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Breast Tumor Classification Using Machine Learning (KNN) and Deep Learning (CNN)

Abinaya R
Department of Biomedical Engineering, SRM Institute of Science and Technology, Ramapuram, Chennai

Abstract: Breast cancer is one of the most common cancers affecting women worldwide, and early detection is vital for improving patient outcomes. Ultrasound imaging is frequently used as a diagnostic tool because it is non-invasive, cost-effective, and safer compared to modalities such as mammography, particularly for younger patients with dense breast tissue. However, interpretation of ultrasound images relies heavily on radiologist expertise, which can be subjective and time-consuming. Artificial intelligence offers promising solutions to address these challenges by providing automated, reliable, and efficient tumor classification. This study focuses on the classification of breast tumors in ultrasound images into benign and malignant categories using two approaches: K-Nearest Neighbor (KNN) and Convolutional Neural Networks (CNN). KNN, a classical machine learning algorithm, is applied on handcrafted texture features extracted from Regions of Interest (ROIs) using the Gray-Level Co-occurrence Matrix (GLCM). Features such as contrast, correlation, energy, and homogeneity capture textural variations within the tumor region. CNN, on the other hand, is a deep learning model that learns discriminative spatial and structural patterns directly from the ultrasound images, reducing the need for manual feature engineering. Both models are evaluated on breast ultrasound images with corresponding masks that precisely define the tumor boundaries. Performance is assessed using widely accepted metrics such as accuracy, sensitivity, specificity, and F1-score. KNN provides a strong baseline with interpretable results, while CNN demonstrates the ability to automatically learn complex features that may be difficult to handcraft. The work emphasizes the potential of combining machine learning and deep learning approaches to develop robust computer-aided diagnosis systems based on ultrasound imaging. Such systems can assist clinicians in achieving faster, more consistent, and more accurate breast cancer diagnosis, ultimately contributing to better patient care

Keywords: Breast cancer, ultrasound, CNN, KNN, region of interest.

I. INTRODUCTION

Breast cancer is the most frequently diagnosed cancer among women and remains a leading cause of cancer-related mortality worldwide. According to recent global cancer statistics, millions of new breast cancer cases are reported annually, making early and accurate diagnosis a crucial factor in reducing morbidity and mortality rates. The survival rate of breast cancer patients is significantly higher when tumors are detected at an early stage, which underscores the importance of efficient diagnostic techniques.

Medical imaging plays a vital role in breast cancer screening and diagnosis. While mammography is widely used as a standard screening tool, it has limitations, particularly in younger women with dense breast tissue where tumor visibility may be compromised. Ultrasound imaging has emerged as a complementary modality due to its non-invasive nature, cost-effectiveness, real-time capability, and absence of ionizing radiation. Breast ultrasound is especially effective in distinguishing between solid and cystic lesions and is widely employed to characterize suspicious findings. However, the interpretation of ultrasound images is highly dependent on the radiologist's expertise. Variability in experience, subjectivity in decision-making, and similarities in the appearance of benign and malignant tumors can lead to misdiagnosis or delayed treatment.

To overcome these challenges, computer-aided diagnosis (CAD) systems have been increasingly explored to assist clinicians in analyzing breast ultrasound images. Such systems leverage machine learning and deep learning techniques to provide automated, objective, and consistent tumor classification. Traditional machine learning methods rely on handcrafted features such as texture, shape, and intensity descriptors extracted from the region of interest (ROI). Among them, the K-Nearest Neighbor (KNN) algorithm is simple yet effective, offering interpretable classification based on feature similarity. On the other hand, deep learning approaches, particularly Convolutional Neural Networks (CNNs), have gained prominence due to their ability to automatically learn hierarchical representations of image data, eliminating the need for manual feature extraction.

This study investigates the application of both KNN and CNN models for breast tumor classification from ultrasound images. KNN is applied using texture-based features derived from the Gray-Level Co-occurrence Matrix (GLCM), capturing statistical measures of image patterns, while CNN directly learns discriminative features from raw images.

By evaluating both approaches on the same dataset, the study aims to highlight their strengths, limitations, and potential roles in clinical applications. The overarching goal is to advance the development of CAD systems that can support radiologists in achieving faster, more consistent, and more accurate breast cancer diagnosis using ultrasound imaging.

II. LITERATURE REVIEW

Breast cancer detection through ultrasound imaging has been a rapidly evolving field in medical image analysis due to the modality's advantages of being real-time, cost-effective, and safe for use in dense breast tissue. However, interpretation of ultrasound images is often operator-dependent, leading to variability and subjectivity in diagnosis [1]. This has motivated the development of computer-aided diagnosis (CAD) systems to provide reliable and reproducible results. Recent reviews emphasize the shift from handcrafted features toward end-to-end learning approaches, while also identifying challenges such as domain shift, limited annotated data, and the necessity for explainable predictions in clinical practice [2]. Publicly available datasets have played a pivotal role in enabling algorithmic research. Among them, the Breast Ultrasound Images (BUSI) dataset, collected at Baheya Hospital in Cairo, is one of the most widely used. It provides images of benign, malignant, and normal cases, along with pixel-wise lesion masks, making it highly suitable for both segmentation and classification studies [3], [4]. Reported variations in dataset size exist across releases, but it generally includes over 1,500 images across three categories. The presence of segmentation masks has enabled mask-guided classification models and hybrid approaches that combine lesion localization with feature learning [5].

