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RESEARCH ARTICLE

Deep Learning-Enhanced Ultrasound Analysis: Classifying Breast Tumors Using Segmentation and Feature Extraction

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ABSTRACT Breast cancer remains a significant global health challenge, requiring accurate and effective diagnostic methods for timely treatment. Ultrasound imaging is a valuable diagnostic tool for breast cancer because of its affordability, accessibility, and non-ionizing radiation properties. This study proposes a classification method for breast ultrasound images that integrates segmentation and feature extraction. Initially, ultrasound images are pre-processed to enhance quality and reduce noise, followed by segmentation using the U-Net++ architecture. Feature extraction is then performed using MobileNetV2, and these features are used to train and validate classification models to differentiate between malignant and benign breast masses. The model's performance is assessed using accuracy, precision, recall, Mean IoU, and Dice Score metrics. The U-Net++ model achieved superior segmentation performance with a Dice Score of 0.911 and a Mean IoU of 0.838, outperforming related methods such as U-Net (0.888 Dice, 0.79 IoU) and Efficient U-Net (0.904 Dice, 0.80 IoU). In the classification task, MobileNetV2 when paired with the ANN classifier, produced the highest test accuracy at 96.58%, with a precision of 97% and recall of 96%. Our approach demonstrates superior performance compared to other models, such as RMTL-Net, which achieved 91.02% accuracy, and hybrid CAD models with 94% accuracy. This highlights the benefits of combining advanced segmentation and feature extraction techniques, with MobileNetV2 proving to be the better model, offering superior accuracy and robustness in classification tasks. This approach has the potential to support promise for supporting radiologists, enhance diagnostic accuracy, and ultimately improve outcomes for breast cancer patients. In the future, we will use comprehensive datasets to validate our methodology.

INDEX TERMS Classification, MobilenetV2, segmentation, feature extraction.

I. INTRODUCTION

Breast cancer is caused by combination of factors such as unhealthy lifestyle, environmental factors, and genetic mutations [1], [2]. Breast cancer develops in breast cells, forming a cancerous cell that can proliferate neighbouring tissues and spread throughout the body [1]. Cancer typically starts in the cells lining the ducts (ductal carcinoma), which are the tubes that carry milk from the glands to the nipples [3].Moreover, cancer can also originate in the lobules, which are clusters of milk-producing glands [4]. According to the International agency (Cancer Tomorrow), breast cancer is the most common invasive cancer in women worldwide. It is projected that approximately 2.7 million new cancer diagnoses and 0.86 million fatalities will occur globally by 2030 [5]. Breast cancer is responsible for 19% of new cases and represents 30% of all cancer cases among females. Additionally, it is worth noting that breast cancer incidence rates have been steadily rising by approximately 0.5% annually since the mid-2000s, and early detection is crucial for successful treatment [6]. Ultrasound imaging is a non-invasive and widely available diagnostic tool that can help to evaluate breast masses and identify potential cancerous growths. Compared with other imaging modalities such as X-rays, mammography, ultrasound is inexpensive and do not expose patients to ionizing radiation. Furthermore, ultrasound is particularly

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useful for distinguishing between solid masses and fluid-filled cysts [7], and it can help to guide further diagnostic testing and treatment decisions. However, like all medical procedures, the accuracy of ultrasound imaging depends on the skill and experience of the radiologist performing the examination. Therefore, it is important to seek out qualified and experienced radiologists to ensure the most accurate diagnosis and treatment plan.

Various Computer aided design (CAD) system designs for the automatic classification of breast ultrasound images (BUSI) have utilized both original and pre-processed images in the era of Artificial Intelligence, as illustrated in Figure 1. These CAD designs majorly divided in three categories: (a) Machine learning-based CAD designs, (b) Deep Learning-based CAD system designs, and (c) hybrid CAD system designs that use deep feature extraction followed by classification using Machine learning classifiers [8]. This study leverages the strengths of both deep learning and traditional machine learning. Deep learning models are applied for feature extraction. The extracted features are fed into traditional machine learning classifiers that enhance the accuracy and interpreting results.

CAD systems can help radiologists interpret breast ultrasound images more accurately, and mass segmentation is a critical step in these systems. Accurate segmentation can facilitate better analysis of features related to breast mass shape, which in turn can improve the accuracy of mass classification [9], [10], [11], [12]. However, automatic segmentation in ultrasound imaging is challenging due to factors such as low image contrast, speckle noise, and variations in breast mass sizes and shapes [13]. Overall, deep learning-based CAD systems have the potential to significantly improve the accuracy and efficiency of breast mass analysis in ultrasound imaging [12], [13], [14], [15]. However, further research is needed to optimize these methods and evaluate their clinical utility in real-world scenarios. Deep learning algorithms, such as convolutional neural networks (CNNs), have shown promise in breast mass image analysis [16]. These methods are data-driven and can automatically learn high-level representations of images for segmentation and classification. Recently, Jabeen et al. [17]. presented a breast cancer classification method that use ultrasound images, and merges computer vision and deep learning techniques. It involves crucial steps like tumor segmentation, feature extraction, and image pre-processing for enhancing classification accuracy. accuracy whereas their method rely on high-quality labelled datasets for better performance.

