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Deep Learning with Saliency-Guided Attention for Accurate Breast Lesion Characterization

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ABSTRACT

Breast cancer is the second leading cause of cancer-related mortality among women, accounting for 12% of cases. Early diagnosis, based on the identification of radiological features, such as masses and microcalcifications in mammograms, is crucial for reducing mortality rates. However, manual interpretation by radiologists is complex and subject to variability, emphasizing the need for automated diagnostic tools to enhance accuracy and efficiency. This research proposes an intelligent breast lesion characterization system using mammography images by combining deep learning feature extraction with machine learning classification techniques. In this approach, deep features are extracted from mammography images using the Convolutional self-Attention Transformer (CoaT) model, which effectively captures complex visual patterns and structural characteristics of breast tissues. The extracted features are then used to train several classification models including Natural Gradient Boosting (NGB), Histogram Gradient Boosting (HGB), Extreme Gradient Boosting (XGB), and the proposed Fast Interpretable Oblique Tree (FIOT) classifier for accurate lesion classification. The system also integrates an explainable AI module to validate mammography images and provide additional diagnostic insights before classification. Experimental results demonstrate that the proposed FIOT classifier achieves superior performance compared to existing models in terms of accuracy, precision, recall, and F-score. A graphical user interface (GUI) is also developed to enable dataset upload, model training, and prediction operations in a user-friendly manner. The proposed system provides an effective computer-aided diagnostic solution that can support radiologists in improving the accuracy and efficiency of breast lesion detection from mammography images.

Keywords: Breast cancer detection, Mammography imaging, Breast lesion characterization, Deep feature extraction, Radiological features, Microcalcifications, Mass detection, Computer-aided diagnosis.

1. INTRODUCTION

Breast cancer is the most common malignancy among women worldwide, second only to lung cancer, affecting approximately 10–12% of the female population and causing around 500,000 deaths annually. The highest incidence occurs in women aged 40–49 years (41%), with a lower prevalence in those over 71 (21%). Risk factors include genetic predisposition (e.g., BRCA1/BRCA2 mutations), lifestyle, prolonged hormone therapy, therapeutic radiation, and benign proliferative breast diseases. Early stages are often asymptomatic, but initial signs may include hard lesions, breast shape alterations, nipple changes, or unexplained weight loss. Advancements in therapeutic strategies and screening programs have progressively reduced mortality rates. The World Health Organization (WHO) revised its 2003 classification to improve lesion characterization, distinguishing categories such as intraductal proliferative lesions, papillary lesions, mesenchymal and fibroepithelial tumors, and rarer malignancies, like lymphomas and metastases. Additionally, abnormalities, such as masses and microcalcifications, while not strictly histological, are key mammographic indicators of breast cancer risk. Accurate diagnosis begins with medical history, clinical examination, and imaging

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techniques, as shown in figure 1. Mammography remains the gold standard for early detection, particularly in asymptomatic cases, but tissue overlap can hinder interpretation, leading to false positives or negatives.