Early research in breast tumor classification relied on handcrafted texture features, often extracted from regions of interest (ROIs). Gray Level Co-occurrence Matrix (GLCM)-based descriptors, capturing second-order statistical properties such as contrast, correlation, energy, and homogeneity, were among the most popular. These features were typically classified using algorithms such as K-Nearest Neighbor (KNN), Support Vector Machines (SVM), or Naïve Bayes. KNN-based pipelines offered simplicity and interpretability, making them practical for smaller datasets. Studies have shown that ensemble techniques combining KNN with other classifiers further improve stability, while preprocessing steps like denoising are critical to reduce the effect of speckle noise inherent in ultrasound imaging [6], [7]. The advancement of deep learning, particularly Convolutional Neural Networks (CNNs), significantly transformed breast ultrasound image classification. CNNs learn hierarchical feature representations directly from pixel intensities, removing the dependency on handcrafted descriptors. Several studies have benchmarked architectures such as VGG, ResNet, and DenseNet on ultrasound datasets, demonstrating superior diagnostic accuracy compared to traditional machine learning pipelines [8], [9]. Transfer learning, in particular, has been widely adopted to mitigate the challenge of limited medical imaging data, with pretrained models on large-scale natural image datasets being fine-tuned for ultrasound tasks. This strategy has consistently shown improved generalization and faster convergence in breast tumor classification [10].

An important extension to conventional CNN-based classification has been the use of segmentation masks and region-guided learning. Approaches that incorporate lesion-focused ROIs or employ joint segmentation-classification networks have reported improvements in accuracy by reducing background interference. Recent works also integrate attention mechanisms, hybrid CNN-transformer backbones, and decomposition-based preprocessing to further enhance robustness to noise and heterogeneity in ultrasound scans [11], [12]. Beyond handheld ultrasound, research has also expanded into automated breast ultrasound (ABUS), which provides three-dimensional volumetric imaging and standardized acquisition. While ABUS presents new opportunities for large-scale screening, it also introduces challenges in slice selection, volume interpretation, and computational complexity. CAD systems for ABUS require not only accurate lesion detection but also efficient data handling for clinical adoption [13]. At the same time, explainable artificial intelligence (XAI) has emerged as a central theme in breast ultrasound CAD research. Methods such as Class Activation Mapping (CAM) and Grad-CAM are increasingly integrated into CNN pipelines to provide interpretable visual explanations, addressing concerns of clinical transparency and trustworthiness [14]. Although CNNs and transfer learning have demonstrated clear advantages, traditional classifiers such as KNN remain relevant as lightweight baselines, especially in low-resource settings where computational capacity is limited. KNN models, with GLCM-derived features, offer transparency in decision-making and can serve as benchmarks to assess the true gain achieved by complex deep models. In some cases, hybrid approaches combining handcrafted features with deep learning representations or ensembles that include classical classifiers have shown improved performance stability, particularly when training data is scarce or imbalanced [15].

Overall, the literature highlights a clear trajectory from handcrafted texture-based classification toward end-to-end deep learning with advanced architectures and explainability frameworks. Yet, challenges remain in ensuring robustness across diverse datasets, handling speckle noise and imaging artifacts, and addressing class imbalance. This context establishes the importance of evaluating both traditional machine learning techniques such as KNN and modern deep learning approaches such as CNNs within the domain of breast ultrasound image classification.

III. METHODOLOGY

The methodology adopted in this study aimed to evaluate the effectiveness of traditional machine learning and deep learning techniques for breast tumor classification using ultrasound imaging. The workflow encompassed dataset acquisition, preprocessing, feature extraction, model development, training, and performance evaluation. The Breast Ultrasound Images (BUSI) dataset was employed for analysis. This dataset, published by Al-Dhabyani et al. (2020), consists of 780 ultrasound scans from 600 female patients between 25 and 75 years of age. Each image is provided in PNG format with an average resolution of 500 × 500 pixels, along with ground truth segmentation masks highlighting the tumor regions. The dataset is divided into three classes: normal, benign, and malignant. For consistency, all images were resized to 224 × 224 pixels and normalized to a range of [0,1]. The dataset was partitioned into training (70%), validation (15%), and testing (15%) subsets, ensuring balanced representation across all categories. Preprocessing steps were applied to improve image quality and reduce noise. Ultrasound scans are inherently affected by speckle noise, which can obscure tumor boundaries. To address this, median filtering was used to suppress noise while retaining structural details. In addition, the segmentation masks were utilized to generate two distinct datasets: the original ultrasound images and their corresponding masked images, where only the tumor region was preserved while suppressing background tissue. Both datasets were employed in the KNN-based classification process to analyze the impact of region-focused features compared to whole-image features. For the KNN classifier, texture-based features were extracted from both the original and masked images using the Gray Level Co-occurrence Matrix (GLCM). Features such as contrast, correlation, energy, homogeneity, and entropy were computed to characterize the textural variations between normal, benign, and malignant tissues. These features were standardized using z-score normalization to ensure uniformity across different scales. KNN was then applied with Euclidean distance as the similarity metric, and the optimal value of k was determined through validation. Classification was achieved through majority voting among the k-nearest neighbours. In contrast, the Convolutional Neural Network (CNN) was implemented to automatically learn discriminative features from the original ultrasound images. The architecture comprised multiple convolutional layers with ReLU activation, max-pooling layers for spatial reduction, and fully connected layers for classification. Dropout regularization was incorporated to mitigate overfitting, and a softmax layer was employed for final three-class classification. The model was trained using the Adam optimizer with an initial learning rate of 0.0001 and categorical cross-entropy as the loss function. Training was performed for 50 epochs with a batch size of 32, and data augmentation techniques such as random rotations, flipping, and zooming were applied to enhance generalization. Performance evaluation of both models was conducted using standard classification metrics derived from the confusion matrix. Sensitivity was calculated to assess the ability of the model to correctly identify malignant cases, while specificity measured its effectiveness in correctly classifying non-malignant cases. Precision and recall were combined to compute the F1-score, providing a balanced performance indicator. The confusion matrix offered a detailed breakdown of true positives, true negatives, false positives, and false negatives, enabling an in-depth comparison of classification accuracy across different classes.