Furthermore, Cao et al. [18] evaluated several CNN models for tumor detection, including Fast Region-based Convolutional Neural Network (FR-CNN), Faster R-CNN, You Only Look Once (YOLO) network, and Single Shot Multibox Detector (SSD). These networks are commonly used for real-time object detection. According to the results, the SSD model obtained the highest F1-score of 0.79. Overall, the results suggest that the SSD model is a promising option for tumor detection using CNN models. On the other hand, SSD exhibits limitations in detecting low-contrast tumors, which affects the robustness of the model. CNNs have been successfully applied to the detection, segmentation, and classification of breast masses in ultrasound images, and they have demonstrated high accuracy compared to traditional machine learning methods. Yap et al. [19] analyzed four Fully Convolutional Network (FCN) architectures—FCN-AlexNet, FCN-32s, FCN-16s, and FCN-8s—for breast ultrasound lesion segmentation. Their results showed that FCN-16s achieved the highest mean Dice score of 0.7626 for benign lesions, while FCN-8s performed best for malignant lesions with a mean Dice score of 0.5484. Although deep learning-based segmentation techniques outperformed traditional methods, variations in performance between benign and malignant cases highlighted the need for improvements in model generalizability. In their study Podda et al. [20] presented an automated multilayer process for classifying breast cancer risk from ultrasound images. It involves testing various CNN architectures, combining them into ensembles for improved discrimination, and employing a novel optimization cycle that refines segmentation and classification iteratively. Achieving a Dice coefficient of 82% and a classification accuracy of 91%, the proposed method demonstrates effectiveness, rivalling current leading approaches. However, the complexity of ensemble models presents challenges for real-time usage in a clinical environment.Various deep learning-based approaches have been proposed for breast mass segmentation and classification in ultrasound imaging [21], [22]. One popular approach is based on convolutional neural networks (CNNs), which can learn to produce pixel-wise segmentation maps directly from input images [23]. CNNs have been used for breast mass segmentation in 2D and 3D ultrasound images, and they have demonstrated higher accuracy than traditional segmentation methods [16], [24], [25], [26], [27]. Punn et al. [28]. focuses on residual cross-spatial attention-guided Inception U-Net (RCAIU-Net), integrating residual cross-spatial attention and inception modules within the U-Net framework. This architecture provides more accurate visualizations of breast tumors in ultrasound images with an intersection over union IoU of 91%, enhancing classification potential. However, the model's complexity increases training time and computational cost. Zhao et al [29] also proposes a breast tumor ultrasound image segmentation method using an enhanced U-Net framework with residual blocks and attention mechanisms with IoU is 85%. These enhancements aim to increase the network's efficiency in tumor recognition and diagnosis, thereby improving classification outcomes. Nevertheless, this method struggles with high inter-class variability in tumor morphology, affecting its generalizability. A Recent study by Pramanik et al [30] introduced a variant of the U-Net architecture, known as dual branch U-Net (DBU-Net),with an IoU of 74.34%. The dual-branch structure of DBU-Net is designed to enhance feature extraction and segmentation accuracy. By improving segmentation, the study indirectly contributes to more accurate tumor classification, as precise segmentation is a critical step in classifying tumors effectively.

Shia et al. [31] presented an unsupervised machine learning approach for breast tumor classification in ultrasound images, achieving a sensitivity of 81.64% and specificity of 87.76% (AUC = 0.847). While their method eliminates the need for prior region selection, reducing human effort, it depends heavily on feature selection and computational resources. Benaouali et al. [32] introduced a segmentation and classification framework using texture characterization methods (HOG and LBP). The best results were obtained using SVM, achieving an accuracy of 96%, sensitivity of 97%, and specificity of 94%. Although combining multiple feature extraction techniques improved classification performance, the study was limited by dataset constraints. Ramesh et al. [33] proposed a deep learning-based approach leveraging GoogLeNet for tumor segmentation and classification. Their method achieved a 99.12% accuracy, outperforming AlexNet by 3.78%. However, the high computational cost and reliance on large datasets remain significant limitations. Sinduja et al. [34] developed a hybrid segmentation and feature extraction approach for tumor detection, integrating feature selection techniques. Their method demonstrated enhanced segmentation and classification accuracy across various imaging modalities. However, the complexity of the methodology requires careful tuning to ensure optimal performance.

In this study we introduce a novel three-step algorithm in which the first step focuses on the segmentation of pre-processed BUSI using U-Net++ [35]. U-Net++ was chosen for its effectiveness in capturing fine details in medical images, nested skip pathways, and feature aggregation. Importantly, U-Net++was trained from scratch on our dataset, ensuring that the model learns domain-specific features, such as tumor boundaries and speckle-noise patterns, which are critical for accurate segmentation. While pre-trained models like MobileNetV2 are employed for feature extraction, the use of a customized U-Net++ architecture trained from scratch represents a novel contribution to breast cancer diagnosis. This combination of pre-trained and custom models enhances the overall performance and robustness of the system. The next step involves feature extraction from deep architectures to improve classification using MobileNetV2. For classification, we considered multiple classifiers, as traditional approaches may use a limited set of classifiers, potentially missing out on finding the most effective one.

II. METHEDOLOGY

We have utilized three step algorithms in which one focuses on segmentation of pre-processed BUSI using U-Net++ [35] because of its effectiveness in capturing fine details in medical images, nested skip pathways, and feature aggregation. After segmentation, we carried out further analysis to

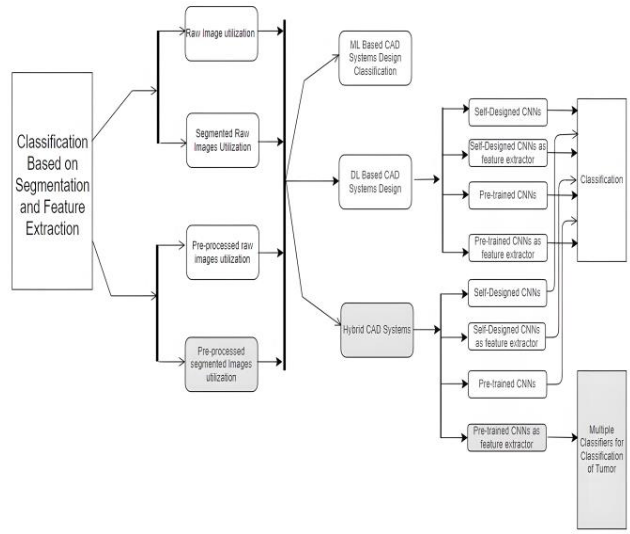

FIGURE 1. Comprehensive characterization of CAD system designs for classifying BUSI gray color indicates the experimentation conducted in this study.

classify the breast tumors into normal, benign, or malignant. The next step was feature extraction from deep architectures to improve classification, using MobileNetV2. MobileNetv2 provides a lightweight model suitable where the data is limited, because it uses depth wise separable convolutions to reduce computation cost without compromising performance [36] [37]. For classification, we considered multiple classifiers since, traditional approaches may use a limited set of classifiers, potentially missing out on finding the most effective one. Therefore, we included a diverse set of classifiers, namely Support Vector Machines (SVM), Random Forest, Artificial neural network (ANN), K-Nearest Neighbours (KNN), Long Short-Term Memory (LSTM) [38], [39]. A detailed description of these classifiers is provided in the following section.