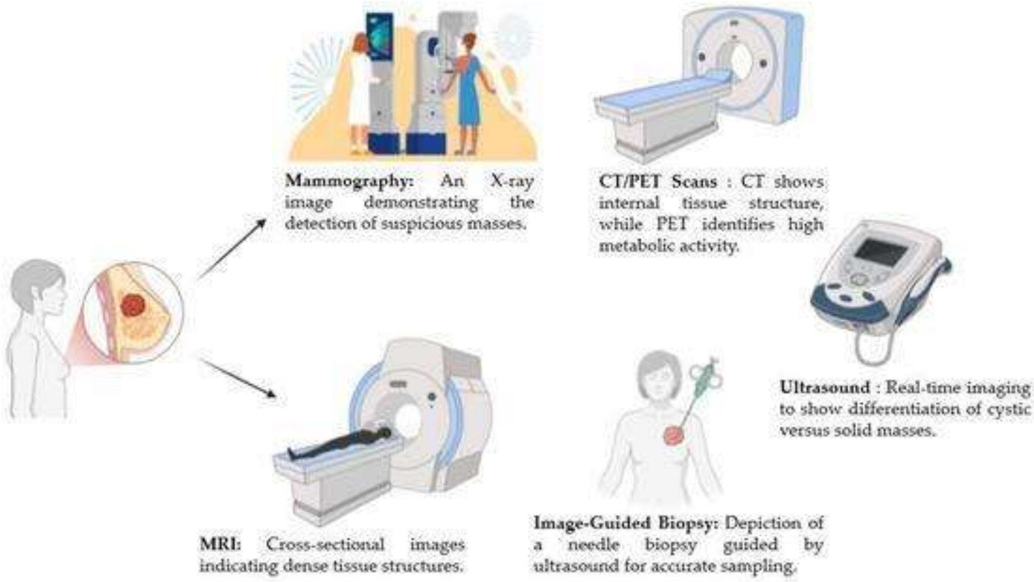

Figure 1: Automated detection of breast lesion characteristics

To address these limitations, tomosynthesis provides a near 3D breast reconstruction, reducing tissue superimposition and improving lesion detection. Ultrasound complements mammography by distinguishing solid from cystic formations, particularly in dense breast tissue, where mammography is less effective. MRI further enhances sensitivity (up to 92%) but has lower specificity (~60%) due to challenges in lesion characterization. The Breast Imaging Reporting and Data System (BI-RADS) ensures standardized reporting, aiding risk assessment and clinical decision-making. Computer-aided diagnosis (CAD) systems refine mass classification, improving diagnostic precision. Radiomics is gaining prominence for its ability to extract high-dimensional quantitative features (e.g., shape, texture, intensity) from medical images, correlating them with clinical outcomes. Therefore, early BC detection is significant in increasing patient survival rates. The high morbidity and considerable cost of healthcare-associated with cancer have instigated researchers to implement more precise models for cancer detection. Mammography and biopsy are the two most common methodologies for BC detection. In mammography, radiologists use a specific type of breast images to detect early symptoms of cancer in women. Studies have shown that mammography has led to a reduction in death rates caused by BC. A biopsy is another efficient diagnostic methodology for BC detection. Automatic identification and localization of cancer cells are the main challenges in BC images due to their variance in size, shape, and location.

2. LITERATURE SURVEY

Zhang et al. [1] highlighted the value of attention mechanisms and ensemble learning strategies in enhancing model robustness and generalization across multicenter datasets. Among CNNs, EfficientNet employs a compound scaling method, which simultaneously scales the depth, width, and input resolution in a balanced manner. For instance, Tan and Le [2] showed that EfficientNet models outperform deeper conventional CNNs on benchmark datasets, and more recent applications have validated their use in radiology workflows, particularly in breast cancer imaging. According to [3], more than 70% of research work for breast cancer analysis is conducted on mammograms. The standard mammography examination consists of two researchions for each breast CC and MLO and most of the research work considers these views separately. Petrini et al. [4] proposed a two-view classifier as a pair of single-view classifiers with the upper layers removed, followed by a concatenation of the outputs for both views. The single-view classifier was created by learning a patch classifier and modifying the top layers. The patch classifier was learned on ten patches selected from a given region of interest (ROI) and another ten from the background with a patch size of 224 × 224 px for each breast mammogram. Feature fusion of two-view mammograms was considered in by Li et al [5] he performed a binary classification task (benign, malignant) using one patch cut from the annotation area. The size of the patch originally depended on the dimensions of the cut breast mass and was eventually changed to 512 × 512 px.

Another study by Yang and Guan [6] classified pathological medical images of breast cancer using the BreakHis image dataset and an improved network DenseNet201-MSD model; the new DL model classified pathological images of the BreakHis dataset with accuracies of 99.4%, 98.8%, 98.2%, and 99.4% at four magnifications. Additionally, Burçak and Uuz [7] concluded that CNN models are robust feature selection strategies in four categories of histopathological images. Amin et al. [8] proposed a hybrid semantic model that employed pre-trained Xception and deeplabv3+ models to classify microscopic cancer images into malignant and benign classes, with 95% and 99% accuracy for benign and malignant, respectively. Togaçar et al. [9] proposed custom CNN model for BC ultrasound image detection. The proposed consist of only one convolution layer with 20 filters, which achieved 100% accuracy while outperforming eight different pre-train CNN models.

Ting et al. [10] presented CNN for BC detection (CNNI-BCC). This framework uses a supervised DL neural network to do the classification. The experimental findings demonstrated that CNNI-BCC performed better than previously conducted research and achieved an accuracy of 89.47% Nahid et al. [11] Presented A novel deep neural model for BC classification utilizing Histopathological images, comprised of a clustering algorithm and CNN. The model is based on CNN and LSTM. At the classification layer of the model, Softmax and SVM are both used. The proposed model achieved 91% accuracy. Ragb et al. [12] presented their own proposed CNN model for the diagnosis of BC in their study. In addition, they employed a TL technique to combine nine different pre-trained DL models to classify two BC datasets. The suggested model obtained the finest accuracy of 99.5%.