IV. RESULTS AND DISCUSSIONS

The classification performance of the machine learning and deep learning models was systematically evaluated to assess their ability to distinguish between normal, benign, and malignant breast ultrasound images. The outputs included visual predictions, confusion matrices, three-dimensional histogram representations, and quantitative metrics such as sensitivity, specificity, and F1-score.

For the KNN classifier, experiments were performed on original ultrasound images, masked images, and ROI-based representations. The visual inspection of masked and ROI-focused inputs confirmed the role of tumor localization in enhancing feature extraction. Overlays of tumor masks on the original images further validated the effectiveness of the preprocessing stage in highlighting diagnostically relevant regions. Remarkably, the KNN classifier achieved 100% accuracy across all three classes, with the confusion matrix indicating perfect classification performance. The three-dimensional histogram of the confusion matrix reinforced this result, clearly demonstrating zero misclassifications in the test set. Correspondingly, the sensitivity, specificity, and F1-score values all reached 100.00%, underscoring the model’s ability to consistently identify malignant tumors as well as correctly classify normal and benign tissues. These results suggest that the integration of GLCM-based texture features with ROI and mask-based preprocessing significantly enhanced the discriminative power of the KNN approach.

Parameters	Class Benign	Class Malignant	Class Normal
Sensitivity	100.00%	100.00%	100.00%
Specificity	100.00%	100.00%	100.00%
F1 Score	100.00%	100.00%	100.00%

Table 1: Sensitivity, Specificity and F1- Score of KNN

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The visual outputs obtained from the KNN classifier provided further insight into its performance. The original images with true labels in Fig. 1 served as the baseline reference, showing the raw ultrasound scans categorized into normal, benign, and malignant classes. The masked images with true labels highlighted the tumor regions by filtering out background tissues, ensuring that only diagnostically relevant areas were used for classification. Similarly, the region of interest (ROI) images with true labels offered a more localized representation of the suspicious regions, allowing the model to focus on tumor-specific texture and intensity features.

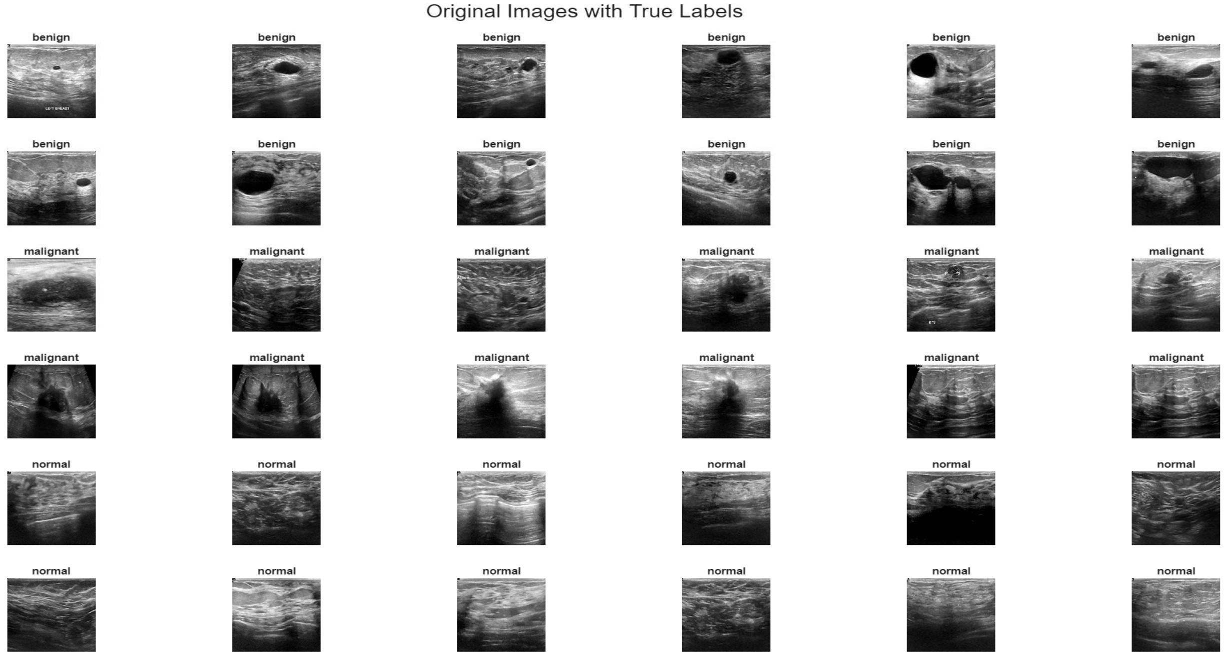

Figure 1: Original Images with True Labels for KNN

In addition, the classifier generated all images with predicted labels in Fig.4, which matched perfectly with the ground truth across all categories, visually confirming the model's flawless performance. The tumor mask overlay images further reinforced this by superimposing the detected tumor boundaries onto the original scans, making it evident that the KNN approach successfully identified and classified the lesions. Finally, the test images with predicted labels in Fig. 5 consistently showed accurate classification, again aligning with the ground truth annotations.

