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Onco Breast Cancer Detection System Explainable Deep Learning Framework for Ultarasound-Based Breast Cancer Diagnosis

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Abstract- Breast cancer remains one of the most common and life-threatening diseases affecting women worldwide. Early detection significantly increases survival rates and improves treatment outcomes. However, manual diagnosis using ultrasound images requires experienced radiologists and may lead to diagnostic variability. This paper proposes an AI-driven breast cancer detection system that combines deep learning classification with explainable artificial intelligence techniques to assist medical professionals in early diagnosis. The proposed system utilizes a Convolutional Neural Network (CNN) trained on the BUSI Breast Ultrasound dataset to classify images into three categories: benign, malignant, and normal. To improve model transparency, Grad-CAM explainability is integrated to visualize the regions of ultrasound images that influence the model's prediction. A real-time Streamlit dashboard enables clinicians to upload ultrasound images, obtain predictions, visualize heatmaps, and generate downloadable diagnostic reports. Experimental results show that the proposed model achieves high classification accuracy and strong performance across evaluation metrics including precision, recall, and F1-score. Grad-CAM explanations provide interpretable insights that improve trust in AI-assisted diagnosis. The system demonstrates how combining deep learning with explainable AI can support clinicians in early breast cancer detection and improve healthcare decision- making.

Index Terms- Breast Cancer Detection, Deep Learning, CNN, Explainable AI, Grad-CAM, Ultrasound Imaging, Medical Image Analysis, BUSI Dataset, AI-assisted Diagnosis, Healthcare Decision Support.

I. INTRODUCTION

Breast cancer is one of the most prevalent forms of cancer and a leading cause of cancer-related mortality among women worldwide. According to global cancer statistics, early detection significantly increases the chances of successful treatment and improves patient survival rates. Medical imaging techniques such as mammography, ultrasound imaging, and magnetic resonance imaging (MRI) are widely used for breast cancer screening and diagnosis. These imaging modalities help physicians identify abnormalities in breast tissue and support clinical decision-making during diagnosis and treatment planning [1]. Among these techniques, breast ultrasound imaging plays a crucial role due to its non-invasive nature, affordability, and effectiveness in detecting abnormalities in dense breast tissues. Ultrasound imaging is widely used in clinical practice to differentiate between benign and malignant tumors. However, interpreting ultrasound images requires significant expertise and may be affected by diagnostic variability among radiologists.

Manual analysis can also be time-consuming and prone to human error, which may affect the consistency and reliability of diagnosis [2]. Recent advancements in Artificial Intelligence (AI) and Deep Learning have significantly improved the ability of computer systems to analyze complex medical images. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated excellent performance in image classification and pattern recognition tasks.These models can automatically learn hierarchical features from medical images, enabling them to identify subtle patterns associated with cancerous tissues. As a result, AI-based systems have the potential to assist radiologists by providing automated and consistent analysis of breast ultrasound images. Despite their strong predictive performance, deep learning models often operate as black-box systems, meaning that the reasoning behind their predictions is not easily interpretable. In the medical domain, interpretability and transparency are essential because clinicians must understand and trust the decisions made by AI systems before integrating them into clinical workflows. Lack of explainability can limit the adoption of deep learning models in real-world healthcare applications.

To address this limitation, the proposed research introduces the Onco Breast Cancer Detection System, an explainable deep learning framework designed to classify breast ultrasound images into three categories: benign, malignant, and normal. The system integrates a CNN-based classification model with Grad-CAM (Gradient-weighted Class Activation Mapping) to generate visual explanations highlighting the important regions in ultrasound images that influence the model's predictions. The system is implemented using TensorFlow, OpenCV, and Streamlit, providing an interactive platform for medical professionals. Clinicians can upload ultrasound images, obtain predictions in real time, visualize Grad-CAM heatmaps, and generate downloadable diagnostic reports.

