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AN EXPLAINABLE AI-POWERED CLINICAL DECISION SUPPORT SYSTEM FOR BREAST CANCER DIAGNOSIS USING MAMMOGRAM IMAGE ANALYSIS

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ABSTRACT

Early detection of breast cancer via mammography is vital for improving survival rates, yet manual interpretation remains challenging due to image noise and low contrast. This paper presents an Explainable AI (XAI)-powered Clinical Decision Support System (CDSS) to automate diagnosis while ensuring transparency. The system utilizes medical image preprocessing and a Convolutional Neural Network (CNN) for classification. To address the "black-box" nature of deep learning, Grad-CAM and LIME are integrated to provide visual justifications by highlighting suspicious regions. Deployed as a web application, the system enhances diagnostic reliability and clinical trust, offering radiologists an ethical, interpretable tool for more accurate breast cancer screening.

KEYWORDS: Breast Cancer, Mammography, Clinical Decision Support System, Deep Learning, Convolutional Neural Network, Explainable AI, Grad-CAM, LIME.

1. INTRODUCTION

Breast cancer remains a leading global health concern where early detection via mammography significantly improves survival rates. However, manual interpretation is often hindered by dense tissue, noise, and low contrast, leading to potential oversights. While deep learning, specifically Convolutional Neural Networks (CNNs), has shown high accuracy in automating this analysis, these models often function as "black boxes." This lack of transparency limits clinical trust and adoption.

To bridge this gap, this paper proposes an Explainable AI (XAI)-based Clinical Decision Support System (CDSS). By integrating deep learning with interpretability techniques, the system provides both accurate diagnostic predictions and visual justifications, ensuring transparency and reliability in clinical breast cancer screening.

2. RELATED WORK

The application of AI in breast cancer diagnosis has evolved rapidly since 2020, focusing on clinical readiness and transparency [4, 15]. Traditional CAD systems are increasingly being replaced by deep learning models that offer superior classification accuracy [12, 13]. This section reviews three foundational models and identifies the existing research gap.

2.1.*Cascaded Deep Learning for Mass Detection (Dhungel et al., 2017)*

Dhungel et al. proposed a two-level architecture combining CNNs for initial mass detection with Random Forest classifiers to reduce false positives. While this approach automated feature extraction and improved sensitivity over traditional systems, it focused strictly on detection rather than classification (benign vs. malignant). Furthermore, it lacked interpretability mechanisms, making it difficult for radiologists to trust its automated findings.

2.2.*Transfer Learning for Classification (Arevalo et al., 2016)*

Arevalo et al. utilized pre-trained CNNs to classify mammographic lesions. By leveraging transfer learning, the model achieved high accuracy even with limited medical datasets. However, the system operated as a "black box," providing diagnostic outcomes without highlighting the specific image features that influenced the decision, which limits its clinical accountability.

2.3.*Grad-CAM for Interpretable Medical Imaging (Selvaraju et al., 2017)*

Selvaraju et al. introduced Gradient-weighted Class Activation Mapping (Grad-CAM) to

provide visual justifications for CNN predictions. By generating heatmaps from the final convolutional layer, Grad-CAM identifies regions of interest (ROIs) that drive the model's output. While effective for global visualization, Grad-CAM alone may lack the granular, localized explanations required for complex clinical tasks.

2.4. *Research Gap*

Existing literature reveals a significant gap: most systems focus on either high-accuracy classification or limited interpretability, but rarely both. There is a lack of end-to-end Clinical Decision Support Systems (CDSS) that integrate robust preprocessing, CNN classification, and multi-layered explainability (combining tools like Grad-CAM and LIME). The proposed system fills this gap by providing a unified, web-based platform that ensures diagnostic accuracy alongside transparent, clinically meaningful insights.
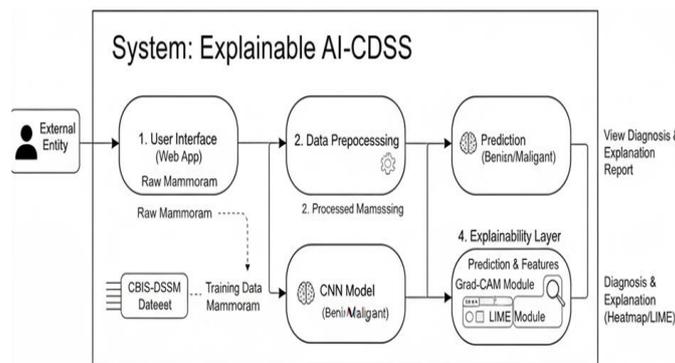
METHODOLOGY

Figure 1: Work Flow of Proposed System.

2.5. *Dataset Collection*

The CBIS-DDSM dataset was selected due to its expert-verified labels and region-based annotations, which are essential for benchmarking and validating explainability [14, 18]. Pre-processing ensured a balanced distribution of benign and malignant samples to prevent model bias.