A. SEGMENTATION USING U-NET++

Our study enhanced the U-Net [40] framework to improve its performance for segmenting breast tumors in US images and utilizes the U-Net++ architecture for the initial segmentation of ultrasound images illustrated in Figure 2 [35]. This advanced neural network model is specifically designed to improve the accuracy of segmentation tasks by employing nested skip pathways and deep supervision mechanisms as shown in panel a. Panel (b) shows the detailed pathway of convolution operations within the network, emphasizing the integration of features from both previous and deeper layers to refine segmentation outputs. Panel (c) illustrates how the network operates at multiple levels (L1 to L4), each processing and integrating features at different scales to handle complex segmentation tasks effectively. Unlike pre-trained models that leverage weights from large datasets like ImageNet, the U-Net++ model was trained from scratch on the BUSI dataset. This approach ensures that the model

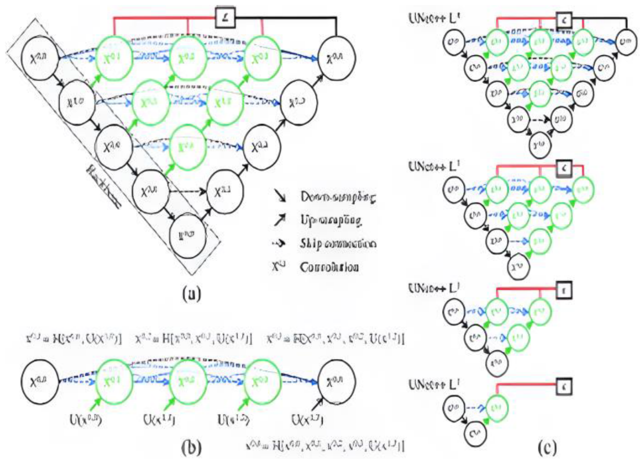

FIGURE 2. Workflow of U-Net++ architecture.

learns domain-specific features, such as tumor boundaries and speckle noise patterns, which are critical for accurate segmentation in breast ultrasound images. In the context of our study, U-Net++ was tasked with delineating the boundaries of masses within the breast ultrasound images, effectively isolating the regions of interest from the surrounding tissues. The output from U-Net++ is a set of segmented images where the regions containing potential tumors are precisely marked. It excels in medical imaging tasks by capturing fine-grained details in images [35]. It provides strong support for accurately segmenting tumor regions, which is critical for further classification. The following subsections provide a detailed overview of the U-Net++ architecture.

1) ENCODER PATHWAY

U-Net++ begins with an encoder pathway similar to that of U-Net. The encoder down-samples the input image and extracts feature at different scales. Convolutional layers and max-pooling operations reduce the spatial dimensions of the feature maps while increasing the number of channels [35].

2) NESTED SKIP PATHWAYS

The core innovation of U-Net++ is the introduction of nested skip pathways [35]. These pathways create multiple levels of feature aggregation and context modeling. Instead of a single skip connection between the corresponding encoder and decoder layers.

3) DECODER PATHWAY

The decoder pathway in U-Net++ is responsible for up-sampling the feature maps and generating the final segmentation mask. Up-sampling is achieved through transposed convolution (also known as deconvolution) layers. The feature maps from the encoder are combined with the feature maps from the nested skip pathways at each decoder level. Skip connections facilitate the flow of information from both the encoder and nested skip pathways, which allows the decoder to refine the segmentation mask [35].

4) FINAL OUTPUT

The final output of U-Net++ is a segmentation mask with the same spatial dimensions as the input image, 256×256 pixels.

B. FEATURE EXTRACTION USING MOBILENETV2

MobileNetV2 model is used for feature extraction. This process begins with the pre-processing of images, where each image is resized to a uniform dimension of 256×256 pixels and segmented to focus on key regions, such as tumor areas. MobileNetV2 employs depth-wise separable convolutions, which decouple spatial and channel-wise operations, significantly lowering computational costs while maintaining the integrity of essential features. Additionally, the model incorporates inverted residuals with linear bottlenecks, expanding the data into a higher-dimensional space before compressing it back down, thereby preserving critical spatial features in a compact, efficient manner. As the pre-processed images are processed by MobileNetV2, the network generates a $7 \times 7 \times 1280$ feature map, effectively capturing detailed and abstracted information from the input images. This feature map is flattened into a 1D vector of 1280 elements, transforming the multi-dimensional data into a streamlined format suitable for classification. The MobileNetV2 architecture is employed to generate feature tensors for each segmented ROI. These feature tensors are designed to capture essential patterns and characteristics in the segmented regions [41], [42]. We chose not to fine-tune MobileNetV2 to avoid overfitting, given the limited size of the BUSI dataset. By keeping the convolutional layers frozen, we leveraged the general features learned from ImageNet while focusing on training the classifiers to adapt to the specific task Extracted features are saved and can be utilized for various purposes, such as classification, analysis, or decision-making in medical image analysis and other applications [42], [43]. This approach enhances the accuracy and significance of insights derived from segmented ultrasound data, contributing to improved diagnostic and analytical capabilities [18].

C. CLASSIFICATION NETWORK

We employed deep learning models for feature extraction and traditional machine learning classifiers for the classification task. Specifically, MobileNetV2 was used as feature extractors, as a pre-trained on the ImageNet dataset and used without their top classification layers, as illustrated in Figures 3. The feature vectors extracted were then passed to various classifiers, including SVM, Random Forest, K-Nearest Neighbors, LSTM, and ANN [42], [44], [45]. For the ANN and LSTM models, the architecture consisted of a fully connected Dense Layer with 512 neurons using a ReLU activation function, followed by a Dropout Layer (rate 0.5) and an Output Layer with three neurons corresponding to the three classes, utilizing a SoftMax activation function. The Dense Layer transforms the high-dimensional feature vectors obtained from MobileNetV2 into a form suitable for classification by reducing the complexity of the model and

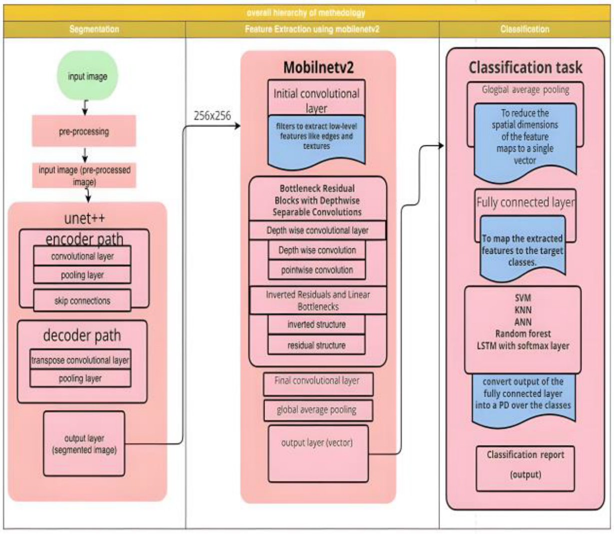

FIGURE 3. **Detailed workflow of proposed methodology Using MobileNetv2.**

preventing overfitting [46]. The SoftMax activation function is applied in the classifiers to produce a probability distribution across the three classes. The models were trained using the Adam optimizer with a learning rate of 0.0005 and evaluated on training, validation, and test datasets using accuracy, precision, recall, and F1-score metrics.