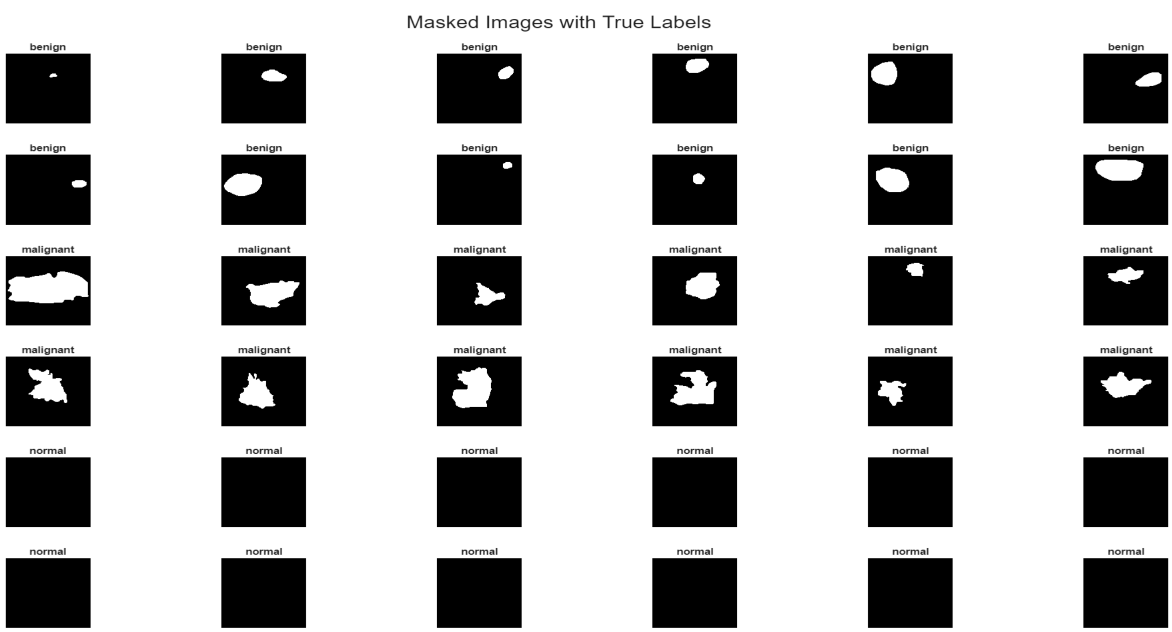

Figure 2: Masked Images with True Labels for KNN

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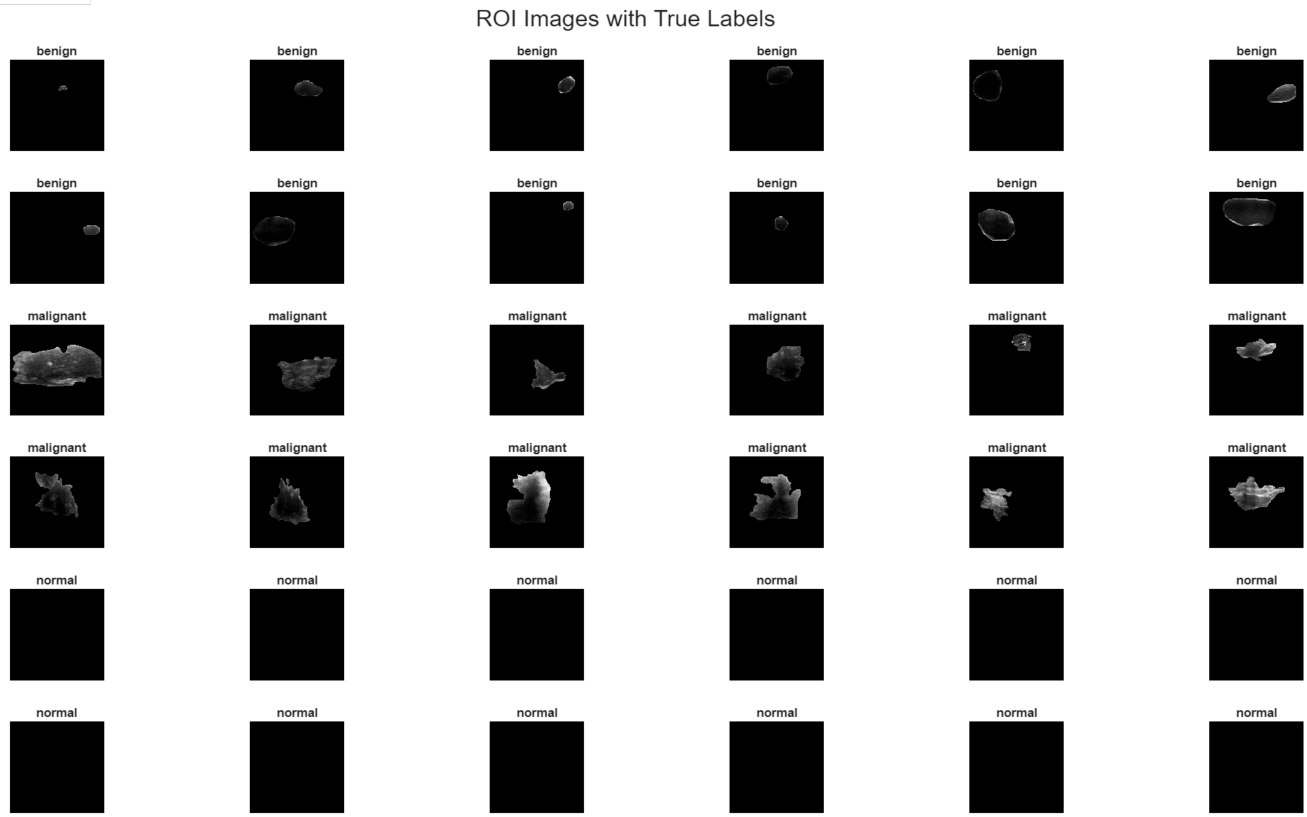