2.6. *Data Preprocessing*

To standardize inputs and improve feature clarity, a multi-step pipeline was implemented:

- Resizing & Normalization: Images were standardized to fixed dimensions and pixel ranges for computational efficiency.
- Noise Reduction & Contrast Enhancement: Filtering and histogram equalization were applied to reduce artifacts and highlight subtle tumor patterns.

- Data Splitting: The dataset was partitioned into training, validation, and testing sets to ensure unbiased evaluation.

2.7. Deep Learning Model Development

A CNN-based architecture was developed to automatically extract hierarchical features [12, 13]. The model utilizes convolutional layers, ReLU activation, and pooling layers, culminating in a Softmax layer that outputs classification probabilities for Benign or Malignant categories.

2.8. Model Training and Validation

Training utilized Binary Cross-Entropy loss and the Adam optimizer. To ensure generalization and prevent overfitting, the system employed:

- Data Augmentation: Rotation, flipping, and zooming.
- Regularization: Dropout layers and early stopping.
- Metrics: Accuracy, Precision, Recall, F1-score, and ROC-AUC.

2.9. Integration of Explainable AI (XAI)

To resolve the "black-box" limitation, two XAI techniques were integrated [5, 7]:

- Grad-CAM: Generates heatmaps highlighting the global regions that influenced the model's prediction.
- LIME: Provides localized interpretability by perturbing image segments to observe changes in the output. Together, these provide clinicians with visual justifications for every diagnostic decision.

2.10. Web-Based CDSS Deployment

The system is deployed as a Streamlit-based web application. The workflow involves:

1. Upload: User provides a mammogram.
2. Analysis: The CNN classifies the image.
3. Explanation: Grad-CAM and LIME generate visual evidence.
4. Result: The interface displays the diagnosis with probability scores and heatmaps, transforming the model into a functional Clinical Decision Support System (CDSS).

3. SYSTEM FLOWCHART

The proposed system is an end-to-end diagnostic pipeline that integrates prediction and explanation into a multi-layered framework. It consists of six interconnected layers:

3.1. Image Acquisition Layer

This layer handles the input of high-resolution digital mammograms (PNG/JPG/DICOM). It validates format compatibility and filters out corrupted files, ensuring the system processes high-quality medical data for analysis.

3.2. Preprocessing and Standardization Layer

To optimize diagnostic accuracy, images undergo:

- Region Cropping & Resizing: Standardizing the input area.
- Contrast Enhancement & Normalization: Improving visibility of subtle tissue variations and standardizing pixel intensity.

3.3. Deep Feature Extraction Layer (CNN Backbone)

The core "intelligence" of the system, a CNN, automatically learns hierarchical features. Early layers detect basic edges and textures, while deeper layers identify complex clinical markers such as spiculated margins, architectural distortion, and mass density variations.

3.4. Classification Layer

Flattened feature maps are passed to fully connected layers using a Softmax activation function. The system outputs a probability score (e.g., 0.92 Malignant), providing clinicians with a measure of prediction confidence rather than just a binary label.

3.5. Explainability Layer (Integrated XAI Engine)

This layer converts the "black box" model into a transparent diagnostic tool using two methods:

- Grad-CAM Module: Generates heatmaps highlighting the global regions (e.g., a specific dense mass) that influenced the classification.
- LIME Module: Provides localized sensitivity analysis by identifying which specific segments of the image contributed to the final decision.

3.6. Clinical Interface Layer (Web-Based CDSS)

The final layer serves as the human-AI touchpoint. Through a user-friendly interface, radiologists can upload mammograms, view probability scores, and overlay heatmaps. This design ensures the system acts as a second-opinion tool, supporting rather than replacing clinical expertise.

3.7. *Architectural Strengths*

By bridging the Accuracy Gap (via CNN), the Transparency Gap (via XAI), and the Usability Gap (via web deployment), this architecture ensures a reliable, interpretable, and clinically ready diagnostic system.

4. RESULTS AND DISCUSSION

The model was trained and evaluated on the CBIS-DDSM dataset. The CNN achieved competitive classification performance in distinguishing benign and malignant cases. The integration of Grad-CAM and LIME provided meaningful visual explanations, highlighting regions consistent with clinically relevant features such as masses and calcifications [6, 9, 12].