1) SUPPORT VECTOR MACHINE (SVM)

Support Vector Machines (SVM) are supervised learning models for classification and regression analysis. The primary goal of an SVM is to find the optimal hyperplane that separates data points of different classes with the maximum margin. The hyperplane is determined by the support vectors, which are the data points nearest to the hyperplane. SVMs are effective in high-dimensional spaces and are particularly useful for classification problems with clear separation margins. Effective in high-dimensional spaces, robust to overfitting in high-dimensional space, especially with a clear margin of separation. Nevertheless, it is unsuitable for large datasets due to high training time, and performance may degrade on noisy data [38], [47], [48].

2) ARTIFICIAL NEURAL NETWORK (ANN)

ANNs are designed explicitly for non-linear modeling and provide flexibility and adaptability. We construct feedforward neural networks using TensorFlow and Keras, which comprise multiple layers with varying units and activation functions. The ANN architecture includes input, hidden, and output layers with ReLU activation functions for the hidden layers and SoftMax for the output layer. Dropout layers are added to prevent overfitting. ANNs are powerful due to their flexibility and ability to model complex non-linear relationships, making them suitable for various data types, including images, text, and time series. They also support transfer learning for task-specific fine-tuning. However, they require significant computational resources and large amounts of labeled data, and they are prone to overfitting [49], [50].

3) K-NEAREST NEIGHBOURS (KNN)

KNN is an instance-based classification method that relies on similarity measures. It classifies a sample based on the majority class among its k-nearest neighbors in the feature space. We experimented with k and distance metrics values to tailor the model to the dataset's characteristics. We used the scikit-learn library to implement KNN, adjusting the number of neighbors (k) and distance metric (Euclidean, Manhattan) [38].

4) RANDOM FOREST

Random Forest is a highly effective ensemble learning method for classification and regression tasks. It operates by constructing multiple decision trees during training and outputs the mode of the classes (classification) of individual trees. This method is particularly useful in medical image analysis, including ultrasound imaging. Random Forests provide more robust and reliable predictions by averaging multiple decision trees. In breast ultrasound imaging, Random Forests have been applied to detect and classify lesions. The ensemble nature of Random Forests helps handle the variability in lesion appearance. On the other hand, training requires significant computational resources, especially with many trees [50].

5) LONG SHORT-TERM MEMORY (LSTM)

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) that is particularly effective for sequential data and time-series analysis due to their ability to maintain long-term dependencies. In ultrasound image analysis, LSTMs can be used for tasks that involve temporal sequences or dynamic changes in images. LSTM networks are composed of units called memory cells, which store information over long periods. Each cell has three gates: input gate, forget gate, and output gate, to control the flow of information. LSTMs are robust to variations in the input sequence, maintaining performance even with noisy data. Training LSTMs can be challenging due to issues like vanishing gradients, which require careful tuning and sufficient computational resources [38], [39].

D. ABLATION STUDY DESIGN

To evaluate the impact of each component in our proposed model, we designed an ablation study that examines how removing specific modules affects performance [51], [52]. The study focuses on three key components: segmentation (U-Net++), feature extraction (MobileNetV2), and preprocessing (anisotropic diffusion filtering). Each experiment selectively disable these components to assess their impact on accuracy. The study consists of four variations: (1) a baseline model without segmentation, where classification is performed directly on raw images; (2) a model without feature extraction, where MobileNetV2 is removed and classification is based on raw image data; (3) a model without anisotropic filtering to analyze its effect on segmentation quality and classification performance; and (4) the full model, incorporating segmentation, feature extraction, and preprocessing as the baseline. Each variation was tested under identical experimental conditions using the same dataset to ensure valid comparisons. The performance evaluation metric is test accuracy. The results of this ablation study are presented in table 3 under the Results section.

III. RESULTS

The following section provides a comprehensive overview of the experiments performed using our proposed methodology and discusses the evaluation metrics employed. We also present the results obtained for both segmentation and classification tasks. Then, we conduct a comparative analysis of different classification models, comparing the performance of the proposed model to other state-of-the-art models.

This section defines the evaluation metrics used in segmentation from equations 1 to 2 intersection over union (IoU) and dice score. *IoU,* also known as the Jaccard index, measures the overlap between the ground truth and predicted segmented masks. The dice score is twice the area of overlap between the predicted segmentation and ground truth divided by the total number of pixels in both images. For classification tasks, equations from 3 to 6 were used. Recall is defined as the ratio of true positive predictions to the total positives. High recall is crucial for medical imaging problems because it minimizes false negatives, and as a result, the model can miss malignant tumors, which can cause severe consequences. Accuracy is the ratio of correctly predicted instances to the total cases. Accuracy is a fundamental metric that provides a straightforward measure of the model's performance in distinguishing between benign and malignant tumors. Precision is critical in medical diagnostics to ensure that when the model predicts a tumor as malignant, it is indeed malignant. High precision reduces the number of false positives, which is crucial in clinical settings to avoid unnecessary anxiety and follow-up procedures for patients. F1-score is the harmonic mean of precision and recall in uneven datasets f1-score is crucial because it ensures that neither precision nor recall is disproportionality favoured [53], [54]. These equations are widely used in segmentation and classification problems.

$$IoU_{class} = \frac{TP_{class}}{TP_{class} + FP_{class} + FN_{class}} \tag{1}$$

$$Dice - score_{class} = \frac{2TP_{class}}{2TP_{class} + FP_{class} + FN_{class}} \tag{2}$$

$$recall_{class} = \frac{TP_{class}}{TP_{class} + FN_{class}} \tag{3}$$

$$Precision_{class} = \frac{TP_{class}}{TP_{class} + FP_{class}} \tag{4}$$

$$F1score_{class} = \frac{2 * recall_{class} * Precision_{class}}{recall_{class+}Precision_{class}} \tag{5}$$

$$Accuracy = \sum \frac{True\ positives\ ofall\ classes}{Total\ number\ of\ all\ classes} \tag{6}$$

In the context of segmentation, the Dice score and IoUserve as similarity metrics, where the Dice score quantifies the ratio of twice the area of overlap between the ground truth and predicted mask images to the total number of pixels in both images [11]. Similarly, the IoU measures the overlap between the ground truth and the predicted mask. Dice and IoU are useful for measuring image similarity, and accuracy computes the percentage of matching pixels between the predicted masks and ground truth in segmentation tasks [55]. However, in the case of classification, where there are three distinct classes - benign, malignant, and every day - we use four key metrics: accuracy, precision, recall, and F1-score [18], [56]. The formula for the F1 score aligns with the dice score, as shown in mathematical equations. Moreover, precision and recall are calculated differently for the classification model. To derive these metrics, we first calculate four essential values: True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN), which are based on the three classes of US images: malignant, benign, and routine.

