Deep Learning-Based Classification of Breast Cancer in Mammogram Images

***Abstract*—Breast cancer is one of the most common and life-threatening diseases among females all over the world, and thus early and accurate detection is the major factor contributing to increased survival rates. Deep learning models have appeared on the horizon of medical image analysis with high potential during recent years, particularly for breast cancer classification. In this work, a novel hybrid deep learning model named BreastNet is proposed for binary classification of mammographic images as benign or malignant. For evaluation of its performance, various deep learning architectures were compared. Among them, the developed BreastNet model was the best with an accuracy of 99.50% that surpassed MobileNetV2 (97.17%), Xception (96.17%), VGG19 (94.00%), DenseNet201 (93.17%), and ResNet50 (80.83%). To further validate generalization capability, the BreastNet model was tested on the widely accepted INbreast dataset. The model also showed excellent performance, with 97.32% accuracy for the Cancer class and 94.43% for the Non-Cancer class and with a mean accuracy of 95.55%. The model was also excellent in recall, precision, and F1-score, which indicate its consistency in real-world clinical usage. These results verify that BreastNet is highly efficient in boosting diagnostic accuracy and providing consistent assistance to radiologists for the early diagnosis of breast cancer.**

Keywords—Breast, Cancer, Mammogram, INbreast, Health, Medical, Image, Detection, Classification, CNN, Deep Learning.

I. INTRODUCTION

Breast cancer (BC) represents one of the most common and fatal malignancies affecting women, constituting approximately 25% of all female cancers globally [1]. In 2022 alone, an estimated 2.3 million women received BC diagnoses, establishing it as a significant worldwide health challenge [2]. Although advances in medical imaging and therapeutic interventions have been achieved, early-stage identification and diagnostic precision continue to be critical factors influencing patient survival outcomes. Traditional diagnostic modalities including mammography, ultrasonography, and magnetic resonance imaging are commonly employed for screening and diagnostic purposes. Nevertheless, these approaches demonstrate substantial dependence on radiologist expertise, require considerable time investment, and may result in diagnostic delays or inconsistencies, particularly within resource-limited environments.

BC exhibits considerable heterogeneity encompassing various histological classifications, including invasive ductal carcinoma (IDC) and ductal carcinoma in situ (DCIS), along with specialized variants such as medullary, metaplastic, mucinous, lobular, and tubular carcinomas [3]. Although approximately 5–10% of breast malignancies demonstrate hereditary patterns, 30% correlate with modifiable risk elements (including dietary habits, sedentary lifestyle, alcohol consumption, and reproductive variables) [4]. Age constitutes an additional significant risk determinant, with incidence rates increasing markedly beyond 40 years and reaching maximum levels within the 50–69 year demographic.

Deep learning (DL) has established itself as a robust methodology for medical image analysis, offering potential improvements in diagnostic accuracy and operational efficiency for cancer identification. Specifically, Convolutional Neural Networks (CNNs) have demonstrated considerable capability in breast cancer classification, effectively differentiating between benign and malignant lesions within mammographic images [5]. Transfer learning utilizing pre-trained architectures including ResNet, VGG, GoogLeNet, AlexNet, Inception, and MobileNet has significantly improved classification performance through leveraging extensive image databases. These improvements diminish reliance on manual assessment and facilitate more standardized and dependable results, establishing DL methodologies as beneficial tools for clinical decision-making support.

Whereas previous models have shown competitive performance, opportunities exist for performance improvement, generalization, and computational speedup. To fill these voids, this paper introduces a new hybrid deep model, BreastNet, specifically tailored for binary classification of mammogram images as benign or malignant. Along with the proposed model, the performance of other fine-tuned models, including Xception, InceptionV3, ResNet50, VGG16, and MobileNet, is also compared for complete comparison. The aim of this research is to develop an effective and efficient automatic breast cancer detection system for facilitating early detection and enhancing treatment planning and patient prognosis.

This study has several notable contributions in the classification of BC. They are –

- This study utilized a very recently published dataset containing 745 mammogram images and applied several advanced preprocessing techniques (Image

Resize, CLAHE, Contrast Stretching, Bilateral Filtering, and Image Augmentation) to make the dataset's quality better.

- This study developed a hybrid model (BreastNet) and compared its performance with other pretrained models; DenseNet201, ResNet50, VGG19, MobileNetV2 and Xception.
- This study also conducted a validation test on the proposed BreastNet model using a widely used public dataset INbreast to ensure the generalizability of the model.
- This study showed a comparative analysis of the results of this study and other existing studies.