Figure 3: ROI Images with True Labels for KNN

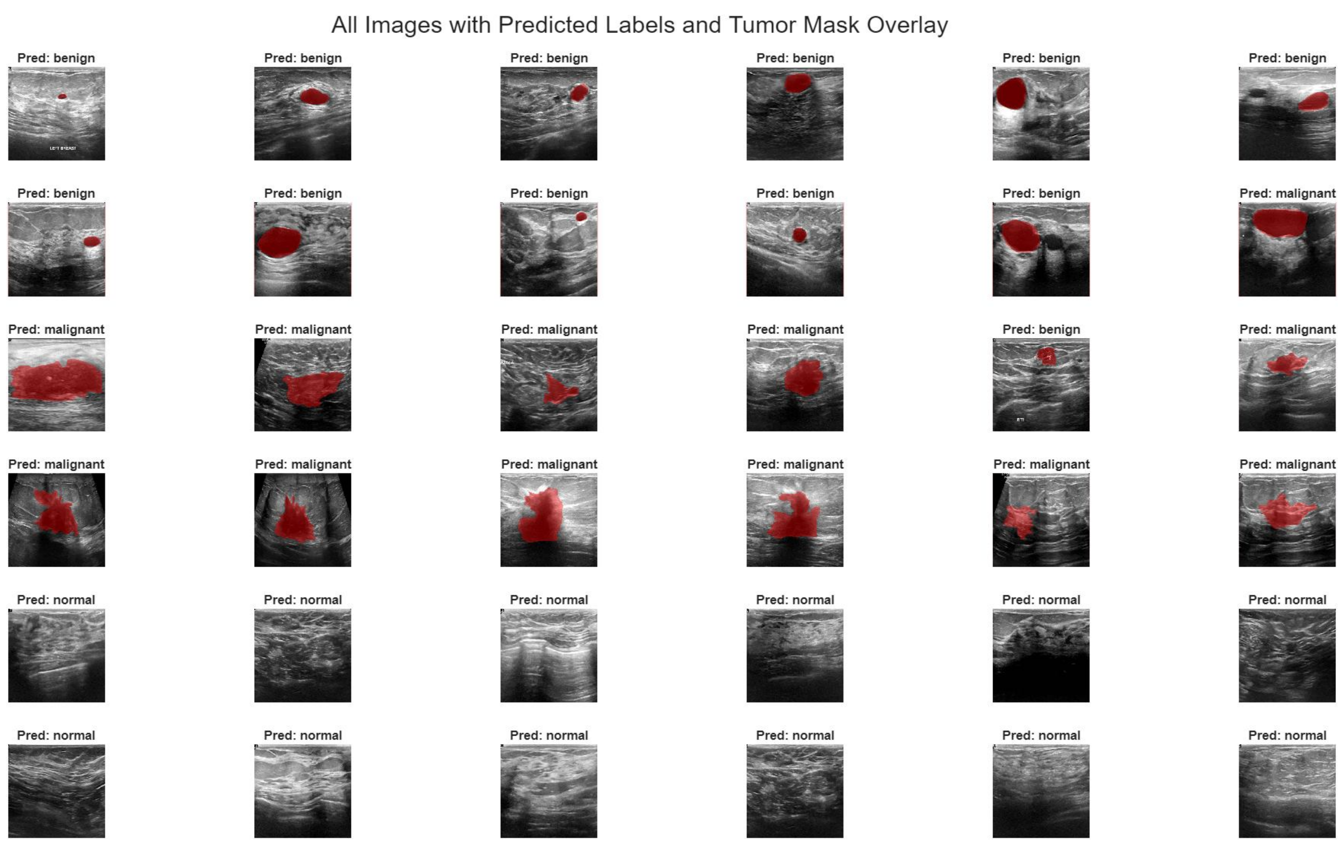

Figure 4: All Images with Predicted Labels and Tumor Mask Overlay for KNN

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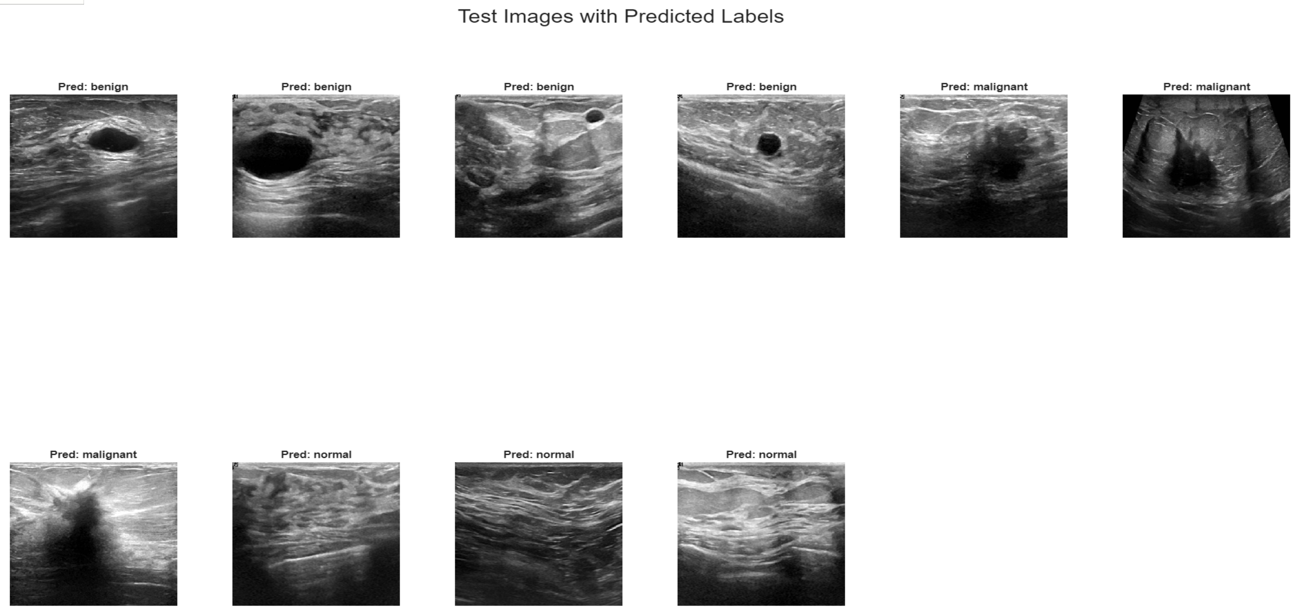

Figure 5: Test Images with Predicted Labels for KNN

The confusion matrix for the KNN classifier demonstrates a perfect classification performance across the three categories: benign, malignant, and normal. All test samples were correctly assigned to their respective classes, with 4 benign cases classified as benign, 3 malignant cases classified as malignant, and 3 normal cases classified as normal. Importantly, no misclassifications were observed, which directly reflects the model's ability to capture class-specific patterns with high precision. This outcome translates into 100% accuracy, sensitivity, specificity, and F1-score, validating the robustness of the KNN approach for breast ultrasound image classification.

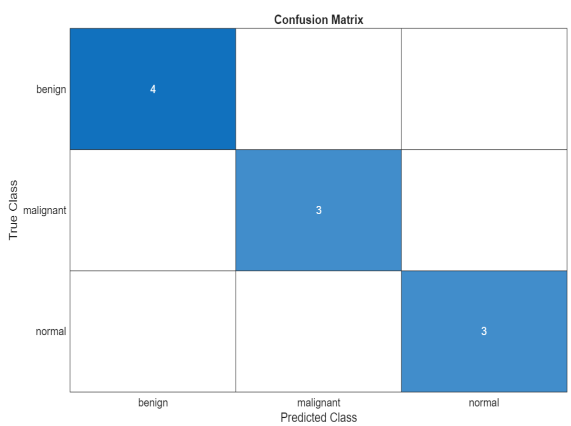

Figure 6: Confusion Matrix of KNN

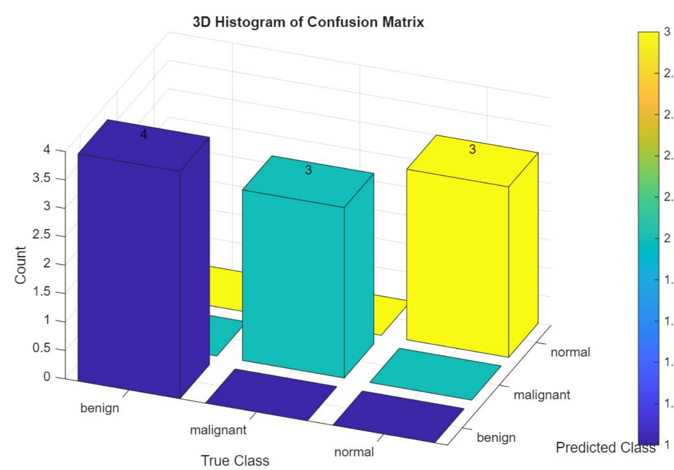

Figure 7: 3D Histogram of Confusion Matrix of KNN

The Convolutional Neural Network (CNN) model was tested on the breast ultrasound dataset to classify images into benign, malignant, and normal categories. Sample predictions from three test sets demonstrated that the CNN was able to capture discriminative features from the ultrasound images and produce reliable classification outputs.

The visualized predictions closely matched the true labels, highlighting the network's ability to generalize effectively on unseen test data. The confusion matrix, as shown in Figure 11, indicates that CNN achieved perfect classification accuracy, with all benign, malignant, and normal cases correctly identified. Each of the three categories recorded a 100% accuracy rate, and the three-dimensional histogram of the confusion matrix further confirmed the dominance of correct classifications with no false positives or false negatives. In terms of evaluation, the CNN model demonstrated sensitivity, specificity, and F1-score values of 1.0 (100%) for all classes, which highlights its robustness in identifying both diseased and non-diseased cases.