A. DATASET

A data collection initiative was conducted in 2018 to gather baseline information on women aged 25 and 75 [57]. The dataset contains 780 breast ultrasound images of 600 female patients. These images were saved in PNG format with an average size of 500 × 500 pixels. The dataset was divided into three categories: normal, benign, and malignant. Table 1 provides an overview of the distribution of images across these classes, while Figure 4 displays sample images from the dataset for visual reference. Each image has a paired ground truth and was carried out by expert radiologists at Baheya Hospital [57]. These specialists used a freehand technique to delineate the boundaries of each tumor on the ultrasound images presented as a mask image in Figure 5. A standardized image pre-processing approach is applied to ensure consistency in the experiment. Regardless of their original dimensions, all images are resized to

TABLE 1. Distribution of BUSI dataset.

Cases	Number of images
Normal	133
Benign	437
Malignant	210
Total	780

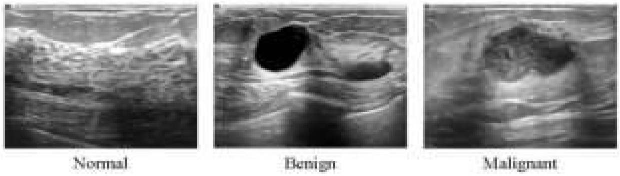

FIGURE 4. Sample images from the dataset for all three classes.

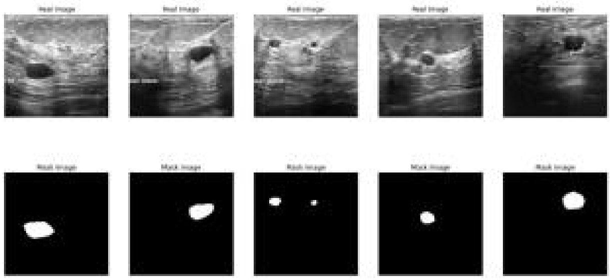

FIGURE 5. Real Images and their respective mask images in the original BUSI.

a uniform size of 256 × 256 pixels. Anisotropic diffusion is applied to reduce speckle noise, which is dominant in ultrasound images. This technique effectively reduces noise while preserving critical structural details such as edges and boundaries, with parameters set to 50 iterations,a kappa value of 150for edge thresholding, and a gamma value of 0.2 to control the diffusion speed. This method was chosen over traditional filters due to its superior ability to maintain image integrity while smoothing textures [58], [59]. This approach ensures that images are optimized for further processing steps, specifically segmentation, by improving clarity and reducing noise-related artifacts that could hinder model performance. These pre-processing steps collectively enhance image quality by reducing speckle noise, smoothing textures, and improving contrast, as demonstrated in Figure 6.

B. SEGMENTATION

The proposed methodology, focusing on the BUSI dataset [57], addresses the class imbalance challenge within the dataset. Initially, the dataset is organized into distinct categories representing benign, malignant, and normal breast tissues. To ensure impartial evaluation, a subset of images from each category is randomly reserved in a separate folder for later testing. Augmentation techniques [60], [61], [62], including random rotations and horizontal flipping, were then applied systematically to the BUSI dataset and generated augmented images in Figure 7. Subsequently, a U-Net++ architecture is employed for precise breast tissue segmentation, as shown in Figure 8 [35].

The performance assessment of the proposed U-Net++ model involves evaluation of key metrics such as *IoU*, Dice-score, and number of parameters. This evaluation includes a thorough comparison with state-of-the-art methods, all of which were trained and evaluated using identical parameter configurations on the BUSI dataset [63], [40] as shown in Table 2.

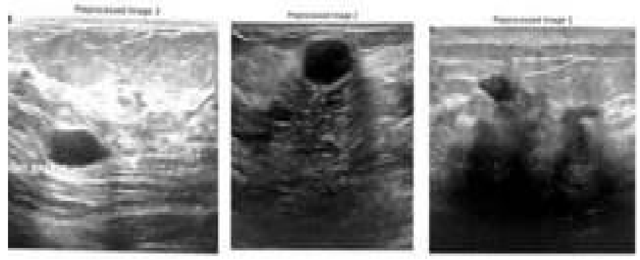

FIGURE 6. Example of preprocessed images.

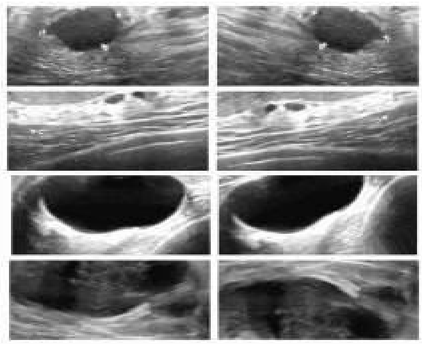

FIGURE 7. Example image augmentation for various images.

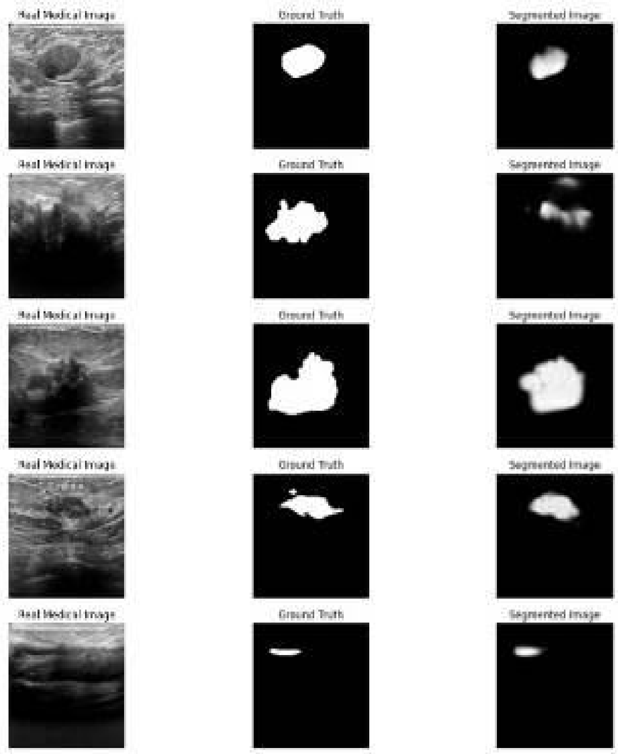

FIGURE 8. Example segmentation results for various input images. The Left column shows the original image data, the middle column is the Ground truth reference, and the right column shows the result of the segmentation process.

TABLE 2. Comparison of U-Net++ segmentation results and state-of-the-art models on different BUSI dataset.

Network	Parameters	Dice score	Mean *IoU*
U-Net [40]	9.34M	0.888	0.79
Efficient U-Net [63]	8.6M	0.904	0.80
U-Net++	9.7M	**0.911**	**0.838**

Overall, this comprehensive experimental design includes image resizing and normalization. The dataset is divided into training, validation, and test sets using k-fold cross-validation (with k = 5 in our task segmentation and classification). This ensures robust model evaluation and generalization.

