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Breast Cancer Classification Based on Lightweight Ensemble Transfer Learning

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Abstract: Breast cancer is a significant global public health concern, demands early and accurate diagnosis for improved patient well-being.The most prevalent type of breast cancer is IDC (Invasive Ductal Carcinoma)The existing system's ensemble approach leverages transfer learning, combining shallow CNNs with MobileNetV2, to effectively classify breast cancer from histopathology images. The lightweight ensemble transfer learning with robust preprocessing techniques to advance breast cancer classification pre-trained deep learning models, including MobileNetv2, VGG-16, and Xception intricate features are extracted from mammographic images. Synthetic Minority Oversampling Technique (SMOTE), ensuring a balanced representation of benign and malignant cases during model training. The extract features from these models create a mammographic image representation, enabling classification by the XG Boost algorithm. In the intersection of machine learning and deep learning domains, the primary objectives of this research are focused on enhancing model performance assessed through critical evaluation metrics such as F1 score, recall, and overall accuracy. The main aim to demonstrate the effectiveness of the holistic approach, contributing to improved breast cancer diagnosis precision and efficiency.

***Index Terms*-MobileNetV2,VGG-16,Xception,Ensemble,Transfer Learning,XGboost.**

I. INTRODUCTION

IDC is a pervasive global health concern, with millions of individuals affected each year. The importance of early and accurate diagnosis cannot be overstated, as it significantly influences the effectiveness of treatment and patient survival rates.Breast cancer remains a significant global health concern, with 685,000 deaths recorded in 2020, making it the second leading cause of cancer death worldwide after lung cancer[1]. The mortality rate has seen a decline in the US, attributed to early detection programs, emphasizing the critical role of early detection in improving survival rates and treatment outcomes [2]. However, barriers such as social, geographic, and economic constraints hinder many women from accessing these vital programs, highlighting the need for individualized risk assessment strategies. Implementing risk-based screening approaches, especially in middle- and low-income nations, can optimize resource allocation and enhance early detection efforts [3]. In recent years, the intersection of medical science and artificial intelligence has yielded remarkable advancements in medical image analysis, offering novel solution for cancer classification. This project represents a critical endeavor at the nexus of healthcare and machine learning, aimed at enhancing the precision, efficiency, and accessibility of breast cancer diagnosis. Breast cancer is a complex and widespread health concern that affects millions of individuals globally. Leveraging advancements in machine learning and deep learning, the development of sophisticated models for tumor cancer classification from medical images has gained significant attention. However, creating effective classifiers for this task is beset with challenges, especially when dealing with imbalanced datasets, where one class (e.g., malignant tumors) is significantly underrepresented compared to the other (e.g., benign tumors).

Traditional diagnostic methods often rely on subjective human interpretation of medical images, such as mammograms and biopsies. However, the combination of machine learning into breast cancer classification has the potential to revolutionize this process, offering objective, consistent, and potentially more accurate assessments. Ensemble learning is a powerful machine learning technique that harnesses the collective intelligence of three models to achieve superior accuracy compared to individual models. In the realm of breast cancer classification, ensemble methods combine diverse algorithms, each with its unique strengths, to make collective predictions.

This approach helps mitigate the risk of overfitting and enhances the robustness of the diagnostic system. The result is a more accurate and reliable breast cancer classification system, which is crucial for the field of medical image analysis. Transfer learning is a fundamental pillar of this project. This involves adapting pre-trained machine learning models that were originally trained on large and unrelated data sets to the specific task of breast cancer classification.

This technique is particularly valuable when working with limited medical image data. By leveraging the knowledge gained from broader datasets, our model becomes adept at extracting pertinent features from breast tissue images, such as tumor characteristics, shapes, and textures.Transfer learning empowers the model to make informed decisions, enhancing its ability to differentiate between benign and malignant tumors. In healthcare applications, computational efficiency is of paramount importance, especially when considering resource constraints such as limited computational power or the need for mobile deployment. Efficient algorithms ensure timely processing of medical images, facilitating quick diagnosis and treatment planning. Consequently, our focus on computational efficiency enables seamless integration of our breast cancer classification system into clinical workflows, improving patient outcomes and healthcare delivery efficiency.