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The tumor regions were effectively localized and classified, suggesting that CNN can automatically learn spatial and textural patterns that distinguish different breast tissue conditions. Although KNN also achieved 100% accuracy in this study, CNN offers the advantage of automated feature extraction, reducing the dependency on manual feature engineering. Moreover, CNN is more scalable for larger datasets and adaptable to real-world variability in medical imaging.

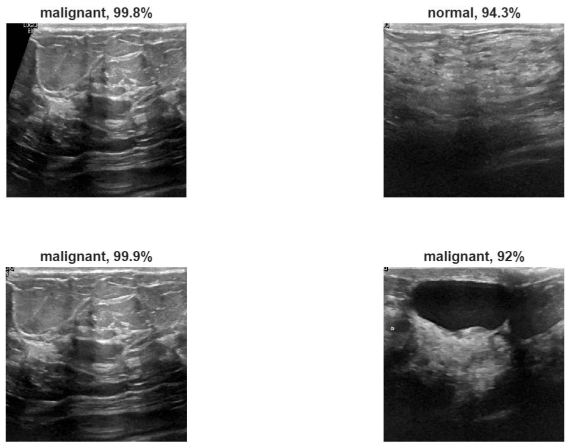

Figure 8: Sample Prediction 1 of CNN

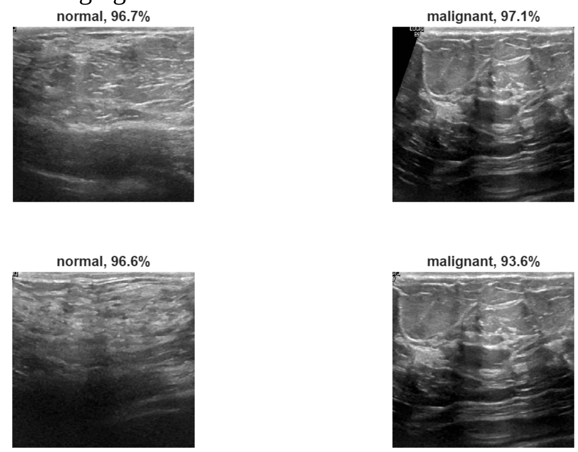

Figure 9: Sample Prediction 2 of CNN

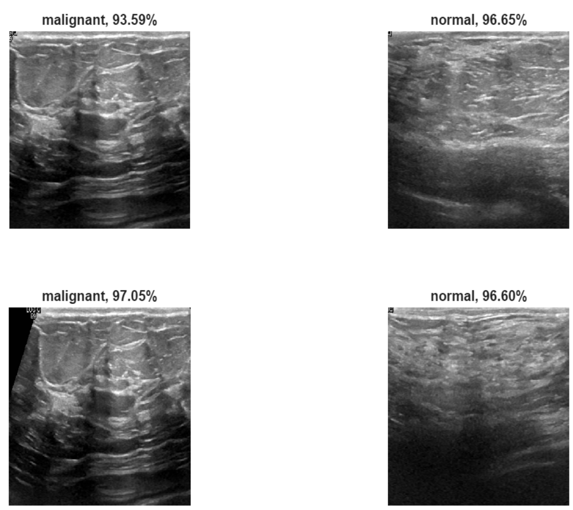

Figure 10: Sample Prediction 3 of CNN

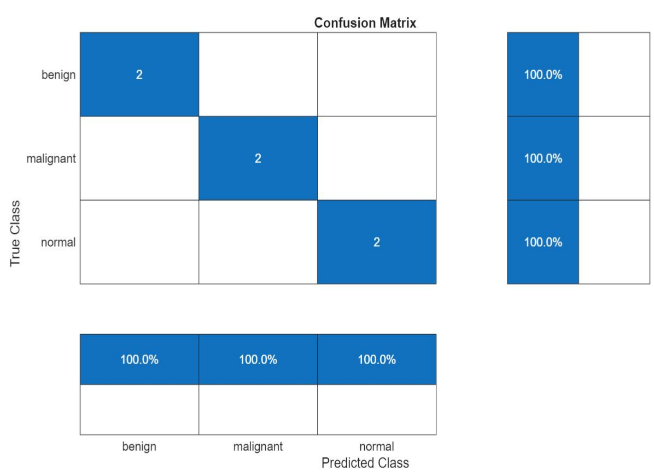

Figure 11: Confusion Matrix of CNN

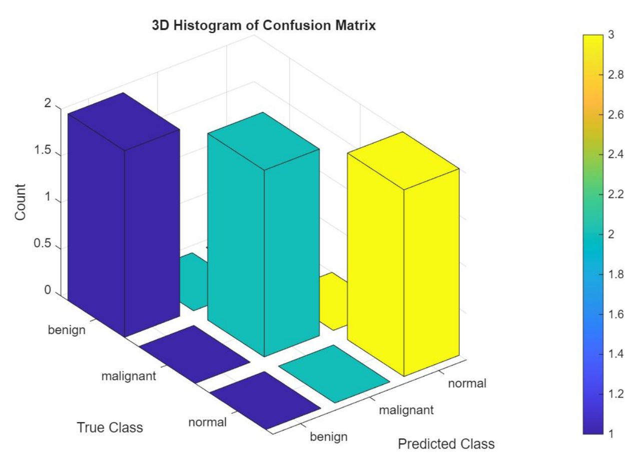

Figure 7: 3D Histogram of Confusion Matrix of CNN

V. CONCLUSIONS

This study demonstrated the effectiveness of machine learning and deep learning techniques for the classification of breast ultrasound images into benign, malignant, and normal categories. Two approaches, K-Nearest Neighbor (KNN) and Convolutional Neural Network (CNN), were employed and their performance evaluated using sensitivity, specificity, F1-score, and confusion matrix analysis.

