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Research Paper

Explainable and Efficient AI-Based System for Automated Breast Cancer Diagnosis Using EfficientNet-B3, CBAM, and Grad-CAM

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Abstract—Breast cancer is one of the leading causes of cancer-related deaths among women worldwide, making early and accurate diagnosis essential for improving patient survival and treatment outcomes. Traditional histopathological examination is considered the gold standard for breast cancer diagnosis; however, manual analysis is time-consuming, labor-intensive, and subject to inter-observer variability. To address these challenges, this paper presents an Explainable and Efficient AI-Based System for Automated Breast Cancer Diagnosis using deep learning. The proposed methodology employs the BreakHis histopathological image dataset, where images are preprocessed through resizing and normalization before being analyzed using a fine-tuned EfficientNet-B3 model integrated with a Convolutional Block Attention Module (CBAM) to enhance feature representation. Gradient-weighted Class Activation Mapping (Grad-CAM) is incorporated to provide visual explanations of the model's predictions, improving transparency and interpretability. The trained model achieved a classification accuracy of 97.47% on the test dataset, demonstrating high performance in distinguishing benign and malignant breast cancer images. Furthermore, a Streamlit-based web application enables real-time image upload, prediction, confidence estimation, and explainability visualization. The proposed system offers an efficient, accurate, and interpretable decision-support tool that has the potential to assist pathologists in clinical breast cancer diagnosis while promoting trust in AI-driven healthcare applications.

Index Terms—Breast Cancer Diagnosis, EfficientNet-B3, Convolutional Block Attention Module, Grad-CAM, Explainable AI, Deep Learning, Histopathology

I. Introduction

Breast cancer is one of the most common and life-threatening cancers affecting women worldwide. It occurs when abnormal cells in the breast tissue grow uncontrollably and form a tumour. If not detected and treated at an early stage, breast cancer can spread (metastasize) to other parts of the body, leading to severe health complications and increased mortality rates. Early and accurate diagnosis plays a crucial role in improving survival outcomes and reducing treatment complexity.

Breast cancer diagnosis is commonly performed using imaging techniques such as mammography, ultrasound, MRI, and histopathological examination. Among these, histopathological analysis is considered the gold standard for confirming cancer presence. However, manual microscopic examination by pathologists is time-consuming, subjective, and prone to inter-observer variability. Recently, deep learning-based Computer-Aided Diagnosis (CAD) systems have gained significant attention for assisting pathologists in classifying histopathological images with high accuracy. Furthermore, Explainable Artificial Intelligence (XAI) techniques improve the transparency of these systems by highlighting the image regions influencing the prediction.

Deep learning models automatically extract features from images and classify them without manual feature engineering, making them highly suitable for histopathological image analysis. Transfer learning, in which a model pre-trained on a large dataset is adapted to a new task using domain-specific data, reduces training time, improves performance, and is particularly useful when medical datasets are limited. EfficientNet is a family of convolutional neural network (CNN) architectures introduced by Google Research that employs a compound scaling method to uniformly scale network depth, width, and input resolution, achieving high classification accuracy with fewer parameters and lower computational cost than conventional CNN models.

Despite achieving high prediction accuracy, many deep learning models operate as black-box systems, producing classification results without providing any explanation for their decisions. In healthcare, this lack of transparency reduces clinicians' confidence in AI-assisted diagnosis and limits the adoption of deep learning systems in clinical practice. To address this challenge, this work incorporates Gradient-weighted Class Activation Mapping (Grad-CAM), which generates a heatmap highlighting the image regions that contributed most to a prediction, thereby improving interpretability and clinical trust.

This paper presents an Explainable and Efficient AI-Based System for Automated Breast Cancer Diagnosis that combines a fine-tuned EfficientNet-B3 backbone with a Convolutional Block Attention Module (CBAM) for efficient and accurate classification of histopathological images into benign and

malignant categories, together with Grad-CAM-based visual explanations and a Streamlit web application for real-time deployment.