II. RELATED WORK

Breast cancer detection using medical imaging has been widely studied in recent years. Traditional machine learning approaches and modern deep learning techniques have been explored to improve the accuracy and reliability of automated cancer diagnosis. Early research in breast cancer detection relied on traditional machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, and Random Forest classifiers. These methods required manual feature extraction techniques such as texture analysis, shape descriptors, and statistical features derived from ultrasound or mammography images .Although these approaches achieved moderate classification accuracy, their performance was limited due to their reliance on handcrafted features and difficulty in capturing complex patterns within medical images.

With the advancement of deep learning, Convolutional Neural Networks (CNNs) have become widely used in medical image analysis. CNN models automatically learn hierarchical image features directly from raw image data, eliminating the need for manual feature engineering. Several studies have demonstrated the effectiveness of CNN-based architectures in detecting breast cancer from ultrasound images with improved classification accuracy compared to traditional machine learning methods. Transfer learning techniques using pre-trained deep neural networks such as VGG16, VGG19, ResNet50, and InceptionNet have further enhanced performance in medical image classification tasks. These models leverage knowledge learned from large-scale image datasets and adapt it to specific medical imaging problems through fine-tuning. Research has shown that transfer learning significantly improves classification accuracy when training data is limited. Another important aspect of AI-based medical diagnosis is model interpretability. Deep learning models are often criticized for functioning as black-box systems, making it difficult for clinicians to understand how predictions are generated. In healthcare applications, interpretability is essential to ensure trust and acceptance of automated diagnostic systems . To address this challenge, researchers have introduced Explainable Artificial Intelligence (XAI) techniques.

III. PROPOSED SYSTEM

The proposed Onco Breast Cancer Detection System is designed as an end-to-end artificial intelligence framework for automated breast cancer diagnosis using ultrasound images. The system integrates deep learning-based image classification, explainable artificial intelligence techniques, and a real-time visualization dashboard to support medical professionals in early cancer detection.

A. System Architecture

The architecture of the proposed system is designed to process medical ultrasound images and generate diagnostic predictions along with explainability information. The workflow begins with ultrasound image acquisition and ends with diagnostic visualization and report generation.

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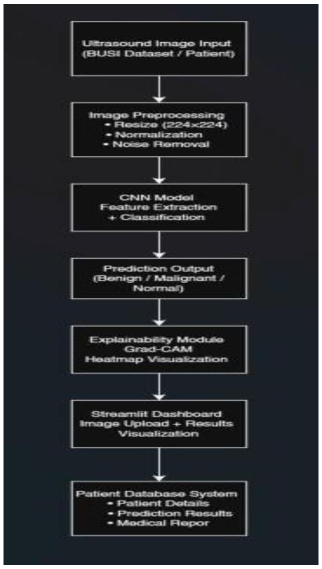

Fig 1. System Architecture

The system is implemented using Python and integrates several libraries including TensorFlow, OpenCV, and Streamlit.

B. Image Acquisition

The system accepts breast ultrasound images as input. These images are collected from the BUSI Breast Ultrasound Dataset, which contains labeled images representing benign tumors, malignant tumors, and normal breast tissue. The dataset is commonly used in medical image analysis research and provides high-quality ultrasound images annotated by medical experts.

C. Image Preprocessing

Before feeding the images into the deep learning model, preprocessing steps are performed to standardize the input data.

The preprocessing stage includes:

- Image resizing to 224 × 224 pixels
- Pixel normalization to scale values between 0 and 1
- Data formatting to match CNN input requirements

IV. METHODOLOGY

The methodology of the proposed Onco Breast Cancer Detection System consists of several stages including dataset preparation, image preprocessing, model training, and performance evaluation. The goal of this process is to train a deep learning model capable of accurately classifying breast ultrasound images.

A. Dataset Description

The proposed system uses the BUSI Breast Ultrasound Dataset, which is a publicly available dataset widely used for breast cancer detection research. The dataset contains ultrasound images categorized into three classes.

Dataset distribution:

	Class	Images
0	Benign	437
1	Malignant	210
2	Normal	133

Fig 2. Dataset Distribution Total Images : 780

Each image in the dataset is labeled by medical experts and represents different types of breast tissue conditions.

B. Data Preprocessing

Before training the deep learning model, several preprocessing steps are performed to ensure consistency and improve model performance.