C. ABLATION STUDY

To evaluate the contribution of each component in our proposed model, we conducted an ablation study by systematically removing key elements: segmentation (U-Net++), feature extraction (MobileNetV2), and pre-processing (anisotropic diffusion filtering). The results, presented in Table 3, highlight the necessity of segmentation-driven classification, optimized feature extraction, and noise-reduction pre-processing. Moreover, we compare ablation study test accuracies with our best performing classifier which is ANN (0.9658) mentioned in Table 4.

TABLE 3. Ablation study results.

Experiment	Accuracy	Accuracy Change
No Segmentation	0.887	9.4%
No Feature Extraction	0.912	5.6%
No Anisotropic Filtering	0.942	2.5%

Ablation experiments revealed that removing segmentation decreased accuracy to 87.5% (-9.4%), highlighting its role in isolating tumor regions. Eliminating feature extraction reduced accuracy to 91.2% (-5.6%), indicating the importance of deep-learning features. Removing anisotropic filtering led to a 2.5% drop, confirming its role in reducing noise and enhancing segmentation. The full model achieved 96.58% accuracy in Table 4, demonstrating the cumulative benefits of all components.

D. MODEL'S EVALUATION AND RESULTS

In this section, we delve into the classification phase of our breast cancer diagnosis framework, utilizing the rich feature vectors extracted from the segmented BUSI dataset. To comprehensively assess and evaluate the system's diagnostic performance, we employ a range of classification models, including SVM, ANN, KNN, Random Forest, and LSTM networks [39], [47], [48], [64].

We assess the performance of each classification model using a range of metrics, including accuracy, precision, recall, and F1-score [8], [14], [65]. The evaluation provides insights into each model's strengths and weaknesses, aiding in selecting the most suitable approach for breast cancer diagnosis. The classification models obtained using MobileNetV2 are thoroughly analyzed and shown in Table 4. Performance was evaluated regarding training, validation, test accuracies, F1 measure, recall, and precision. Our analysis of the MobileNetV2 architectures for breast tumor classification using ultrasound images indicated that MobileNetV2 outperformed various pretrained networks across all classifiers, particularly in test accuracy, F1 measure, recall, and precision. For instance, when used with MobileNetV2, the SVM classifier achieved a significantly higher test accuracy of 95.01%. This trend was consistent across other classifiers as well. The Random Forest classifier, for example, demonstrated a test accuracy of 94.86% with MobileNetV2. Furthermore, the ANN classifier paired with MobileNetV2 achieved the highest test accuracy at 96.58%, along with an F1 measure of 96.62% and a precision of 97.00%. The LSTM classifier also improved performance with MobileNetV2,yielding a test accuracy of 93.17%. These results underscore the superior capability of MobileNetV2 in handling feature extraction from ultrasound images, mainly when dealing with limited datasets. MobileNetV2's architectural innovations, such as depth-wise separable convolutions and inverted residuals, appear more effective in capturing essential features and ensuring that the model generalizes well to unseen data. In contrast, other pre trained, despite its complexity and strength in capturing hierarchical features, showed a more pronounced decline in performance from training to test data, indicating challenges with overfitting and generalization. These findings strongly support the selection of MobileNetV2 as a more suitable and reliable model for breast tumor classification in this specific context [8].In particular, MobileNetV2's ability to effectively capture both local and global features in a compact form proved advantageous for the classification task, yielding superior accuracy and highlighting the efficiency and adaptability of its architecture in handling the complexity of breast ultrasound images [42]. These feature datasets are the foundation for subsequent classification tasks and further analysis.

Feature extraction using Mobilenetv2 performed better than other pre trained because they have more complex structure and hidden layers than MobileNetV2. As the results show, it performed comparatively better on training datasets;

however, its performance is inadequate regarding validation and test accuracy. Based on the results shown in Table 4, we can conclude, that when the datasets are limited, then architectures with simple structures like MobileNetV2 come in handy and are valuable for getting desired results. ANN performed better than other classifiers among all the classifiers used in the experiments in this study. The reason for selecting these specific classifiers is that they are widely used in the literature on deep learning-related problems to make the model robust [38], [66], [67].

TABLE 4. Performances of different classifiers with Mobilenetv2+segmentation.

	Training accuracy	Validation accuracy	Test accuracy	F1 measure	Recall	Precision
SVM	0.9799	0.9099	0.9501	0.9594	0.9587	0.9603
Random forest	**1.00**	0.8966	0.9486	0.9481	0.9427	0.9603
KNN	0.9671	0.8949	0.9456	0.9489	0.9579	0.9508
ANN	**1.00**	0.9204	**0.9658**	**0.9662**	**0.9660**	**0.9700**
LSTM	0.9850	**0.9259**	0.9317	0.9334	0.9416	0.9246