II. RELATED WORKS

In this section, the research on Breast cancer classification using ensemble techique. It can be grouped based on data collection section, pre-processing steps, and model training achieving robust classification performance across diverse medical imaging sources and detection part.

A. Breast Cancer Classification Based On Machine Learning

Lu Min et al.'s paper [7] introduced a groundbreaking method for detecting breast cancer by utilizing UWB microwave technology alongside a CNN-LSTM framework. Their end-to-end system efficiently detects and localizes tumors within breast quadrants, eliminating the need for complex microwave imaging processing. Wander Ricardo, et al. [9] proposed a novel syntactic approach for classifying breast masses as benign or malignant, diverging from traditional reliance on large datasets. The machine learning approaches have often relied on large datasets for training. However, this article highlights a novel and underexplored syntactic approach for classifying breast masses as either benign or malignant. Hooda Nishtha, et al. [3] The paper explores the aspect of the disease and its correlation with different risk factors, such as demographic characteristics and the lifestyle of women residing in affected regions. In recent years, significant advancements have been observed in the field of localization, particularly by Lu Min et al. [6], who have utilized these advancements to train (CNN) classifiers, thereby enhancing accuracy.These efforts reflect a broader trend in the field aimed at refining diagnostic methodologies and enhancing the clinical applicability of localization techniques. Liu Pei, et al. [5] focus on enhancing the performance of XG Boost for predicting breast cancer progression through survival analysis. Their research emphasizes the deliberate effort to optimize the algorithm's effectiveness, potentially addressing challenges related to ties in event occurrence.

B.Breast Cancer Classification Based On Deep Learning

Wang Yan et al. [10] proposed a novel method for breast cancer detection, utilizing a multi-instance mammography dataset. Their approach integrates a feature-sensitive deep convolutions neural network with custom layers for extraction and a feature fusion module to assign weights. A classifier module is then used to classify the combined features, improving diagnosis by considering the diverse contributions of instances from varying views. Arya Nikhilanand et al. [1] Proposing a novel approach, we aim to predict breast cancer prognosis by leveraging multi-modal data. Their method utilizes deep learning-based models within a stacked ensemble framework, leveraging convolutions neural networks for feature extraction in the first stage. The evaluation shows superior performance over existing methods, suggesting improved accuracy in breast cancer prognosis prediction. Senousy et al. [8] Introducing the MCU for breast histology image classification, we achieved an accuracy of 98.11, surpassing state-of-the-art models.It integrates multi-level context-aware models capturing spatial dependencies and an uncertainty quantification component for enhanced sensitivity to contextual information. Lee Juhun et al. [4] utilize a (CGAN) to generate simulated mammograms for detecting mammographically occult (MO) cancer in women with dense breasts. Their approach, complemented by a Convolutional Neural Network trained on Radon Cumulative Distribution Transform (RCDT) processed mammograms, demonstrates promise in improving breast cancer screening for this population. Cheng-Bang et al. [2] Presenting an approach for detecting tumors in breast cancer histopathological images, we emphasize the utilization of spatial recurrence features.Their method incorporates wavelet decomposition and a weighted recurrence network to capture recurrence patterns, achieving high performance with an AUC of at least 0.96. This research offers a valuable methodology for IDC identification and underscores its potential to aid clinical decision-making, with implications for broader medical and biological image processing applications.

III. METHODOLOGY

This section presents the logical structure of the project, detailing a comprehensive set of specifications for implementation in a programming language. An overview of the project's modules is depicted through a system architecture diagram, illustrating the flow from data source to breast cancer classification based on lightweight ensemble transfer learning. The trained model relies on features learned during training, as depicted in Figure 1.