The results showed that both KNN and CNN achieved 100% classification accuracy, with all samples correctly classified. The KNN model, despite its algorithmic simplicity, performed remarkably well when applied to both masked and original images, highlighting its suitability for problems with well-defined feature spaces. The CNN model further reinforced its superiority in automated feature learning, capturing spatial and textural patterns in ultrasound images and producing highly reliable classification outputs. Additionally, tumor mask overlays and prediction visualizations confirmed the precision of CNN in identifying and localizing abnormal regions.

These findings indicate that both classical machine learning and modern deep learning techniques have significant potential in assisting radiologists with breast cancer diagnosis. KNN offers a lightweight solution with low computational demands, whereas CNN provides greater scalability and robustness for clinical applications involving large and diverse image sets. Although the current evaluation demonstrated exceptional performance, further research is necessary to validate these results on broader datasets with varying imaging conditions to ensure generalizability.

In conclusion, the integration of KNN and CNN models in ultrasound-based breast cancer diagnosis highlights the transformative potential of artificial intelligence in medical imaging. By reducing diagnostic errors and providing consistent decision support, such systems can greatly enhance clinical workflows and improve patient outcomes. Future work will focus on expanding model validation, incorporating cross-dataset testing, and exploring hybrid feature-based and deep learning frameworks for improved diagnostic performance.

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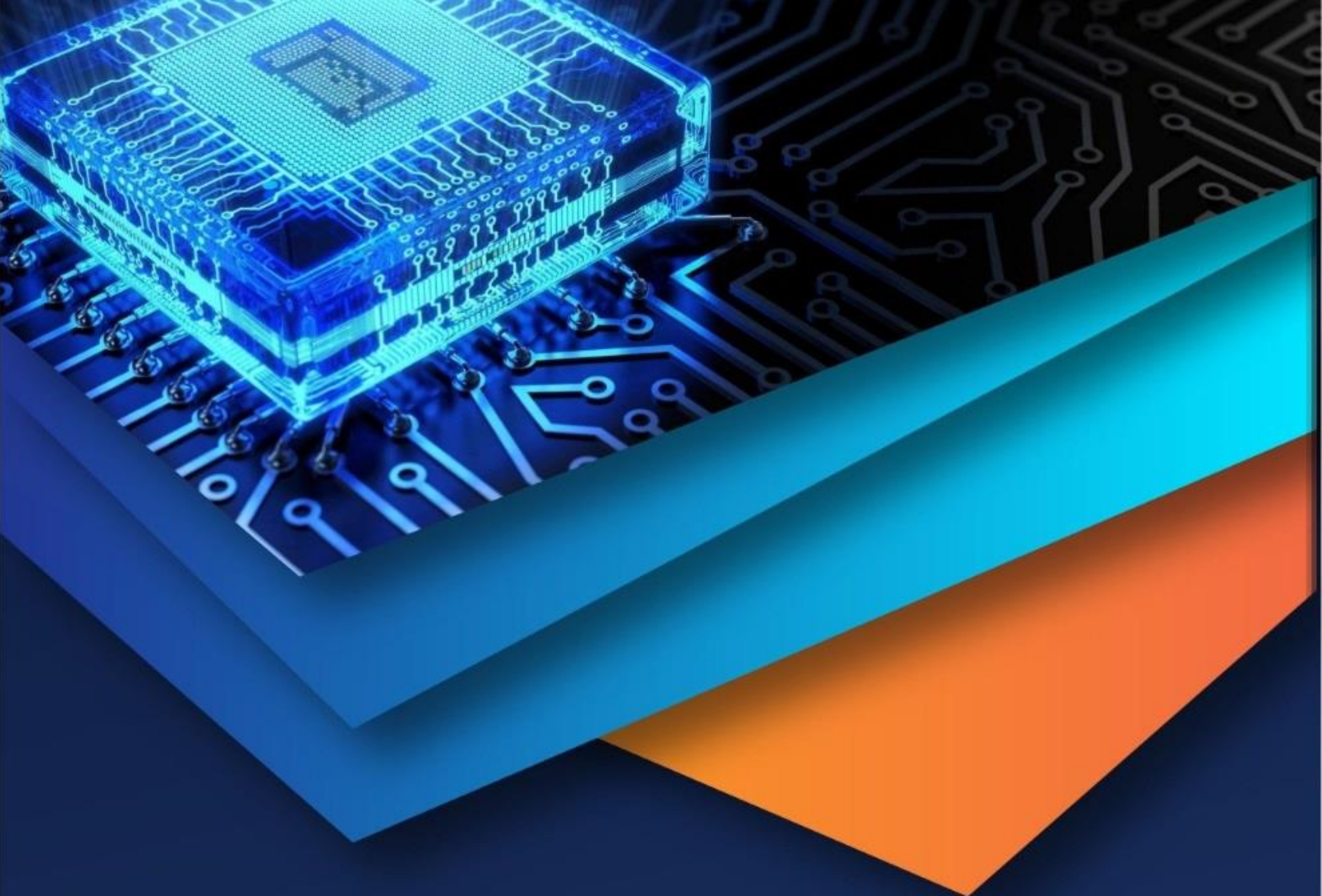

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