The major contributions of this research are summarized as follows:

- Development of an automated breast cancer diagnosis system capable of accurately classifying histopathological images into benign and malignant categories.
- Implementation of the EfficientNet-B3 deep learning architecture using transfer learning for robust feature extraction and improved classification performance.
- Integration of the Convolutional Block Attention Module (CBAM) with EfficientNet-B3 to enhance the model's ability to focus on the most relevant features in histopathological images.
- Incorporation of Gradient-weighted Class Activation Mapping (Grad-CAM) for visualizing the regions that influence the model's predictions, thereby improving interpretability and transparency.
- Evaluation of the proposed model using standard metrics such as accuracy, precision, recall, F1-score, confusion matrix, and ROC-AUC.
- Development of a Streamlit-based web application that enables users to upload histopathological images, obtain classification results, view prediction confidence, and visualize Grad-CAM heatmaps for explainable diagnosis.

The remainder of this paper is organized as follows. Section II reviews existing literature on breast cancer diagnosis using deep learning. Section III describes the proposed methodology and system architecture. Section IV presents the implementation details and experimental results. Section V discusses the performance of the proposed system, and Section VI concludes the paper with future research directions.

II. Literature Review

Breast cancer diagnosis using deep learning has become an active research area, with recent work exploring advanced segmentation architectures, transformer-based models, multimodal fusion, and explainability techniques to improve both classification accuracy and clinical trust.

Abugabah [1] proposed a deep learning framework integrating an Attention-Guided Deep Atrous-Residual U-Net (AG-DATUNet) for tumour segmentation with VGG19/ResNet50 feature extraction, Levy Flight-based Red Fox Optimisation for hyperparameter tuning, and an Efficient Capsule Network for classification. The framework achieved state-of-the-art accuracy on the WBCD and BreakHis datasets, but required substantial computational resources, limiting practical deployment.

Nobil et al. [2] introduced CancerNet, which integrates convolutional, involutional, and transformer components to capture both local and global contextual features from histopathological images. The model achieved 98.77% accuracy on a histopathological dataset and incorporated Explainable AI techniques, though its multi-component architecture increases training complexity and hardware requirements.

Ametefe et al. [3] combined deep transfer learning with U-Net segmentation for breast ultrasound images, evaluating VGG16, VGG19, and EfficientNet backbones for classification into normal, benign, and malignant categories. VGG19 achieved the best classification performance, while U-Net achieved a Dice Similarity Coefficient of 85.97% for segmentation, though the study was limited by a relatively small annotated dataset.

Li et al. [4] proposed HI-Net, a feature pyramid network with a Top-Down Attention mechanism for segmenting metastatic breast cancer in whole slide images, along with a lightweight dataset constructed from CAMELYON16, CAMELYON17, and ICIAR 2018. The approach reduced computational overhead but focused solely on segmentation rather than integrated classification.

Himel et al. [5] presented an encoder-decoder-based weighted segmentation framework combined with a dual-staged feature fusion meta-classifier for ultrasound-based breast cancer detection, using GAN-based augmentation and pretrained ResNet50V2, NASNetLarge, and EfficientNetB7 backbones, achieving high accuracy at the cost of increased ensemble complexity.

Wang et al. [6] developed a multimodal framework combining DenseNet with Distributed Load-based Dilated Convolution, Multi-Head Dense Dilated Convolution, and Optimal Multi-Level Attention modules for mammography, CT, and MRI-based segmentation and classification, demonstrating strong performance but requiring difficult-to-obtain multimodal datasets.

Wang et al. [7] proposed AWCDL, an automatically weighted calibration deep learning framework using an Inception-V4 backbone to predict HER2 status from whole-slide immunohistochemistry images, reducing dependency on expensive FISH testing while incorporating class activation mapping for interpretability.

Several studies have also examined breast cancer from clinical and epidemiological perspectives rather than automated image-based diagnosis. Engelhardt et al. [8] incorporated a 70-gene signature into the PREDICT prognostication model, improving discrimination for estrogen receptor-positive early-stage breast cancer. Wu et al. [9] investigated the tumor suppressor DACT3 and its role in sensitizing triple-negative breast cancer to apatinib via Wnt/β-catenin pathway inhibition. Zhao et al. [10] conducted a population-based survival analysis of occult breast cancer using SEER data, while Moshina et al. [11] evaluated long-term quality-adjusted life years following screen-detected versus symptomatic breast cancer diagnosis. Alotaibi [12] developed a population-based model of age-specific mammographic density to improve screening efficiency, and Demeester et al. [13] examined hormonal predictors of fertility in breast cancer patients interrupting endocrine therapy in the POSITIVE trial. While these studies provide valuable clinical insights, none incorporate automated, image-based, explainable deep learning diagnosis.