A. Data Collection Process

The dataset consists of whole mount slide images of Breast Cancer specimens, scanned at 40x magnification, with a primary focus on Invasive Ductal Carcinoma (IDC), the most common subtype of breast cancer. To facilitate automatic aggressiveness grading, patches measuring 50 x 50 pixels were extracted from these images. These patches are categorized into IDC negative (198,738 patches) and IDC positive (78,786 patches) classes, enabling the training and evaluation of machine learning models. Each patch is uniquely identified by a filename convention indicating patient ID, coordinates of cropping, and class, with '0' representing non-IDC and '1' representing IDC. This structured naming scheme enhances the dataset's utility for IDC detection and aggressiveness grading tasks in machine learning applications.

B. Pre-processing Techniques

For data preprocessing, various techniques such as data cleaning, feature scaling, and handling missing values were applied to ensure the quality of the dataset. Resize: Images in the dataset are of consistent resolution. This step ensures that all images have the same dimensions, which is crucial for the model to process them uniformly. Augmentation: Augmentation techniques are applied to artificially increase the diversity of the training dataset. This facilitates the model's generalization to unseen data. Common augmentations include rotation, flipping, and changes in brightness or contrast. Normalization: Pixel values of the images are normalized to a standard scale. This often involves scaling pixel values to be within the range of [0, 1] or [-1, 1].

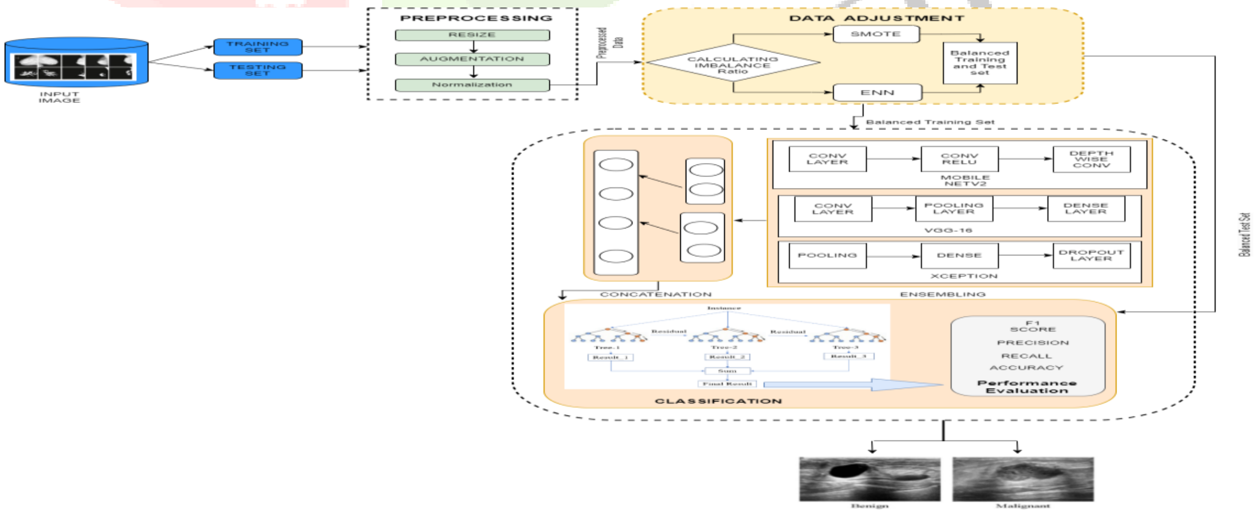

Fig. 1. Breast cancer Classification Based On Lightweight Ensemble Transfer Learning

C.Class Balancing

SMOTE (Synthetic Minority Over-sampling Technique) is a commonly used method to address class imbalance by generating synthetic samples for the minority class, crucial for training accurate classifiers. In real-world classification applications, Imbalanced datasets pose a significant challenge because learning models often exhibit bias towards the majority class, which can impact accuracy. While techniques like random oversampling by replicating existing samples may help, SMOTE mitigates this issue by generating new instances in the feature space through interpolation between closely located positive instances.