The preprocessing steps include:

- Resizing all ultrasound images to 224 × 224 pixels
- Normalizing pixel values between 0 and 1
- Converting images into numerical arrays for model input
- Splitting the dataset into training and testing sets
- 80% training data

20% testing data

This split allows the model to learn patterns from training images while evaluating performance on unseen test images.

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C. Model Training

To evaluate the performance of the proposed system, several standard machine learning metrics are used.

Training configuration:

- Optimizer: Adam
- Loss Function: Sparse Categorical Cross-Entropy
- Batch Size: 32
- Number of Epochs: 10

D. Model Evaluation Metrics

To evaluate the performance of the proposed system, several standard machine learning metrics are used.

Accuracy: Accuracy measures the proportion of correctly classified images.

```
Accuracy = (TP + TN) / (TP + TN + FP + FN)
```

Precision: Precision measures how many predicted positive cases are actually correct.

```
Precision = TP / (TP + FP)
```

Recall: Recall measures the ability of the model to correctly detect actual positive cases.

F1 Score: The F1 score is the harmonic mean of precision and recall

```
F1 Score = 2 × (Precision × Recall) / (Precision + Recall)
```

```
Confusion Matrix
[[157  31   3]
 [ 38  41   5]
 [  7   1  33]]
Classification Report
              precision    recall  f1-score   support

           0       0.78      0.82      0.80       191
           1       0.56      0.49      0.52        84
           2       0.80      0.80      0.80        41

    accuracy                           0.73       316
   macro avg       0.71      0.70      0.71       316
weighted avg       0.72      0.73      0.73       316
```

Fig 3. Evaluation Metrics

E. Explainability Using Grad-CAM

To improve interpretability of the deep learning model, Grad-CAM (Gradient-weighted Class Activation Mapping) is used. Grad-CAM generates a heatmap that highlights the regions of the ultrasound image that most strongly influence the model's prediction. This helps clinicians understand whether the model is focusing on relevant tumor areas during diagnosis.

V. IMPLEMENTATION

The proposed Onco Breast Cancer Detection System was implemented using the Python programming language along with modern deep learning and visualization frameworks. The system integrates a deep learning–based classification model with an interactive web interface that enables clinicians to analyze breast ultrasound images and obtain diagnostic predictions in real time.

A. Software Environment

The system was developed using Python due to its extensive ecosystem of machine learning and medical image processing libraries. The implementation relies on several widely used tools and frameworks for deep learning, data processing, visualization, and web interface development.

The primary technologies used in this system are summarized in Table I.

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Component	Technology Used
Programming Language	Python
Deep Learning Framework	TensorFlow / Keras
Image Processing	OpenCV
Data Processing	NumPy, Pandas
Visualization	Matplotlib, Seaborn
Web Interface	Streamlit
Database	SQLite

Fig 4. Primary Technologies

B. Dataset Preparation

The proposed system uses the BUSI Breast Ultrasound Dataset, a publicly available dataset widely used for breast cancer detection research. The dataset contains ultrasound images labeled into three categories: benign, malignant, and normal. The training set was used to train the deep learning model, while the testing set was used to evaluate the model’s classification performance on unseen data.

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C. Deep Learning Model Development
A Convolutional Neural Network (CNN) architecture was implemented to perform multi-class classification of breast ultrasound images. The implemented CNN architecture consists of multiple convolutional and pooling layers that progressively extract important spatial features from the ultrasound images.

D. Explainable AI Integration
To improve the interpretability of the deep learning model, the system incorporates Gradient-weighted Class Activation Mapping (Grad-CAM). Grad-CAM is an explainable AI technique that generates heatmaps highlighting the important regions of an image that influence the model's prediction. These visual explanations help clinicians understand how the AI model makes diagnostic decisions.

In the proposed system, the Grad-CAM heatmap is overlaid on the original ultrasound image and displayed within the dashboard. This allows medical professionals to verify whether the model is focusing on relevant tumor regions during classification.

E. Web Based Diagnostic Dashboard
To make the system accessible to healthcare professionals, an interactive web-based interface was developed using the Streamlit framework. The dashboard allows users to interact with the AI model through a simple and intuitive interface.