From the reviewed literature, it is evident that existing deep learning approaches for breast cancer diagnosis often

rely on computationally intensive multi-stage pipelines, require multimodal or large annotated datasets that are difficult to obtain, or focus on a single sub-task such as segmentation or biomarker prediction without integrated classification and explainability. Furthermore, many models function as black-box systems, limiting clinical trust. To address these gaps, the present work proposes a lightweight yet accurate EfficientNet-B3 + CBAM framework combined with Grad-CAM explainability and a real-time Streamlit deployment, providing an efficient, interpretable, and practically deployable solution for automated breast cancer diagnosis.

III. Proposed Methodology

A. Existing System and Limitations

Breast cancer diagnosis traditionally relies on microscopic examination of histopathological tissue samples by pathologists, which is time-consuming, labor-intensive, and susceptible to inter-observer variability. Conventional CNN-based CAD systems such as AlexNet, VGG16, ResNet, and DenseNet have improved diagnostic efficiency but often require large computational resources and function as black-box systems, providing predictions without explanation. This lack of interpretability, along with degraded generalization on limited medical datasets, motivates the need for an efficient and explainable alternative.

B. Proposed System

To overcome these limitations, the proposed system utilizes the BreakHis histopathological image dataset, containing microscopic breast tissue images categorized into benign and malignant classes. All images are preprocessed through resizing to 300 × 300 pixels and normalization using ImageNet statistics. The processed images are passed to an EfficientNet-B3 backbone initialized with ImageNet pre-trained weights through transfer learning. A Convolutional Block Attention Module (CBAM), consisting of sequential channel and spatial attention mechanisms, is integrated after the feature extractor to emphasize the most informative tumor-related regions while suppressing irrelevant background information. Gradient-weighted Class Activation Mapping (Grad-CAM) is then used to generate visual heatmaps explaining each prediction, and the trained model is deployed through a Streamlit web application for real-time diagnosis.

C. System Workflow

The overall workflow, illustrated in Fig. 1, begins with acquisition of the BreakHis dataset, followed by data preprocessing, optional data augmentation (rotation, flipping, scaling, brightness adjustment), and an 70:15:15 train–validation–test split. The EfficientNet-B3 backbone, pre-trained on ImageNet, extracts high-level features which are refined by the CBAM attention module before classification into Benign or Malignant. Grad-CAM then generates an explainability heatmap for each prediction, and the final model is deployed as a Streamlit web application.

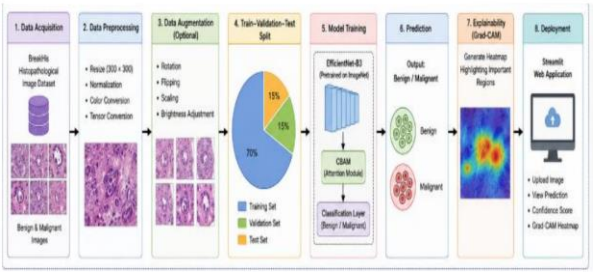

Fig. 1. Workflow of the proposed breast cancer diagnosis system.

D. Methodology

The methodology consists of the following steps:

Step 1 – Dataset Collection: Histopathological breast cancer images are collected from the BreakHis dataset, containing Benign and Malignant classes captured at four magnification levels (40×, 100×, 200×, 400×).

Step 2 – Data Preprocessing: All images are resized to 300 × 300 pixels, converted into tensors, and normalized using ImageNet mean and standard deviation values, as illustrated in Fig. 2.

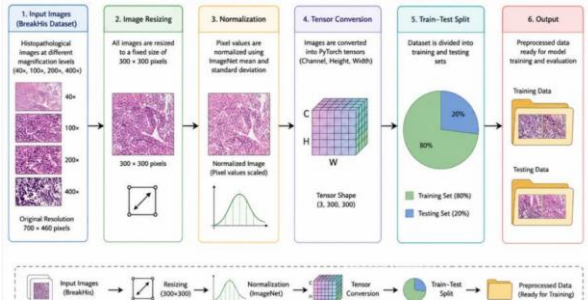

Fig. 2. Data preprocessing workflow.

Step 3 – Dataset Splitting: The preprocessed dataset is divided into training, validation, and testing sets for model development and evaluation.