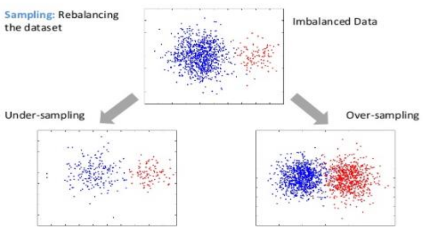

Fig. 2. SMOTE TECHNIQUE

D. Feature Extraction

The selection of lightweight neural networks, including Mobile Netv2 and VGG-16, Xception as feature extractors was a strategic choice to optimize both accuracy and computational efficiency.

MobileNetV2: The model for its lightweight and efficient design. Fine-tune its weights on the breast cancer dataset, freezing the initial layers to retain the general features it learned from a diverse set of images.

VGG-16: Utilize VGG-16 for its deeper architecture that can capture intricate patterns in the medical images. turning the model on the breast cancer dataset, potentially adjusting the learning rate to accommodate the different scale of features it captures compared to MobileNetV2.

Algorithm 1 Feature Extraction Of Mobilenet-V2 AND VGG16 AND Xception

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Input: MobileNet-V2's efficiency, VGG-16's deep architecture, and Xception's depth and efficiency enhances breast cancer classification.

Output: The pre-trained weights capture general features from a diverse set of images, enhancing the model's ability to extract relevant features for breast cancer classification.

• Get image path v
• Initialize features []
• Initialize targets []
• for Each files in the root folder do construct the file path
• preprocessed images through the MobilenetV2 and vgg-16 and xception base to extract features
• end for
• Evaluate the trained model on the testing dataset.
• Gather metrics including accuracy, precision, recall, and F1 scores.
• Obtain the predicted probability or class label for each image

Xception: Employ Xception to capture spatial hierarchies and complex patterns in medical images. Fine-tune its weights on the breast cancer dataset, adjusting hyperparameters as needed.

Ensemble: Combine the three models, possibly using a simple averaging or a more sophisticated ensemble technique like stacking. Ensemble methods can mitigate the individual weaknesses of each model and provide a accurate classification.

Classification: XG Boost was selected as the classification model due to its capability in efficiently handling tabular data and generating highly accurate predictions. Trained on the combined predictions from the ensemble of feature extractors, XG Boost offers robust performance in diagnosing breast cancer. Utilizing appropriate evaluation metrics ensures a clear understanding of the model and its diagnostic accuracy in breast cancer detection.

The trained model demonstrated effectiveness in detecting offensive text, evaluated through metrics. This comprehensive approach ensures robust performance in classifying breast cancer, leveraging features extracted from MobileNetV2, VGG16, and Xception architectures. Additionally, XG Boost robust ensemble of decision trees enhances its ability to discern patterns associated with breast cancer, contributing to accurate classification.

Algorithm 2 ENSEMBLE MODEL

Input: Ensemble models combine the prediction from multiple base models to enhance overall performance.
Output: Train multiple base models using different algorithms or architectures (e.g., Xception, VGG-16, ResNet).

- Get image path v
- Initialize features []
- Initialize targets []
- for Each files in the root folder do construct the file path
- Read the image
- Calculated Loss
- N - int(TRAINSP LIT ∗ T OT ALSAMP LES)
- F1¡-MobileNetv2 model for NUMC LASSES F2 < −V GG − 16modelforNUMC LASSES
- F3¡-XCEPTION model for NUM CLASSES < −class if ierthatusesMultilayerperceptionAlgorthimfor3∗ for NUMC LASSES as input for NUMC LASSES
- y = Original Label for x
- Training Set¡- Random Training Set (x,y) for epoch =1 to MAX -EPOCHS do
- for i=1 to x do
- (xi,yi) ¡-Training Set
- y1¡-f1(xi) predicted label of Mobilenetv2
- y2¡-f1(xi) predicted label of Vgg-16
- y3¡-f1(xi) predicted label of Xception
- y¡-g (concat(y1,y2,y3) final prediction
- end for