II. Literature Review

A large number of studies was conducted in Breast Cancer classification. The indication of these diseases changes over time, hence the researchers continue to update existing works using new datasets. Some previous studies are-

S. Mohapatra et al. [6] utilized mini-DDSM (9752 images) dataset to train and test their models; AlexNet, CGG16 and ResNet50. AlexNet achieved 65% accuracy. However, the dataset contained limited images which forced a low accuracy. Future study will examine more Neural networks along with some hybrid models. B. Asadi and Q. Memon [7] used 3 different datasets. They deployed VGG19, ResNet151, VGG16, ResNet101, MobileNet and ResNet50. The ResNet50 model achieved the highest accuracy 96.61%. In future, they will use additional datasets to enhance the model's accuracy. B. Abunasser et al. [8] trained and tested their models (InceptionV3, MobileNet, Xception, VGG16, ResNet50 and proposed BCCNN) using a dataset collected from Kaggle (7909 images). The proposed BCCNN model gained 98.30% accuracy. Future study will incorporate other advanced models and preprocessing techniques. A. Raza et al. [9] utilized two datasets; BUSI (780 images) and another one collected from Mendeley (250 images). They investigated several deep learning models, among them the proposed DeepBreastCancerNet achieved 99.35% accuracy. In future they will use more samples to make the model more efficient and reliable. B. S. Abunasser et al. [10] collected BreaKHis dataset (7909 images) from kaggle. They examined the Xception model and achieved 97.60% accuracy. In future, they will increase the dataset size and examine other sophisticated models. N. R. Hoque et al. [11] examined the XGBoost model using WBCD dataset (569 images). The model obtained 94.74% accuracy. In the future, the researchers want to explore other models. H. Chen et al. [12] also used WBCD dataset to examine the performance of XGBoost, KNN, RF and LR. The XGBoost achieved 97.4% accuracy. In the future, they want to explore deep learning models. J. Ahmad et al. [13] examined Fused YOLO and BreastNet-SVM using CBIS-DDSM dataset (3373 images). The BreastNet-SVM achieved 99.16% accuracy. This study used a 2D dataset with less abnormalities. Future study will add more abnormalities in 3D image format. A. Batool and Y.-C. Byun [14] used WBCD dataset (569 images) to evaluate RC, ET, LightGBM, LDA and proposed ELRL-E. The proposed model achieved 97.6% accuracy. Future study will extend the dataset along with refining hyperparameters and exploring optimizations to improve the performance. H. Elmannai et al. [15] investigated Inception and Xception models using the BACH dataset. They achieved 97.29% and 100% accuracy in Sub images and whole images respectively. Future study will increase the dataset, evaluate other deep learning models and extend to WSI classification.

It is notable that most of the studies were conducted on a small dataset and just examined some pretrained.

III. Methodology

This section of the research outlines the systematic approach adopted in the research. The research started by data acquisition and then applied several preprocessing techniques followed by model implementation and model evaluation (Fig. 1).

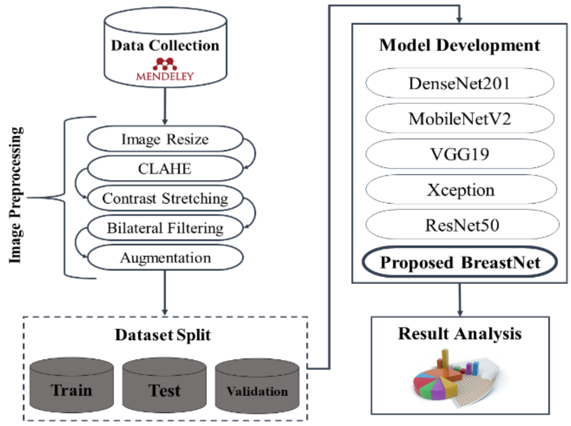

Fig. 1. Research Methodology

A. Data Collection

This study used a very recent dataset collected from the Mendeley Data [16]. The dataset contains a total of 745 mammograms divided into 2 classes; Cancer (125 images) and Non-Cancer (620 images).

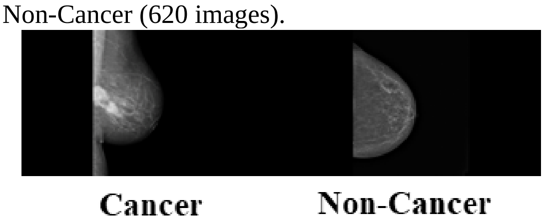

Fig. 2. Dataset Sample

B. Data Preprocessing

This section applied different filters to make the dataset better readable to the models by increasing their visual quality. This section is very crucial for this study as it creates a difference in the results. This study utilized Image Resize, CLAHE, Contrast Stretching, Bilateral Filtering and Augmentation.