Step 4 – Transfer Learning: A pre-trained EfficientNet-B3 model, trained on ImageNet, is used as the backbone network. The final classification layer is modified to output two classes: Benign and Malignant.

Step 5 – Feature Extraction using EfficientNet-B3: The EfficientNet-B3 backbone extracts hierarchical low-level and high-level features (texture, edges, tissue patterns) using compound scaling, which balances network depth, width, and resolution using a scaling coefficient ϕ such that Depth $= \alpha^{\phi}$, Width $= \beta^{\phi}$, and Resolution $= \gamma^{\phi}$, where α, β, and γ are constants determined through optimization.

Step 6 – Feature Enhancement using CBAM: The Convolutional Block Attention Module refines the 1536-channel feature map produced by EfficientNet-B3 through two sequential sub-modules:

Channel Attention Module: computes channel-wise attention weights by passing average-pooled and max-pooled de-

scriptors through a shared multi-layer perceptron, combining the outputs, and applying a sigmoid activation to identify the most informative feature channels.

Spatial Attention Module: computes channel-wise average and max feature maps, concatenates them, and applies a 7×7 convolution followed by a sigmoid activation to highlight the most relevant spatial (tumor) regions.

The channel-refined and spatial-refined feature maps are multiplied element-wise with the original feature map in sequence, producing an attention-enhanced representation that suppresses irrelevant background information.

Step 7 – Classification: The attention-enhanced feature maps are passed through a Global Average Pooling layer followed by a fully connected classification layer. A Softmax activation computes the probability of each class, and the image is classified as Benign or Malignant.

Step 8 – Model Training: The model is trained using the Cross-Entropy Loss function and the Adam optimizer, with parameters updated iteratively over multiple epochs until stable validation performance is achieved.

Step 9 – Performance Evaluation: The trained model is evaluated using Accuracy, Precision, Recall, F1-Score, Confusion Matrix, and ROC-AUC.

Step 10 – Explainability using Grad-CAM: Grad-CAM computes gradients of the predicted class score with respect to the activations of the final convolutional layer, and uses their global-average-pooled values as channel importance weights. A weighted combination of the activation maps, followed by a ReLU operation, produces a heatmap highlighting the image regions most responsible for the prediction.

Step 11 – Deployment using Streamlit: The trained EfficientNet-B3 + CBAM model is deployed using a Streamlit web application that allows users to upload an image and view the predicted class, confidence score, and Grad-CAM visualization in real time.

E. System Architecture

The complete system architecture is shown in Fig. 3. The input layer accepts a user-uploaded histopathology image, which is resized, normalized, and tensor-converted in the preprocessing layer. The feature extraction and classification layer passes the processed image through the EfficientNet-B3 backbone (Stem + MBConv blocks), followed by the CBAM module (Channel Attention Module and Spatial Attention Module), Global Average Pooling, a Fully Connected layer, and a Softmax classifier, producing a Benign/Malignant prediction with an associated confidence score. The explainability layer generates a Grad-CAM heatmap and overlays it on the original image. Finally, the deployment layer, implemented as a Streamlit web application, handles image upload, preprocessing, model inference, prediction and confidence display, Grad-CAM visualization, and the user interface.

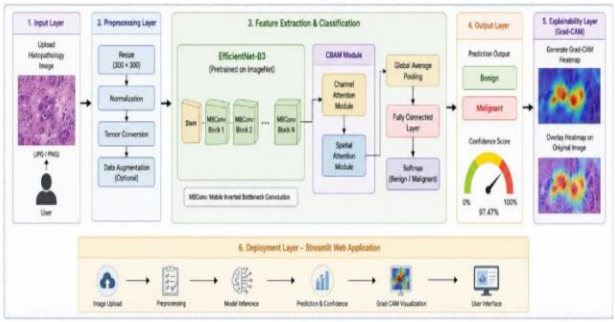

Fig. 3. Complete system architecture of the proposed breast cancer diagnosis system.

IV. Implementation and Results

A. Dataset Description

The proposed system was developed and evaluated using the BreakHis (Breast Cancer Histopathological Image Classification) dataset, a publicly available benchmark containing 7,909 microscopic histopathological images of breast tumor tissue collected from biopsy specimens of 82 patients. The benign category consists of four subclasses (Adenosis, Fibroadenoma, Phyllodes Tumor, and Tubular Adenoma), while the malignant category includes four subclasses (Ductal Carcinoma, Lobular Carcinoma, Mucinous Carcinoma, and Papillary Carcinoma). Images were captured at four magnification levels (40×, 100×, 200×, 400×) with an original resolution of 700×460 pixels in PNG format.