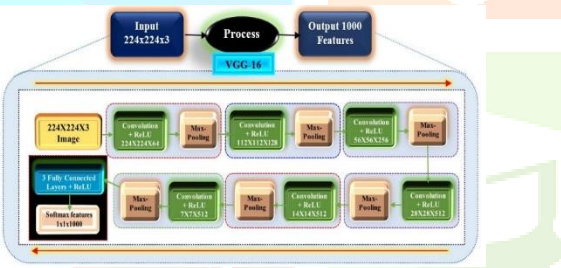

Fig. 3. VGG-16

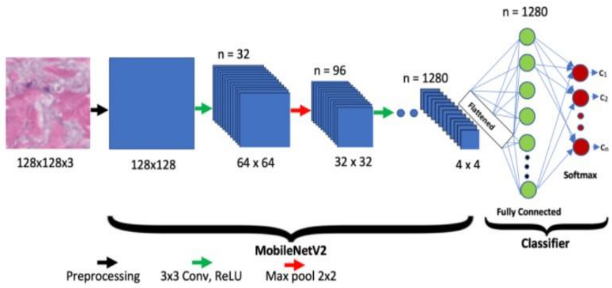

Fig. 4. MobileNetV2

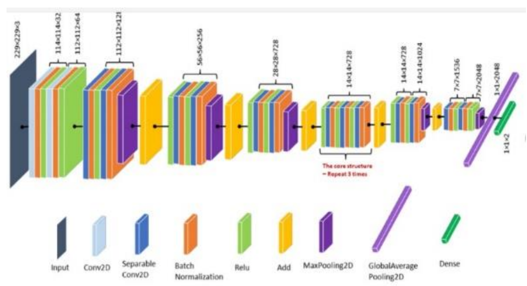

Fig. 5. Xception

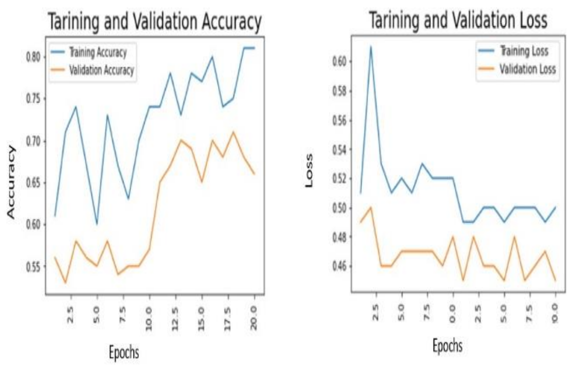

Fig. 6. Mobilenetv2

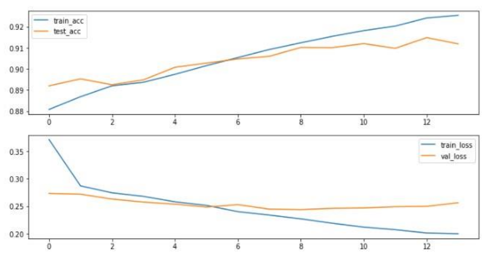

Fig. 7. VGG-16

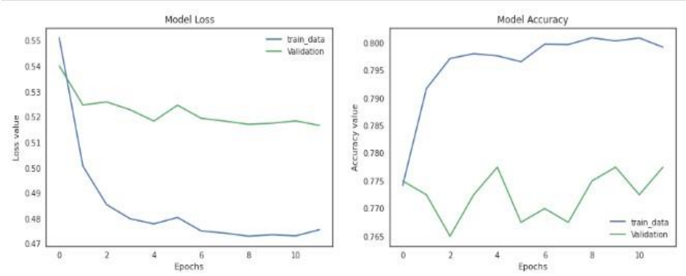

Fig. 8. Xception

IV. RESULT AND ANALYSIS

In this section, we present the comprehensive results and evaluation metrics of the implemented modules and model. The model is evaluated using metrics such as precision, recall, F1- score, and accuracy.