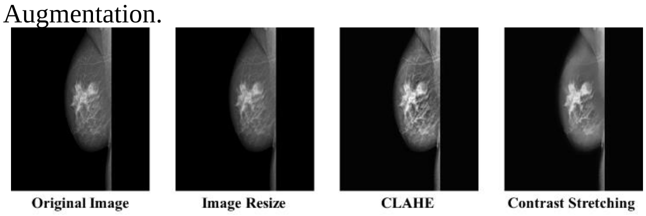

Fig. 3. Preprocessing Steps

a) Image Resize: Image resizing is a well known technique used to change the dimension of an image to desired dimension [17]. In the collected dataset, the images had different dimensions hence this study used resizing technique to ensure a uniform size (224x224).

b) CLAHE: CLAHE is an image processing technique that improves local contrast by carrying out histogram equalization in small regions (tiles) of the image while limiting noise amplification [18]. CLAHE is used in medical imaging of this study to improve important details without noise over-amplification.

c) Contrast Stretching: Contrast Stretching improves the quality by changing the intensity values, making the dark areas more darker and bright regions more brighter [19]. As this study worked with mammograms it used this technique to enhance the visibility.

d) Bilateral Filtering: Bilateral Filtering makes the image smoother and also preserves the edges while smoothing [20]. It also reduces the noises keeping the edges sharp by considering both spatial proximity and pixel intensity differences during filtering.

e) Image Augmentation: Image Augmentation is a technique which artificially increases the dataset size and variability by applying different transformations to the original images [21]. This study also applied 10 widely used transformations.

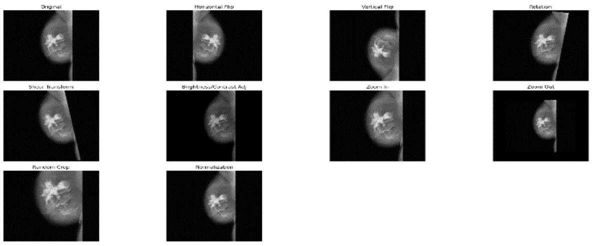

Fig. 4. Image Augmentation Techniques

The dataset had an imbalance situation before augmentation with 125 images and 620 images in Cancer and Non-Cancer classes, but after augmentation the dataset was made balanced by increasing both classes' data; Cancer and Non-Cancer both contained 2500 images each.

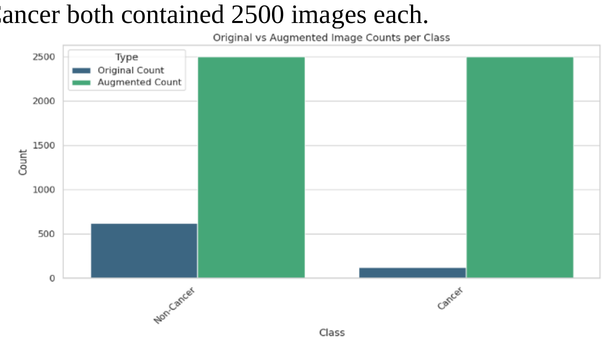

Fig. 5. Augmented and Original Image Count

C. Dataset Split

After preprocessing, the dataset was readily available to feed into the models. To do so, this study split the dataset into training (80%), testing (12%) and validation (8%).

D. Model Development

This study examined different deep learning models including DenseNet201, ResNet50, MobileNetV2, Xception, VGG19 and a proposed hybrid model named BreastNet which was developed in this study.

a) DenseNet201: DenseNet201 is a convolutional neural network with 201 layers, so that every layer receives inputs from all previous layers. It is useful for image classification because of its deep connection, which promotes feature reuse, better gradient flow, and fewer parameters [22].

b) ResNet50: ResNet50 is a 50 layer Residual network with skip connections for learning residual mappings. These connections help to deal with the vanishing gradient issue, and thus allow very deep networks to be trained with high accuracy [23].

c) MobileNetV2: MobileNetV2 is a light-weight model for mobile and low-power devices. It uses depthwise separable convolutions and inverted residual blocks with linear bottlenecks, which decreases computation while preserving accuracy [24].

d) Xception: Xception replaces regular convolutions with depthwise separable convolutions, dividing processing by spatial and channel-wise. This improves efficiency and performance compared to earlier Inception models [25].

e) VGG19: VGG19 is a 19 layer network of stacked layers of 3x3 convolution and max pooling [26]. It is extensively used for feature extraction as it is uncomplicated but efficient in design.

f) Proposed BreastNet: This work proposes BreastNet, which is a combination of DenseNet201-Xception as a classification model for breast tumors. DenseNet201 is able to learn dense hierarchical features, and Xception is able to learn channel-wise and spatial features efficiently. They combined them for richer feature representation, generalization, and more accurate classification than standalone models.

