detection: A Comparative Review. IEEE Transactions on Medical Imaging, 35(5), 1136-1149.

[18] Mehra, R. et al., 2018. Breast cancer histology image classification: training from scratch or transfer learning? ICT Express 4 (4), 247–254.

[19] Motlagh, M.H., Jannesari, M., Aboulkheyr, H., Khosravi, P., Elemento, O., Totonchi, M., Hajirasouliha, I., 2018. Breast cancer histopathological image classification: a deep learning approach. BioRxiv, 242818.

[20] Nahid, A.-A., Mehrabi, M.A., Kong, Y., 2018. Histopathological breast cancer image classification by deep neural network techniques guided by local clustering. BioMed Res. Int. 2018.

[21] Pereira, S., Pinto, A., Alves, V., Silva, C.A., 2016. Brain tumor segmentation using convolutional neural networks in mri images. IEEE Trans. Med. Imag. 35 (5), 1240-1251.

[22] Pöllänen, I., Braithwaite, B., Ikonen, T., Niska, H., Haataja, K., Toivanen, P., Tolonen, T., 2014 Computer-aided breast cancer histopathological diagnosis: Comparative analysis of three docs-based features: Sw-docs, sw-wdtocs and sw-3-4-dtocs. In: 2014 4th International Conference on Image Processing Theory, Tools and Applications (IPTA). IEEE. pp. 1-6

[23] Shen, S., Zhao, T., Feng, Y., Cai, Y., Li, H., Li, J., & Wang, X. (2021). Breast cancer detection and classification using Xception deep learning. Journal of X-Ray Science and Technology, 29(4), 751-764.

[24] Choi, H. Y., Lee, S., Choi, J., Lee, J., & Kim, H. H. (2021). A Deep Learning-based breast cancer diagnosis system using mammography images and DenseNet201. Scientific Reports, 11(1), 1-10.

[25] Zhang, M., Zhang, Y., Li, S., Li, X., & Chen, S. (2021). A deep learning-based approach for breast cancer detection and diagnosis using VGG16 network and mammography images. Journal of Medical Systems, 45(2), 1-9.

[26] Nam, J. G., Park, S., Hwang, E. J., Lee, J. H., Kim, J. Y., Park, H., & Park, S. H. (2018). Development and validation of deep learning–based automatic detection algorithm for malignant pulmonary nodules on chest radiographs. Radiology, 290(1), 218-228.

[27] Yao, Y., Tang, Y., Chen, H., Zhang, Y., & Zhang, Y. (2020). Breast cancer detection based on Inception-ResNetV2 and fine-tuning. In 2020 International Conference on Computer Engineering and Application (ICCEA). pp. 163-166.

[28] Hernandez, A., Hughes, W., Silva, D., Pérez, C., & Rodríguez, C. Machine Learning for Predictive Analytics in Engineering Procurement. Kuwait Journal of Machine Learning, 1(2). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/124

[29] Farnoosh, R., Rastegari, H., & Zolnoori, M. (2020). Automated classification of breast masses in mammography images using deep learning Inception-ResNetV2 architecture. Computer Methods and Programs in Biomedicine, 185, 105210.

[30] Wang, Z., Dong, N., Dai, W., Rosario, S.D., Xing, E.P., (2018). Classification of breast cancer histopathological images using convolutional neural networks with hierarchical loss and global pooling. In: International Conference Image Analysis and Recognition. Springer. pp. 745–753.

[31] Yao, H., Zhang, X., Zhou, X., Liu, S., 2019. Parallel structure deep neural network using cnn and rnn with an attention mechanism for breast cancer histology image classification. Cancers 11 (12), 1901.

[32] Yildirim, O., Baloglu, U.B., Tan, R.-S., Ciaccio, E.J., Acharya, U.R., (2019). A new approach for arrhythmia classification using deep coded features and lstm networks. Comput. Methods Programs Biomed. 176, 121-133

[33] Muhammad Rahman, Automated Machine Learning for Model Selection and Hyperparameter Optimization , Machine Learning Applications Conference Proceedings, Vol 2 2022.

[34] Scherer, D., Müller, A., Behnke, S., (2010). Evaluation of pooling operations in convolutional architectures for object recognition. In: International conference on artificial neural networks. Springer. pp. 92–101.

[35] Ferreira, C.A., Melo, T., Sousa, P., Meyer, M.I., Shakibapour, E., Costa, P., Campilho, A., 2018. Classification of breast cancer histology images through transfer learning using a pre-trained inception resnet v2. In: International Conference Image Analysis and Recognition. Springer. pp. 763–770

[36] Golatkar, A., Anand, D., Sethi, A., (2018). Classification of breast cancer histology using deep learning. In: International Conference Image Analysis and Recognition. Springer. pp. 837-844.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9s
DOI: https://doi.org/10.17762/ijritcc.v11i9s.7456
***Article Received**: 18 May 2023 **Revised:** 10 July 2023 **Accepted:** 01 August 2023*

[37] Roy, K. Banik, D. Bhattacharjee D. Nasipuri M. (2019) Patch-based system for classification of breast histology images using deep learning. Comput. Med Imaging Graph. 71, 90-103

[38] Saxen, F., Werner, P., Handrich, S., Othman, E., Dinges, L., Al-Hamadi, A., (2019). Face attribute detection with mobilenetv2 and nasnet-mobile. 11th International Symposium on Image and Signal Processing and Analysis (ISPA), IEEE 2019, 176-180.0.