B. Experimental Setup

The experimental setup used for developing and evaluating the proposed system is summarized below:

- Programming Language: Python 3.x
- Deep Learning Framework: PyTorch
- Development Environment: Kaggle Notebook
- GPU: NVIDIA Tesla T4
- Pre-trained Backbone: EfficientNet-B3
- Attention Module: CBAM
- Explainability Technique: Grad-CAM
- Deployment Platform: Streamlit

C. Model Training Configuration

The proposed model was trained using EfficientNet-B3 with transfer learning, with the CBAM attention module integrated to improve feature extraction. Table I summarizes the training configuration.

D. Performance Evaluation

The proposed EfficientNet-B3 + CBAM model was evaluated on the held-out testing dataset using Accuracy, Precision, Recall, F1-Score, Confusion Matrix, and ROC-AUC. The model achieved an overall test accuracy of 97.47%, as summarized in Table II, with a detailed per-class breakdown provided in Table III.

TABLE I
MODEL TRAINING PARAMETERS

Parameter	Value
Backbone Model	EfficientNet-B3
Transfer Learning	Yes
Attention Module	CBAM
Optimizer	Adam
Loss Function	CrossEntropyLoss
Learning Rate	0.0001
Batch Size	32
Epochs	10
Image Size	300 × 300

TABLE II
PERFORMANCE RESULTS OF THE PROPOSED MODEL

Metric	Value
Test Accuracy	97.47%
Precision (Benign)	0.94
Recall (Benign)	0.98
F1-Score (Benign)	0.96
Precision (Malignant)	0.99
Recall (Malignant)	0.97
F1-Score (Malignant)	0.98
Macro Average F1-Score	0.97
Weighted Average F1-Score	0.97

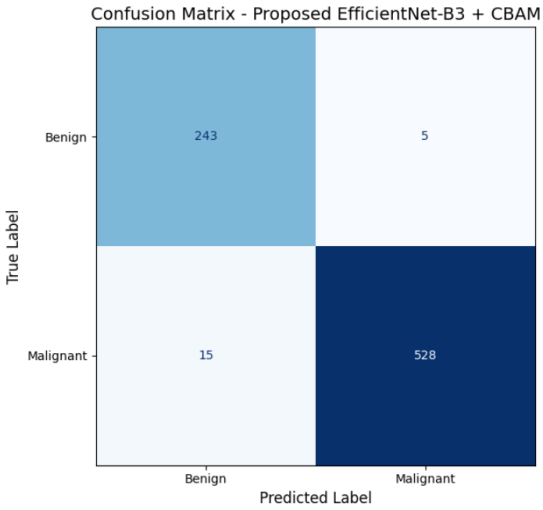

Fig. 4. Confusion matrix of the proposed EfficientNet-B3 + CBAM model.

Fig. 4 shows the confusion matrix of the proposed model on the test set, where 243 of 248 benign samples and 528 of 543 malignant samples were correctly classified. Fig. 5 shows the corresponding ROC curve, which achieved an Area Under the Curve (AUC) of 0.9954, indicating excellent discriminative capability between the two classes.

E. Model Comparison

To demonstrate the effectiveness of the proposed model, its performance was compared with baseline models, including a conventional CNN, a plain EfficientNet-B3, and a fine-tuned EfficientNet-B3 without the CBAM attention mechanism. As shown in Table IV, the integration of CBAM with EfficientNet-B3 improved feature extraction and achieved the highest classification accuracy of 97.47%, outperforming all baseline models.