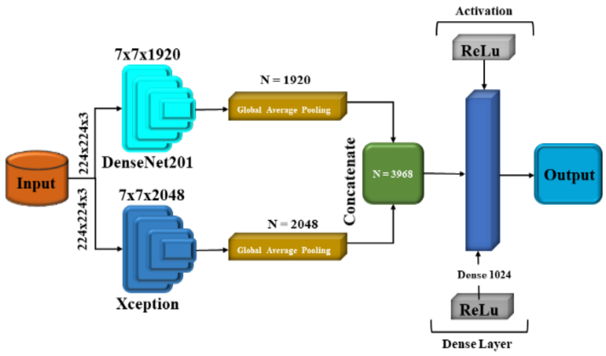

Fig. 6. BreastNet Model Architecture

E. Hyperparameters

TABLE I. DEEP LEARNING MODEL'S HYPERPARAMETERS

Configuration	**Epochs**	**Batch Size**	**Activation Function**	**Learning Rate**	**Optimizer**	**Dropout**	**Loss Function**
Value	50	16	softmax	0.0001	adam	0.5	Categorical crossentropy

F. Model Evaluation

The implemented models have been evaluated using different performance metrics including F1 Score, Precision, Recall, and Accuracy.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

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

IV. Result Analysis and Discussion

This section illustrates the results obtained from the examined models and conducted a comparative analysis among the models and existing works as well.

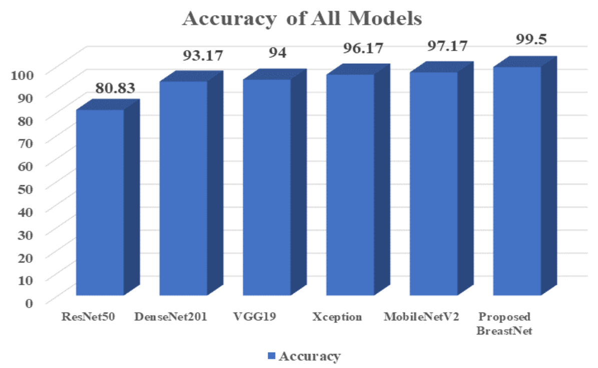

Fig. 7. Performance of All Models

Fig. 7. outlines the accuracy of all investigated deep learning models. The proposed BreastNet model achieved the highest accuracy among all models with 99.50% accuracy. MobileNetV2, Xception, VGG19 and DenseNet201 obtained 97.17%, 96.17%, 94%, and 93.17% respectively. The ResNet50 is the worst performing model with the lowest accuracy of 80.83%.

TABLE II. Classification Report of Models

Models	Class	Class Accuracy	Precision	Recall	F1 Score
ResNet50	Cancer	83.67%	0.79	0.84	0.81
	Non-Cancer	78%	0.83	0.78	0.80
DenseNet 201	Cancer	99.33%	0.88	0.99	0.94
	Non-Cancer	87%	0.99	0.87	0.93
VGG19	Cancer	98%	0.91	0.98	0.94
	Non-Cancer	90%	0.98	0.90	0.94
Xception	Cancer	96.33%	0.96	0.96	0.96
	Non-Cancer	96%	0.96	0.96	0.96
MobileNet V2	Cancer	96.67%	0.98	0.97	0.97
	Non-Cancer	97.67%	0.97	0.98	0.97
Proposed BreastNet	**Cancer**	**99%**	**1.00**	**0.99**	**0.99**
	Non-Cancer	**100%**	**0.99**	**1.00**	**1.00**

Table 2. shows class-wise performance metrics (accuracy, recall, precision, and F1-score) of different CNN models. Among the standalone models, DenseNet201 and VGG19 are high-performing models with very good cancer class classification accuracy (≈99% and 98%) and comparatively lower non-cancer class accuracy. Xception and MobileNetV2 both have balanced performance for both classes. The optimal overall performance is achieved by the proposed BreastNet, with nearly perfect accuracy (99% for cancer and 100% for non-cancer) and precision, recall, and F1-score of almost 1.00 for both. This proves the hybrid architecture properly merges the strengths of DenseNet201 and Xception, which subsequently delivers improved feature extraction, generalization, and extremely consistent classification for both classes.