IV. DISCUSSION

This paper proposes a novel breast tumor classification scheme for ultrasound images based on combining feature extraction using MobileNetV2 with segmentation information. This study comprehensively examines breast cancer segmentation-based classification using advanced deep-learning techniques. Moreover, it aims to integrate medical knowledge into the network and design the segmentation network to obtain the tumor contour and region to extract more effective features for classification. The utilization of U-Net++ architecture for segmentation and the combined application of MobileNetV2 for feature extraction led to classification, which has demonstrated promising results and is suitable for further analysis of images. This modular approach is well-suited for future work in image analysis, as it can be easily integrated into existing medical imaging systems. The segmentation, feature extraction, and classification modules can be independently updated or replaced. Furthermore, the different classifiers adopted in this study made tumor classification more reliable. Our model achieved a Dice Score of 0.911 and a Mean IoU of 0.838 for segmentation, surpassing traditional methods such as U-Net (0.888 Dice, 0.79 IoU) and Efficient U-Net (0.904 Dice, 0.80 IoU) as mentioned in Table 2. This improvement ensures that the model identifies tumor boundaries with greater precision, which is crucial for reducing false positives and false negatives in classification. Since classification depends on the quality of segmented features, our results confirm that a well-optimized segmentation step leads to better diagnostic accuracy. One of the biggest challenges in medical imaging is distinguishing between tumor tissue and surrounding structures, and our segmentation approach directly addresses this by isolating key tumor regions before classification. This approach is supported by previous studies for instance, Xu et al. [52] proposed RMTL-Net for simultaneous segmentation and classification of the BUSI dataset and achieved an accuracy of 91.18% in their model. Similarly, Zhuang et al. [45] used fully extracting Image of Interest (IOI) and (ROIs) models to extract Areas of Interest (AOIs) from breast ultrasound images. They then applied transfer learning combined with SDCB-NET and VGG to classify the extracted AOIs. The study results showed that the combination of transfer learning and SDCB-NET/VGG architectures achieved a maximum accuracy of 92.86% in classifying breast ultrasound images. This suggests that deep learning and transfer learning can improve classification performance. Our model's use of advanced architectures like U-Net++ for segmentation and MobileNetV2 for feature extraction ensures effective tumor contouring and region extraction, leading to high precision and recall values, as indicated in Table 4. Our approach improves current studies by integrating advanced segmentation and feature extraction techniques to automatically identify the most informative frames for classification. Using U-Net++ for segmentation and MobileNetV2 for feature extraction, our method ensures the selected frames represent the underlying pathology and are optimized for deep learning-based classification. Additionally, integrating anisotropic diffusion filtering reduces speckle noise in ultrasound imaging, resulting in improved classification performance compared to existing methods. This offers a more effective solution for frame selection in medical imaging, contributing to the field of computer-aided diagnosis. Yadav et al. [37] developed a novel computer-aided design system for the characterization of thyroid tumors in ultrasound images using an edge-preserving smoothing filter and an encoder-decoder segmentation model with ResNet50. The authors reported a classification accuracy of 99.5% in distinguishing benign from malignant tumors, proving the efficacy of combining advanced pre-processing and deep learning techniques. This also supports using segmentation and feature extraction methods to improve classification performance in medical imaging. Many previous studies have focused solely on classification without segmentation, which limits their ability to extract meaningful features from tumor regions. For instance, Uysal et al. [68] employed models like VGG16, ResNet50, and ResNeXt50, achieving a maximum accuracy of 85.83%. Our model further advances the state of the art by achieving 96.58% accuracy highlights the advantage of segmentation, as it helps models focus exclusively on tumor regions rather than background noise.A study by Shia et al. [69] employed a transfer learning-based approach using a deep residual network for feature extraction and a linear SVM classifier to distinguish benign and malignant breast tumors in ultrasound images. Tested on 2099 images from 543 patients, the model achieved 94.34% sensitivity and 93.22% specificity. Similarly, Rani et al. [70] proposed a hybrid CAD system design for screen film mammograms using deep learning-based feature extraction and machine learning-based classifiers. Their system utilized various CNN architectures, including VGG16, VGG19, GoogleNet, and MobileNetV2, for feature extraction and combined these with classifiers such as adaptive neuro-fuzzy classifier-linguistic hedges (ANFC-LH), PCA-SVM, and GA-SVM. The highest accuracy of 96% was achieved using VGG19 and ANFC-LH, demonstrating the effectiveness of hybrid CAD designs. Further multi-view learning approach for breast ultrasound classification by generating multi-resolution tumor-centered images (TCIs) from a single scan is studied by Yaozhong et al. [71], which achieved a accracy value of 92.212%. Moreover, Arnab et al. [72] used mask images instead of segmented images. For that reason, the recall parameter outperformed the other state of the art for classification and achieved 96.95 %. Md Mijnaur Rahman et al [73] employed classification based on segmentation and achieved 96.2% accuracy and support our approach by achieving such high accuracy. Whereas the segmentation is automatic in our scheme, which can enhance the operability of the system. Our work can provide an effective auxiliary diagnostic tool for the classification of BUSI and help effectively identify tumors in early screening. Additionally, Nguyen et al. [74] demonstrated that segmentation plays a crucial role in classification performance. Their segmentation-only model achieved 98.93% accuracy, but when classification was added without optimized feature extraction, accuracy dropped to 78%. This validates our approach, where segmentation is paired with a specialized feature extractor to maintain high accuracy.Similarly, He Ma et al. [75] developed Fus2Net CNN for ultrasound image classification, which achieved 92% accuracy. Their results emphasize the importance of feature extraction but lacked segmentation, leading to a lower accuracy compared to our model (96.58%). This aligns with our findings that precise segmentation significantly boosts classification performance.Another significant study, Anitha et al. [76], used a Hybrid Convolution-based Trans-MobileUNet++ (HCTMUNet++) for segmentation and Hybrid Adaptive & Attentive Network (HAAN) for classification, incorporating ShuffleNet and MobileNet. Their approach achieved 95.72% accuracy, supporting our MobileNet-based feature extraction strategy and confirming its effectiveness in breast cancer classification. Finally, Verma et al. [77] investigated deep learning frameworks for brain tumor classification, achieving 87.87% accuracy. While their study demonstrates the effectiveness of deep learning in tumor classification, it further supports our findings that segmentation-driven approaches yield better results for ultrasound-based cancer detection as ablation study also shows this fact.

Another Important approach explored by Munteanu et al. [78] is GAN-generated synthetic ultrasound images to improve classifier robustness While their work highlights the potential of data augmentation, our approach focuses on improving feature extraction through segmentation. Detailed

TABLE 5. Comparison of proposed model and state-of-the-art methods.

Reference	Methodology	Accuracy	Key Insights
Xu et al. [52]	RMTL-Net for segmentation and classification	91.18%	Segmentation +classification improves
Zhuang et al. [45]	Transfer learning with SDCB-NET and VGG for breast US classification	92.86%	Transfer learning enhances classification.
Yadav et al. [37]	Encoder-decoder segmentation model with ResNet50 for thyroid tumor classification	99.50%	Preprocessing & segmentation improve tumor detection.
Uysal et al. [68]	Classification-only models (VGG16, ResNet50, ResNeXt50)	85.83%	Classification-only models underperform.
Shia et al. [69]	Deep residual network with SVM for feature extraction	94.34% sensitivity, 93.22% specificity	Deep residual networks + SVM aid feature extraction but lack segmentation.
Rani et al. [70]	Hybrid CAD system with CNN-based feature extraction and ML classifiers	96% (VGG19 + ANFC-LH)	Hybrid CAD achieves high accuracy with CNN +ML
Yaozhong et al. [71]	Multi-view learning for breast US classification	92.21%	Multi-view learning helps but segmentation is key.
Arnab et al. [72]	Mask image-based classification	96.95% recall	Mask-based classification improves recall but lacks segmentation.
Md Mijnaur Rahman et al. [73]	Classification based on segmentation	96.20%	Segmentation-assisted classification enhances
Nguyen et al. [74]	Segmentation-only model	78%	Segmentation alone is strong, but classification must include feature extraction.
He Ma et al. [75]	Fus2Net CNN for US classification	92%	Feature extraction boosts classification when paired with segmentation.
Anitha et al. [76]	Hybrid Convolution-based Trans-MobileUNet++ (HCTMUNet++) for segmentation and HAAN for classification	95.72%	Combining segmentation + classification optimizes breast ultrasound detection.
Verma et al. [77]	Deep learning frameworks for brain tumor classification	87.87%	Deep learning is effective but segmentation enhances results.
Munteanu et al. [78]	GAN-generated synthetic US data for classifier robustness	Improved classifier robustness, no exact accuracy reported	GAN-based data augmentation strengthens model robustness.
Our Model	Segmentation (U-Net++), feature extraction (MobileNetV2), classification (ANN)	96.58%	Segmentation + optimized feature extraction outperforms other classification methods.