F. Grad-CAM Explainability Results

Grad-CAM was used to visualize the histopathological image regions that contributed most to the model's predictions. Fig. 6 shows the original image, the generated Grad-CAM heatmap, and the overlay for a malignant sample correctly classified with 100% confidence. Regions shown in red indicate the highest contribution to the prediction, yellow

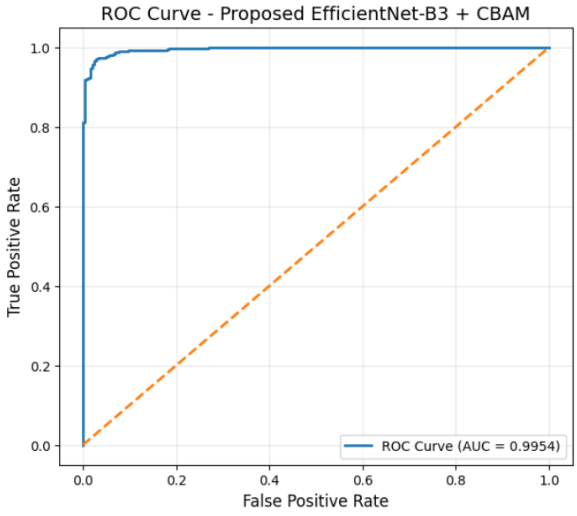

Fig. 5. ROC curve of the proposed EfficientNet-B3 + CBAM model (AUC = 0.9954).

TABLE III
CLASSIFICATION REPORT

Class	Precision	Recall	F1-Score	Support
Benign	0.94	0.98	0.96	248
Malignant	0.99	0.97	0.98	543
Overall Accuracy: 97.47%				791

TABLE IV
COMPARISON OF DIFFERENT MODELS

Model	Accuracy (%)
CNN	87.74
EfficientNet-B3	89.00
Fine-Tuned EfficientNet-B3	96.71
EfficientNet-B3 + CBAM (Proposed)	97.47

represents moderate contribution, and blue indicates minimal contribution. The visualizations confirm that the proposed EfficientNet-B3 + CBAM model focuses primarily on tumor regions rather than irrelevant background information, indicating that the model learns clinically meaningful pathological features.

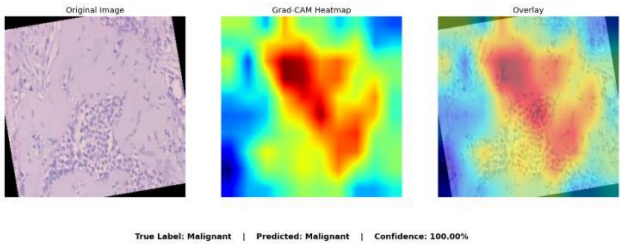

Fig. 6. Grad-CAM visualization for a malignant histopathological sample: original image, Grad-CAM heatmap, and overlay.

G. Streamlit Web Application

The trained model was deployed as an interactive Streamlit web application that allows a user to upload a histopathological image and receive, in real time, the predicted class (Benign/Malignant), a confidence score, and a Grad-CAM heatmap overlay with a plain-language explainability report. Fig. 7 shows the application correctly classifying a benign sample with 99.97% confidence, and Fig. 8 shows a malignant sample correctly classified with 100% confidence, together with the corresponding Grad-CAM heatmaps.

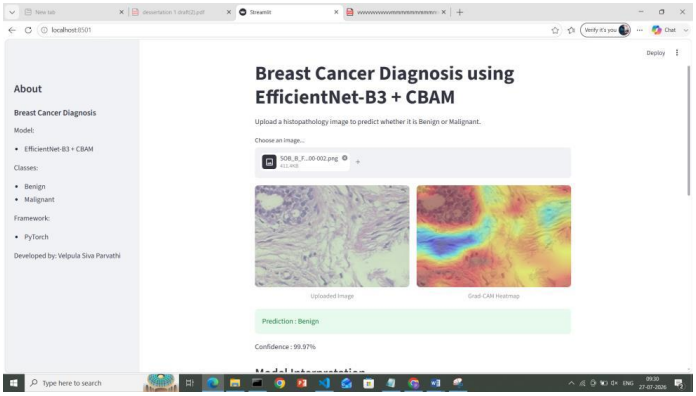

Fig. 7. Streamlit application: benign prediction result with Grad-CAM heatmap.

The application's explainability report also computes a qualitative decision-reliability label (High/Medium/Low) based on the prediction confidence, communicating to the user how certain the model is about its prediction and reinforcing that the output is intended as an AI decision-support visualization rather than a clinical diagnosis.

V. Discussion

The experimental results demonstrate that the proposed EfficientNet-B3 with CBAM model provides highly accurate and reliable breast cancer classification. The integration of the CBAM attention mechanism improved the model's ability to focus on informative image regions, resulting in better feature extraction and improved classification accuracy compared with the baseline CNN, plain EfficientNet-B3, and fine-tuned EfficientNet-B3 models. The Grad-CAM visualizations confirmed that the model concentrated on clinically relevant tissue regions while making predictions, thereby improving the transparency and interpretability of the system. The developed Streamlit application further enhances the practicality of the proposed approach by enabling real-time image classification through an easy-to-use graphical interface.