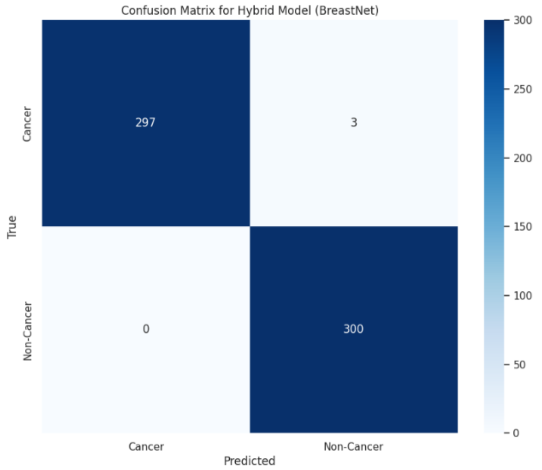

Fig. 8. BreastNet Model Confusion Matrix

Fig. 8 illustrates the proposed BreastNet model's confusion matrix. It shows that, among 300 Cancer cases the model correctly predicted 297 instances and the rest of the 3 instances misclassified. On the other hand, among 300 Non-Cancer instances the model correctly predicted all 300 Non-Cancer samples.

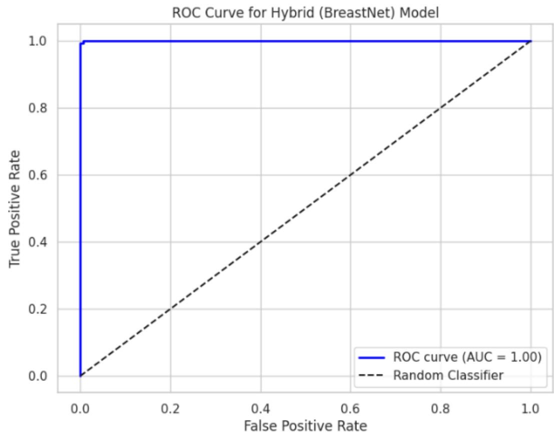

Fig. 9. Proposed BreastNet Model ROC-AUC Curve

This ROC curve illustrates the Hybrid (BreastNet) model's performance in such a way that a perfect classification ability is reflected in an AUC of 1.00 (Fig. 9). The curve hovers around the top-left, reflecting that the model has an excellent trade-off between high true positive rate and extremely low false positive rate.

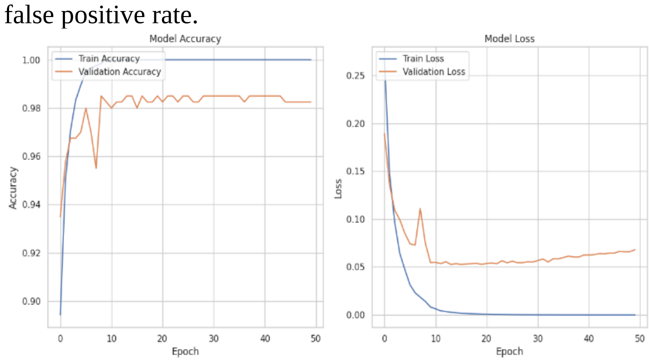

Fig. 10. BreastNet Model Accuracy and Loss Curve

The training curves show that the BreastNet model achieved very quick near-perfect training accuracy (100%) with very low training loss. Validation accuracy was consistent at 97–98%, but the validation loss started to increase after early epochs, showing some degree of overfitting but with high validation accuracy (Fig. 10).

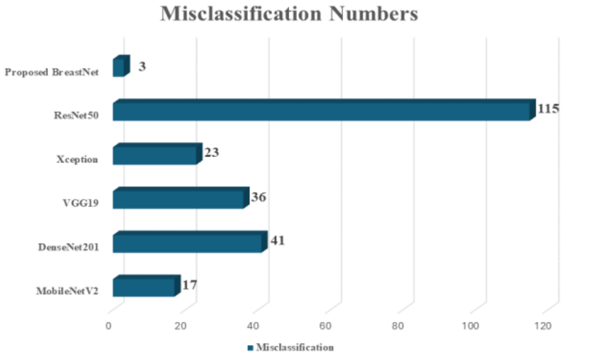

Fig. 11. Model Misclassification Number

The proposed BreastNet model had the lowest misclassification number of 3, while the ResNet50 achieved the highest misclassification number (115). However, Xception, VGG19, DenseNet201 and MobileNetV2 misclassified 23, 36, 41 and 17 instances respectively (Fig. 11).