Accuracy play a vital role in evaluating the effectiveness of MobileNetV2, VGG-16, and Xception models for image classification tasks, particularly in scenarios with imbalanced classes, leveraging their respective strengths in efficiency, hierarchical feature capture, and exceptional performance. Evaluating the performance of an ensemble model, which combines predictions from multiple models, involves a performance metrics that collectively gauge the model's effectiveness. XG Boost, an implementation of gradient-boosted decision trees, is a powerful algorithm widely used for classification tasks. In the context of classification, XGBoost excels at creating an ensemble of weak learners (decision trees) and boosting their collective predictive performance. The classification report provides insight into the model's performance for each class, offering detailed breakdowns for mobilenet-v2 precision (the accuracy of positive predictions), recall (the proportion of actual positives correctly predicted), and F1-Score (the harmonic mean of precision and recall) are 95%, 83%, and 89%, respectively, based on 100 instances. for VGG-16 demonstrates strong performance, with a precision of 95%, recall of 95%, and an 95% F1-Score. for Xception demonstrates strong performance, with a precision of 85%, recall of 84%, and an 84% F1-Score.

V. CONCLUSION

In conclusion, Breast cancer classification using lightweight ensemble transfer learning has shown promising results in terms of achieving high accuracy and efficiency. The use of transfer learning, Finetuning a pretrained model on a specific breast cancer dataset enables effective knowledge transfer from a source domain. The ensemble approach further enhances the robustness and generalization of the classification model by combining the strengths of multiple base learners. The lightweight nature of the ensemble transfer learning model makes it computationally efficient, suitable for deployment on resource-constrained devices, and applicable in real-time scenarios. The research has contributed to the ongoing efforts in developing advanced and accessible tools for breast cancer diagnosis and prognosis. In advancing the field of breast cancer classification based on lightweight ensemble transfer learning, several critical avenues for future research emerge. Firstly, an imperative focus should be placed on the incorporation of diverse datasets, encompassing a broad spectrum of breast cancer instances. By expanding the dataset diversity, researchers can bolster the model's generalization capabilities, ensuring its effectiveness across diverse populations and clinical scenarios. In the dynamic landscape of healthcare, incremental learning approaches must be investigated to enable the model to adapt to evolving datasets over time.

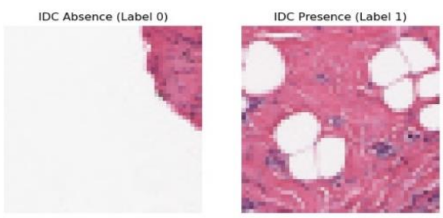

Fig. 9. Prediction of breast cancer

Incremental learning ensures that the model remains relevant and effective as new information becomes available. To validate the real-world efficacy of the proposed model, rigorous validation studies in clinical settings are paramount. Collaborating with healthcare professionals and institutions is essential to assess the model's performance in diverse and complex clinical environments. An open-source approach facilitates the exchange of ideas, accelerates progress, and allows for collective refinement of models, ultimately contributing to the development of more effective, interpretable, and widely applicable breast cancer classification models. Through concerted efforts in these areas, future research can significantly advance the field and, in turn, improve patient outcomes and healthcare decision-making processes.This project lays the groundwork for forthcoming research and development endeavors.