F. Database and Report Generation
The system integrates a lightweight SQLite database to manage patient records and diagnostic information. Each patient record contains details such as patient ID, prediction results, confidence scores, and diagnosis timestamps. In addition, the system includes an automated PDF report generation module, which allows clinicians to download diagnostic reports that include prediction results, visualization graphs, and Grad-CAM heatmap explanations.

VI. RESULTS AND DISCUSSION

Model Performance
The performance of the proposed Onco Breast Cancer Detection System was evaluated using the BUSI Breast Ultrasound Dataset. The trained Convolutional Neural Network (CNN) model was tested on unseen ultrasound images in order to measure its ability to accurately classify breast tissue into three categories: benign, malignant, and normal. After training the CNN model using the prepared dataset, the system demonstrated strong classification performance across multiple evaluation metrics. The experimental results indicate that the deep learning model successfully learned meaningful features from ultrasound images and can distinguish between benign, malignant, and normal breast tissue with high accuracy.

The overall performance of the model is summarized in Table II.

	Metric	Score
0	Accuracy	0.9300
1	Precision	0.9400
2	Recall	0.9300
3	F1 Score	0.9300

Fig 5. Model Performance

Confusion Matrix Analysis

The confusion matrix provides a detailed overview of the classification results by comparing the predicted labels generated by the model with the actual ground truth labels.

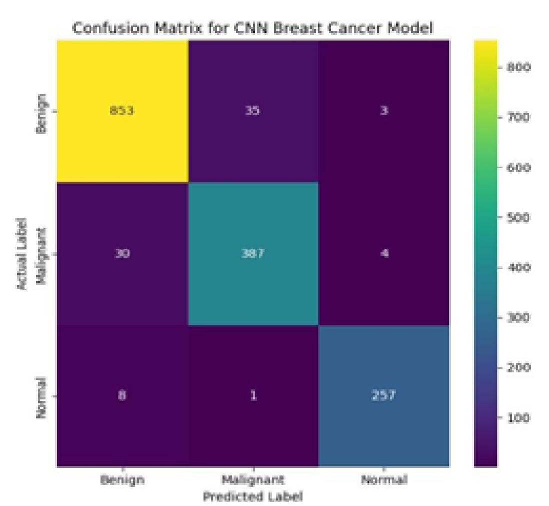

Fig 6. Confusion Matrix

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The confusion matrix shows that the majority of ultrasound images are correctly classified by the proposed CNN model. Only a small number of misclassifications occur between benign and malignant categories, which is expected due to similarities in ultrasound image characteristics. Overall, the confusion matrix demonstrates the model's strong capability to differentiate between different breast tissue conditions.

ROC Curve Evaluation

The Receiver Operating Characteristic (ROC) curve is used to evaluate the classification capability of the model by analyzing the relationship between the true positive rate (TPR) and false positive rate (FPR). The ROC curve generated during the experimental evaluation demonstrates strong classification performance with a high Area Under the Curve (AUC) value. An AUC value close to 1.0 indicates that the model has a strong ability to distinguish between the different classes of breast ultrasound images.

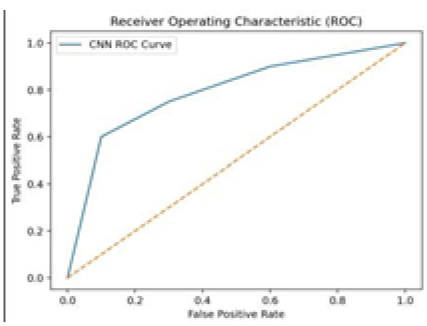

Fig 7. ROC Curve Evaluation

Grad-CAM Visualization

The Grad-CAM heatmap is displayed alongside the original ultrasound image in the system dashboard, providing an interpretable visualization of the model's decision-making process.