TABLE III. BREASTNET MODEL'S CLASSIFICATION REPORT IN INBREAST DATASET

Class	F1 Score	Precision	Recall	Class Accuracy	Accuracy (Overall)
Cancer	0.94	0.92	0.97	97.32%	**95.55%**
Non-Cancer	0.96	0.98	0.94	94.43%	

This study conducted a validation test of the proposed BreastNet model using a famous public dataset named INbreast. The model also performed extremely well in this dataset achieving 97.32% and 94.43% accuracy for Cancer and Non-Cancer class while achieving an overall accuracy 95.55% (Table 3). The model also showed good precision, recall and f1 score.

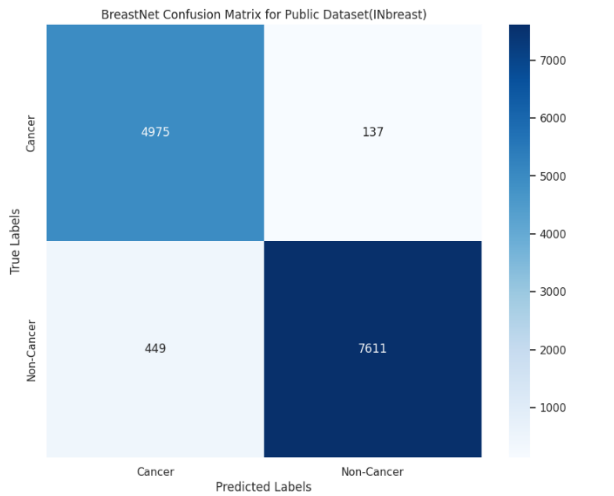

Fig. 12. BreastNet Confusion Matrix in INbreast Dataset

The confusion matrix of the BreastNet model in INbreast dataset has been shown in Fig. 12. The model was tested using 13172 images (5112 Cancer images and 8060 Non-Cancer images). Among 5112 Cancer images the model correctly classified 4975 images and among 8060 Non-Cancer images the model classified 7611 images. The rest of the images were misclassified.

TABLE IV. COMPARISON TABLE WITH EXISTING WORKS

Paper	Dataset Source	Dataset Size	Performance
[10]	BreaKHis	7909 images	Xception 97.60%
[11]	WBCD	569 images	XGBoost 94.74%
[12]	WBCD	569 images	XGBoost 97.40%
[14]	WBCD	569 images	ELRL-E 97.6%
This Research	**Public dataset collected from Mendeley**	**745 images**	**Proposed BreastNet 99.50%**

Table 4. Outlines the comparison of this research with existing research. Here, B. S. Abunasser et al. [10] used BreaKHis dataset (7909 images) and achieved 97.60% accuracy in the Xception model. N. R. Hoque et al. [11], H. Chen et al. [12] and A. Batool and Y.-C. Byun [14] all used WBCD dataset (569 images) in their studies and obtained 94.74% (XGBoost), 97.40% (XGBoost) and 97.6% (Proposed ELRL-E) respectively. However, this study outperformed the other studies in terms of performance achieving 99.50% accuracy in the proposed BreastNet model using a recently published dataset in Mendeley (745 images).

V. CONCLUSION AND FUTURE WORKS

This study showed a comprehensive comparison of different deep learning models with the proposed BreastNet model. It used a very recent dataset collected from Mendeley. Performance comparison of various deep learning models shows that the proposed BreastNet model was found to have the highest accuracy of 99.50% compared with MobileNetV2 (97.17%), Xception (96.17%), VGG19 (94%), DenseNet201 (93.17%), and ResNet50 with the worst accuracy of 80.83%. Validation on the INbreast dataset further established the robustness of BreastNet with 97.32% and 94.43% accuracy for the cancer class and the non-cancer class respectively with an overall accuracy of 95.55% and strong precision, recall and F1-scores. These results fix BreastNet as a better and uniform model for breast cancer classification than other CNN architectures used widely. This study used a comparatively smaller dataset but validated the model using a large enough dataset. In future, the researchers want to train the model using a larger and more variable dataset and also work on the model to make it computational efficient and lightweight for real life deployment.

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