The web-based interface successfully displayed prediction results along with confidence scores and explanation heatmaps. The combined approach improved interpretability and diagnostic confidence [3, 6, 7, 9, 12].
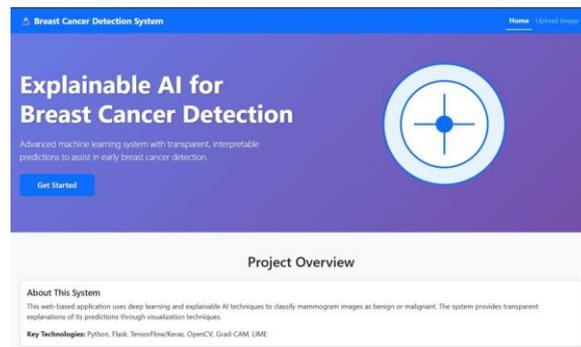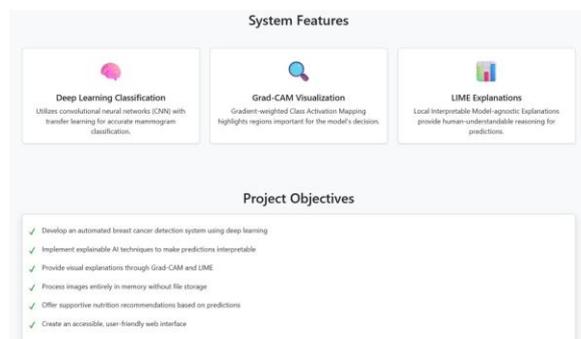
HOMEPAGE:

Figure 3: Homepage.

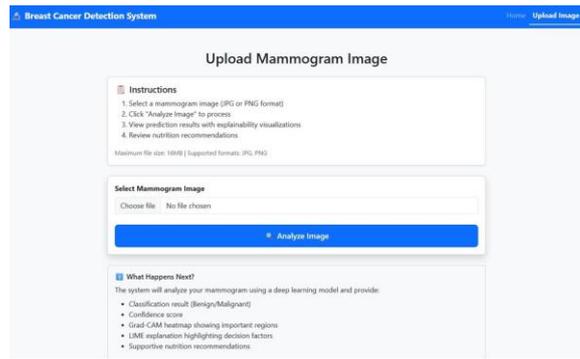**Figure 4: Homepage.**

MODULE: DIAGNOSIS & NUTRITION

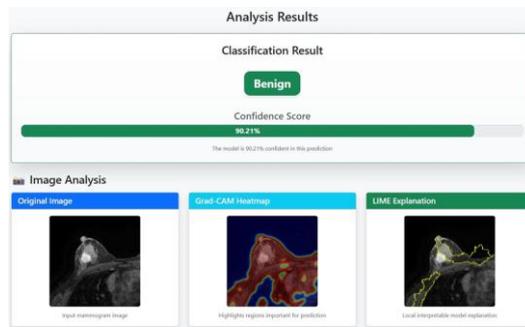**Figure 5: Analysis Module.**

BENIGN:

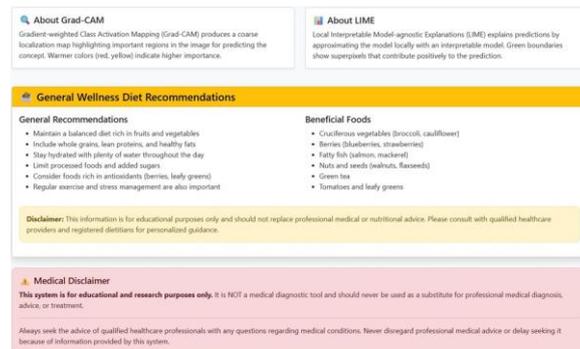
Figure 6: Benign Tumor Analysis.

Figure 7: Nutrition Analysis.
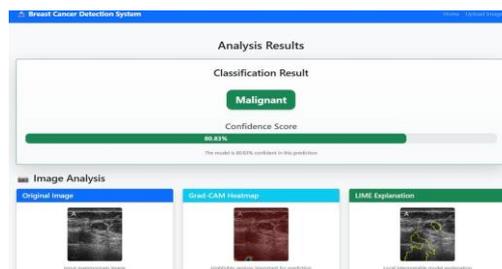
MALIGNANT:

Figure 8: Malignant Tumor Analysis.

The proposed system demonstrates the potential of combining deep learning with explainable AI in medical imaging. While CNNs provide high classification accuracy, XAI techniques ensure transparency and accountability. The integration into a CDSS supports radiologists rather than replacing them [4, 15, 17].

However, limitations include dependency on dataset quality and potential generalization issues across diverse imaging conditions. Future work includes incorporating multi-modal imaging data and advanced transformer-based architectures [1, 8, 16].

5. CONCLUSION

This paper presented an Explainable AI-based Clinical Decision Support System for breast cancer diagnosis using mammogram image analysis. The system integrates preprocessing, CNN-based classification, and explainability techniques such as Grad-CAM and LIME [5, 15, 17]. By combining accuracy with transparency, the proposed approach enhances trust, interpretability, and clinical usability. The web-based deployment further supports real-world adoption. The study highlights the importance of responsible and explainable AI in healthcare applications [19, 20].

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