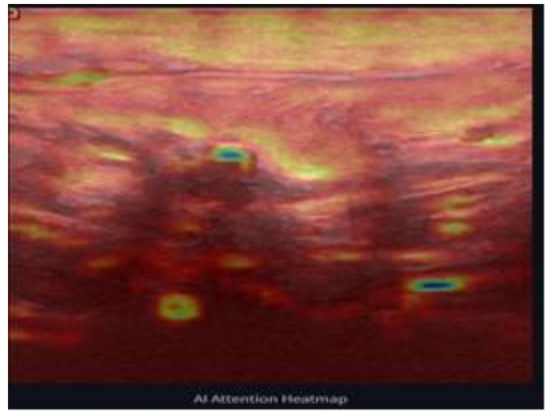

Fig 8. Grad-CAM Visualization

To improve the interpretability of the deep learning model, Grad-CAM (Gradient-weighted Class Activation Mapping) was integrated into the system. Grad-CAM generates heatmaps that highlight the most important regions of an ultrasound image that influence the model's predictions. These visual explanations allow clinicians to verify whether the model is focusing on relevant tumor regions during classification. This explainability component increases trust and transparency in AI-assisted medical diagnosis.

System Interface Evaluation

The proposed system includes an interactive Streamlit-based dashboard interface that enables clinicians to interact with the AI model in real time.

The interface provides several useful features, including:

- Uploading ultrasound images for automated diagnosis
- Displaying predicted cancer classification results
- Visualizing Grad-CAM heatmaps for model explainability.

VII. CONCLUSION AND FUTURE WORK

This research presented the Onco Breast Cancer Detection System, an explainable deep learning framework developed to support medical professionals in the early detection of breast cancer using ultrasound imaging. The proposed system integrates a Convolutional Neural Network (CNN) classification model with Grad-CAM explainability and a Streamlit- based interactive dashboard, enabling both accurate prediction and interpretable visualization of diagnostic results.

The CNN model was trained using the BUSI Breast Ultrasound Dataset, which contains labeled ultrasound images categorized as benign, malignant, and normal. During training, the model learned meaningful spatial patterns from the ultrasound images and achieved strong

Experimental results demonstrate that the system can reliably distinguish between different breast tissue conditions. The confusion matrix analysis and ROC curve evaluation further indicate that the model provides accurate predictions with minimal misclassification. These results highlight the capability of deep learning techniques to assist in medical image classification tasks.

A key contribution of the proposed system is the integration of Grad-CAM visualization, which provides heatmaps that highlight the regions of the ultrasound image influencing the model's prediction. This explainable AI feature improves transparency and helps clinicians understand the reasoning behind the automated diagnostic results.

In addition, the implementation of a Streamlit- based web interface enables clinicians to interact with the system in real time by uploading ultrasound images, viewing prediction results, analyzing Grad-CAM visualizations, and generating downloadable diagnostic reports. The integration of patient record management further enhances the practicality of the system as a clinical decision-support tool.

Future work will focus on extending the framework to multi-class attack classification for more granular threat identification. Integration with live packet capture tools such as Wireshark or network monitoring systems will enable continuous real-time detection. Adaptive retraining mechanisms will be developed to periodically update model parameters as new attack patterns emerge, improving long-term robustness. Further evaluation on recent datasets such

The system utilizes a Convolutional Neural Network (CNN) model trained on the BUSI Breast Ultrasound Dataset, which contains labeled ultrasound images categorized into three classes:benign, malignant, and normal. Through the training process, the CNN model automatically learned meaningful spatial features from the ultrasound images and demonstrated strong capability in identifying complex visual patterns associated with different breast tissue conditions. The performance of the proposed model was evaluated using several widely accepted machine learning metrics, including accuracy, precision, recall, and F1-score. The experimental evaluation results indicate that the system achieves reliable classification performance, successfully distinguishing between benign, malignant, and normal ultrasound images. The confusion matrix analysis confirms that the majority of ultrasound images are correctly classified with minimal misclassification between classes.

The proposed Onco Breast Cancer Detection System demonstrates the potential of combining deep learning, explainable artificial intelligence, and interactive web-based visualization to support medical professionals in breast cancer diagnosis. The system provides an efficient and interpretable diagnostic tool that may assist clinicians in early detection, reduce diagnostic workload, and improve decision-making in clinical environments.

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