comparative studies related to our study has shown in Table 5. Whereas, a promising future direction would be to combine segmentation with GAN-based synthetic image generation, enhancing both data diversity and classification accuracy. GAN-generated synthetic images can introduce new variations of tumors, allowing models to train on rare cases that may not be well-represented in traditional datasets. The study has enlightening implications for breast ultrasound classification and even other types of medical image diagnosis since more effective feature extraction is the basis for further image analysis. It is important to note that binary segmentation outputs are not used directly in clinical practice. Instead, they serve as an intermediate data processing step within our system, where the true utility is realized in the comprehensive classification results that follow. Although the results are promising and compared with ground truths that were observed by radiologists whereas, some limitations must be acknowledged. The dataset used, while sufficiently varied, was limited in size. Future work should aim to include a larger and more diverse set of images to ensure that the model can generalize across different populations and imaging conditions. Additionally, although our results suggest that MobileNetV2 outperformed Other pre-trained networks in terms of feature extraction, this may not hold across all datasets or tumor characteristics. However, the computational efficiency of MobileNetV2 makes it an attractive option for real-world applications where resources are limited. The implications of this research are significant, suggesting a path forward for AI to assist radiologists by providing a second opinion and reducing the workload associated with the segmentation and classification of breast tumors.

V. CONCLUSION

In this research effort, we embarked on a journey to enhance the precision and effectiveness of breast cancer diagnosis by integrating advanced deep-learning techniques and classification models. The objective was to provide a robust and reliable framework that assists medical practitioners in early breast cancer detection, improving patient outcomes and treatment strategies. Our comprehensive framework began with segmenting breast ultrasound images, where we harnessed the power of U-Net++ to delineate regions of interest with a mean IoU of 83.8%, outperforming other state-of-the-art models like U-Net and Efficient U-net. Moreover, it also worked very well when there were multiple tumors in the dataset. The reason for selecting UNET++ is primarily becausesegmentation was not the final goal of our study; rather, it was a pre-processing step to enhance the classification process. UNET++ was chosen for its effectiveness in medical image segmentation and its relatively simple yet robustarchitecture. While other, more complex segmentation architectures exist, UNET++ provides an optimal balance of accuracy and efficiency, making it well-suited for our needs without adding unnecessary complexity to the overall process. Adopting segmentation algorithms not only improved the accuracy of breast mass profiling but also paved the way for subsequent feature extraction. Feature extraction, a pivotal step in the proposed methodology, used MobileNetV2 architecture. MobileNetV2 outperformed other pre-trained, achieving the highest test accuracy, 96.58%, with the combination of ANN classifier. The subsequent classification phase demonstrate to our commitment to thorough evaluation. Leveraging a diverse ensemble of classifiers, including Support Vector Machines, Artificial Neural Networks, k-Nearest Neighbours, Random Forest, and Long Short-Term Memory networks, we explored multiple avenues for accurate diagnosis. Each classifier brought its strengths and nuances to the diagnostic task, allowing us to understand their capabilities comprehensively. Extensive experiments guided by rigorous evaluation metrics provided valuable insights into the strengths and limitations of each model. This analysis empowered medical practitioners with a suite of tools that can aid in their decision-making process. In conclusion, our study contributes to the field of breast cancer diagnosis by presenting a holistic framework that amalgamates the prowess of deep learning, image analysis, and classification techniques. Although no single model emerged as the solution, our ensemble of classifiers provides a versatile toolkit that can be tailored to specific diagnostic scenarios and requirements. As we reflect on our journey, we acknowledge that the path to improving breast cancer diagnosis is an ongoing one. The automated nature of our system significantly reduces the time required for the manual analysis of each image. By quickly processing images and providing preliminary segmentation and classification results, our system allows medical staff to focus on critical cases and spend more time on patient care rather than on routine image analysis. Human interpretation of medical images can vary significantly among practitioners and is subject to fatigue and other human factors. Our system provides a consistent standard for image evaluation, reducing variability in diagnoses and ensuring that every patient receives a reliable assessment based on established imaging markers identified by our models. In the next phase of our research, we plan to collaborate closely with hospital partners to further validate and refine our methodologies. By working directly with clinical settings, we aim to integrate real-time diagnostic feedback and a more diverse array of ultrasound images into our study. This collaboration will not only enhance the robustness of our data but also ensure that our findings are deeply aligned with current clinical practices and challenges. Such partnerships are crucial for advancing the practical application of our research, helping to transition from theoretical models to tools that can make a tangible difference in patient care. Moreover, the decision to use a single dataset is due to avoid inconsistencies and noise from varying imaging protocols, such as the experience of radiologists and machine constraints. The chosen data set is aligned with specific research objectives. Adding more datasets make the problem complex and hard to achieve the objectives because the solution used in this study is already complex and comprehensive. Future work may explore additional modalities, extend datasets, and fine-tune model architectures [79]. Our hope is that this research will serves as a stepping-stone, inspiring further innovation and collaboration in the pursuit of early breast cancer detection and improved patient care.

VI. DATA AVAILABILITY

The data supporting this study's findings is publicly available. Codes will be provided after acceptance and on request.

VII. ETHICS DECLARATIONS

A. CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

B. ETHICAL STANDARDS

This study did not use animal experiments.

C. ETHICS APPROVAL AND CONSENT TO PARTICIPATE

Not applicable

Experiments were conducted on publicly available dataset, and it is cited properly.

D. CONSENT FOR PUBLICATION

Not applicable

E. FUNDING

Not applicable

ABBREVIATIONS

Computer-aided diagnosis (CAD)
Convolutional neural networks (CNNs)
Support Vector Machines (SVM)
Artificial neural network (ANN)
K-nearest Neighbours (KNN
Recurrent Neural Networks (RNN)
Long Short-Term Memory (LSTM)
Intersection over Union (IoU)
Dual branch U-Net (DBU-Net)
residual cross-spatial attention-guided Inception U-Net (RCAIU-Nnet)
Image of Interest (IOI)
Region of Interest (ROI)
Areas of Interest (AOIs)
Long Short-Term Memory Recurrent Neural Network (LSTM-RNN)
You Only Look Once (YOLO)
Fast Region-based Convolutional Neural Network (FR-CNN)
Single Shot Multibox Detector (SSD)
Breast Ultrasound images (BUSI)
True Positives (TP)
False Positives (FP)
True Negatives (TN)
False Negatives (FN)

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