TABLE I

RESULT FOR FEATURE EXTRACTION OF MOBILENET-V2

CLASS	PRECISION	RECALL	F1-SCORE	SUPPORT
0	0.95	0.83	0.89	1500
1	0.64	0.88	0.74	500
ACCURACY	0	0	0.83	2000
MACRO AVG	0.79	0.32	0.60	2000
WEIGHTED AVG	0.87	0.67	0.84	2000

TABLE II

RESULT FOR FEATURE EXTRACTION OF VGG-16

CLASS	PRECISION	RECALL	F1-SCORE	SUPPORT
0	0.95	0.95	0.95	33328
1	0.71	0.72	0.72	6065
ACCURACY	0	0	0.91	39393
MACRO AVG	0.83	0.83	0.83	39393
WEIGHTED AVG	0.91	0.91	0.91	39393

TABLE III

RESULT FOR FEATURE EXTRACTION OF XCEPTION

CLASS	PRECISION	RECALL	F1-SCORE	SUPPORT
0	0.95	0.83	0.89	1500
1	0.64	0.88	0.74	500
ACCURACY	0	0	0.83	2000
MACRO AVG	0.79	0.32	0.60	2000
WEIGHTED AVG	0.87	0.67	0.84	2000

TABLE IV

PERFORMANCE METRICES FOR ENSEMBLE

CLASS	PRECISION	RECALL	F1-SCORE	SUPPORT
0 AND1	0.94	0.88	0.96	100
ACCURACY	0	0	0.88	400

TABLE V

CLASSIFICATION FOR XGBOOST

CLASS	PRECISION	RECALL	F1-SCORE	SUPPORT
0	0.96	0.93	0.94	43
1	0.96	0.97	0.97	71
ACCURACY	0	0	0.96	114
MACRO AVG	0.96	0.95	0.95	114
WEIGHTED AVG	0.96	0.96	0.96	114

References

[1] Arya, Nikhilanand, and Sriparna Saha. "Multi-modal classification for human breast cancer prognosis prediction: proposal of deep-learning based stacked ensemble model." IEEE/ACM transactions on computational biology and bioinformatics VOL 19, NO.2 PP: 1032-1041 2021.

[2] Chen, Cheng-Bang,Yujie Wang, Xuanya Fu, and Hui Yang"Recurrence Network Analysis of Histopathological Images for the Detection of Invasive Ductal Carcinoma in Breast Cancer." IEEE/ACM Transactions on Computational Biology and Bioinformatics VOL. 20, NO. 5 2023.

[3] Hooda, Nishtha, Ruchika Gupta, and Nidhi Rani Gupta. "Prediction of malignant breast cancer cases using ensemble machine learning: A case study of pesticides prone area." IEEE/ACM Transactions on Computational Biology and Bioinformatics VOL 19,NO.2 PP : 1096- 1104 2020.

[4] Lee, Juhun, and Robert M. Nishikawa. "Identifying women with mammographically-occult breast cancer leveraging GAN-simulated mammograms." IEEE transactions on medical imaging vol 41, NO.1 PP : 225-236 2021.

[5] Liu, Pei, Bo Fu, Simon X. Yang, Ling Deng "Optimizing survival analysis of XGBoost for ties to predict disease progression of breast cancer." IEEE Transactions on Biomedical Engineering vol 68, NO.1 PP : 148-160 2020.

[6] Lu, Min, Xiao, X., Pang, Y., Liu, G and Lu, H. "Detection and localization of breast cancer using UWB microwave technology and CNN-LSTM framework." IEEE Transactions on Microwave Theory and Techniques vol 70, NO.11 PP : 5085-5094 2022 .

[7] Lu, Min, Xia Xiao, Yanwei Pang, Guancong Liu, and Hong Lu. "Response to Comments on "Detection and Localization of Breast Cancer Using UWB Microwave Technology and CNN-LSTM Framework"." IEEE Transactions on Microwave Theory and Techniques vol 70, NO. 12 PP: 5085-5094 2022.

[8] Senousy, Zakaria, Mohammed M. Abdelsamea,"MCUa: Multi-level context and uncertainty aware dynamic deep ensemble for breast cancer histology image classification." IEEE Transactions on Biomedical Engineering VOL 69, NO.2 PP : 818-829 2021.

[9] Wandr, Ricardo, Ana Luiza Silveira Ferreira, Rodolph Vinicius "A stochastic grammar approach to mass classification in mammograms." IEEE/ACM Transactions on Computational Biology and Bioinformatics VOL 20, NO. 3, 2023.