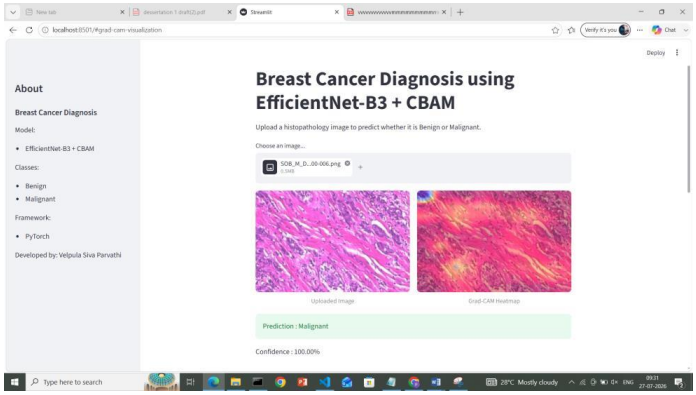

Fig. 8. Streamlit application: malignant prediction result with Grad-CAM heatmap.

Overall, the proposed model achieved an accuracy of 97.47%, along with a macro-average F1-score of 0.97 and an ROC-AUC of 0.9954, demonstrating strong performance in distinguishing between benign and malignant histopathological images. These results indicate that the proposed system is both accurate and explainable, making it a promising tool for computer-aided breast cancer diagnosis. Although the framework performs well under the evaluated conditions, its performance on external, multi-center datasets and on rarer tumor subtypes has not yet been validated, and future work should address dataset diversity, multi-class subtype classification, and lightweight deployment on edge and mobile platforms.

VI. Conclusion

This paper presented an Explainable and Efficient AI-Based System for Automated Breast Cancer Diagnosis using EfficientNet-B3 integrated with the Convolutional Block Attention Module (CBAM) and Grad-CAM. The publicly available BreakHis dataset was used for training and evaluation, with images preprocessed through resizing, normalization, and dataset splitting. Transfer learning with EfficientNet-B3 enabled the extraction of rich feature representations, while the CBAM attention mechanism enhanced the model's ability to focus on the most informative regions of the images. Grad-CAM was incorporated to provide visual explanations of the model's predictions, improving transparency and interpretability.

Experimental evaluation demonstrated that the proposed model achieved a test accuracy of 97.47%, along with high precision, recall, and F1-score for both benign and malignant classes, outperforming a conventional CNN, a plain EfficientNet-B3, and a fine-tuned EfficientNet-B3 without CBAM. The developed Streamlit-based web application further enhances the usability of the system by enabling real-time breast cancer image classification and visualization of prediction results. Overall, the proposed system successfully combines high classification accuracy, explainability, and practical deployment, making it a promising computer-aided diagnostic tool to assist medical professionals in the early detection and diagnosis of breast cancer.

VII. Future Scope

Although the proposed model achieved excellent classification performance, several directions can further enhance its capabilities:

- Increasing the size and diversity of the training dataset by incorporating additional publicly available breast cancer histopathological image datasets.
- Extending the system to perform multi-class classification for identifying specific subtypes of benign and malignant breast cancer.
- Investigating advanced deep learning architectures such as Vision Transformers (ViT), Swin Transformer, and hybrid CNN–Transformer models.
- Exploring additional explainable AI techniques, including LIME, SHAP, and Score-CAM, to provide more comprehensive model interpretability.
- Optimizing the model for deployment on mobile devices and cloud platforms to support remote healthcare and telemedicine applications.
- Integrating the proposed system with hospital information systems and clinical workflows to assist pathologists in routine diagnosis.
- Performing extensive validation using larger multi-center clinical datasets to improve robustness and generalizability.
- Developing a decision support system capable of generating automated diagnostic reports alongside classification results.
- Improving computational efficiency to enable faster inference suitable for real-time clinical applications.

These enhancements can further improve the accuracy, interpretability, scalability, and practical applicability of AI-assisted breast cancer diagnosis systems, ultimately supporting healthcare professionals in making faster and more reliable clinical decisions.

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