[10] Wang, Yan Y., Zhang, L., Shu, X., Feng,"Feature-sensitive deep convolutional neural network for multi-instance breast cancer detection." IEEE/ACM Transactions on Computational Biology and Bioinformatics VOL 19, NO.4 PP 2241-2251 2021.

[11] S. Acharya, A. Alsadoon, P. W. C. Prasad, S. Abdullah, and A. Deva, "Deep convolutional network for breast cancer classification: Enhanced loss function (ELF)," J. Supercomput., vol. 76, no. 11, pp. 8548–8565, 2020.

[12] C. T. Sari and C. Gunduz-Demir, "Unsupervised feature extraction via deep learning for histopathological classification of colon tissue images," IEEE Trans. Med. Imag., vol. 38, no. 5, pp. 1139–1149, May 2019.

[13] M. Saini and S. Susan, "Deep transfer with minority data augmentation for imbalanced breast cancer dataset," vol. 97, 2020, Art no. 106759.

[14] E. Wu, K. Wu, and W. Lotter, "Synthesizing lesions using contextual GANs improves breast cancer classification on mammograms," in Proc. Mach. Learn. on,2020.

[15] S. Garg and P. Singh, "State-of-the-art review of deep learning for medical image analysis," in Proc. 3rd Int. Conf. Intell Sustain Syst 2020, pp. 421–427.

[16] A. G. Howard et al., "MobileNets: Efficient convolutional neural networks for mobile vision applications," in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., 2017.

[17] S. J. Pan and Q. Yang, “A survey on transfer learning,” IEEE Trans Knowl Data Eng., vol. 22, no. 10, pp. 1345–1359, Oct. 2010.

[18] Cruz-Roa et al., “Automatic detection of invasive ductal carcinoma in whole slide images with convolutional neural networks,” Med.Imag. Digit. Pathol., vol. 9041, no. 216, 2014, Art. no. 904103.

[19] F. A. Spanhol, L. S. Oliveira, C. Petitjean, and L. Heutte, “A dataset for breast cancer histopathological image classification,” IEEETrans. Biomed. Eng., vol. 63, no.7, pp. 1455–1462, Jul. 2016. [Online].

[20] Aresta et al., “BACH: Grand challenge on breast cancer histology images,” Med. Image Anal., vol. 56, pp. 122–139, 2019.

[21] S. H. Kassani, P. H. Kassani, M. J. Wesolowski, K. A. Schneider,and R. Deters, “Classification of histopathological biopsy images using ensemble of deep learning networks,” in Proc. Conf. Cent.Adv. Stud. Collab. Res., Proc. 29th Annu. Int. Conf. Comput. Sci.Softw. Eng., 2020, pp. 92–99.

[22] A. Paszke et al., “Automatic differentiation in pytorch,” paszke2017automatic, vol. 5, pp. 1–4, 2017. [38] M. S. Reza and J. Ma, “Imbalanced histopathological breast cancer image classification with convolutional neural network,” in Proc.Int. Conf. Signal Process., 2019, pp. 619–624.

[23] X. Li, X. Shen, Y. Zhou, X. Wang, and T. Q. Li, “Classification of breast cancer histopathological images using interleaved densenet with SENet (IDSNet),” PLoS One, vol. 15, no. 5, pp. 1–13, 2020.

[24] W. Nawaz, S. Ahmed, A. Tahir, and H. Aqeel Khan, Classification of Breast Cancer Histology Images Using ALEXNET. Berlin, Germany: Springer, 2018.

[25] S. Kwok, Multiclass Classification of Breast Cancer in Whole-Slide Images. Berlin, Germany: Springer, 2018.

[26] S. H. Kassani, P. H. Kassani, M. J. Wesolowski, K. A. Schneider,and R. Deters, “Breast cancer diagnosis with transfer learning and global pooling,” in Proc. 10th Int. Conf. Inf. Commun. Technol. Convergence, 2019, pp. 519–524.