Bevilacqua et al. [13] used MR images chosen for training and testing. They employed ANN to classify and detect BC after extracting data and analyzing it. However, When the Machine Learning model was applied to enhance the ANN, the maximum accuracy was increased to 100%. Khan et al. [14] Proposed a framework for detecting and classifying BC TL approaches were adopted by the authors as opposed to GoogLeNet, VGG, and ResNet for feature extraction. Following that, a fully connected layer is provided with the combined extracted characteristics for classification. The unique framework that was suggested has a classification accuracy of 97.52%. Tang et al. [15] provided a detailed overview of recent advanced development in computer-aided detection or diagnosis of BC detection.

3. PROPOSED SYSTEM

The proposed system presents an intelligent automated framework for accurate breast lesion characterization using deep learning and machine learning techniques. The system extracts high-level image features using the CoaT model and performs classification using algorithms such as NGB, HGB, XGB, and the proposed FIOT classifier, as presented in figure 2. Additionally, an explainable AI mechanism is incorporated to validate mammography images before classification. This approach improves diagnostic accuracy, reduces manual workload for radiologists, and provides reliable assistance in medical image analysis.

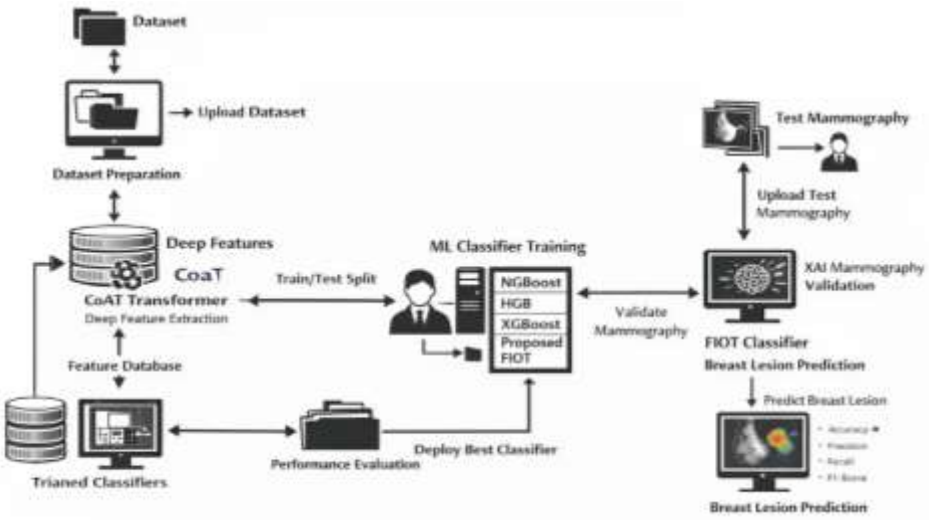

Figure 2: Proposed system architecture

1. Dataset Upload: In the first step, the mammography image dataset is uploaded into the system through the graphical user interface. The dataset contains images categorized into different classes such as benign and malignant. The system automatically reads the dataset directories and identifies the available classes for further processing.

2. Deep Feature Extraction using CoaT: After loading the dataset, deep features are extracted from the mammography images using the CoaT. Each image is resized and normalized before being passed through the pretrained transformer network. The model generates high-dimensional feature representations that capture important visual patterns related to breast lesions.

3. Dataset Splitting: The extracted feature dataset is divided into training and testing sets to evaluate the performance of classification models. The system performs an 80:20 train-test split while maintaining class balance. This ensures that the machine learning models are trained effectively and evaluated on unseen data.

4. Model Training using Machine Learning Algorithms: In this stage, the extracted features are used to train different classification algorithms including NGB, HGB, XGB, and the proposed FIOT classifier. These models learn the relationship between feature patterns and lesion categories, enabling them to distinguish between different types of breast abnormalities.

5. Performance Evaluation: Once the models are trained, their performance is evaluated using standard evaluation metrics such as accuracy, precision, recall, and F1-score. Confusion matrices and ROC curves are also generated to analyze classification performance. This step helps identify the most effective model for breast lesion characterization.

6. Mammography Image Validation using XAI: Before performing prediction, the system uses an explainable AI module based on the Gemini Vision model to verify whether the input image is a valid mammography image. This step ensures that irrelevant or incorrect images are filtered out, improving the reliability of the system.

7. Breast Lesion Prediction: Finally, when a user uploads a new mammography image, the system extracts deep features using the CoaT model and passes them to the trained FIOT classifier for prediction. The system then displays the classification result indicating the type of breast lesion along with visual outputs for better interpretation.

3.2 CoaT Feature extraction

In the proposed system, CoaT is used as the deep feature extraction model for analyzing mammography images. CoaT combines the advantages of CNN and Transformer-based attention mechanisms to capture both local and global image patterns, as displayed in figure 3. and figure 4 also. It efficiently learns complex spatial relationships in medical images and generates rich feature representations that are later used by machine learning classifiers for accurate breast lesion characterization.

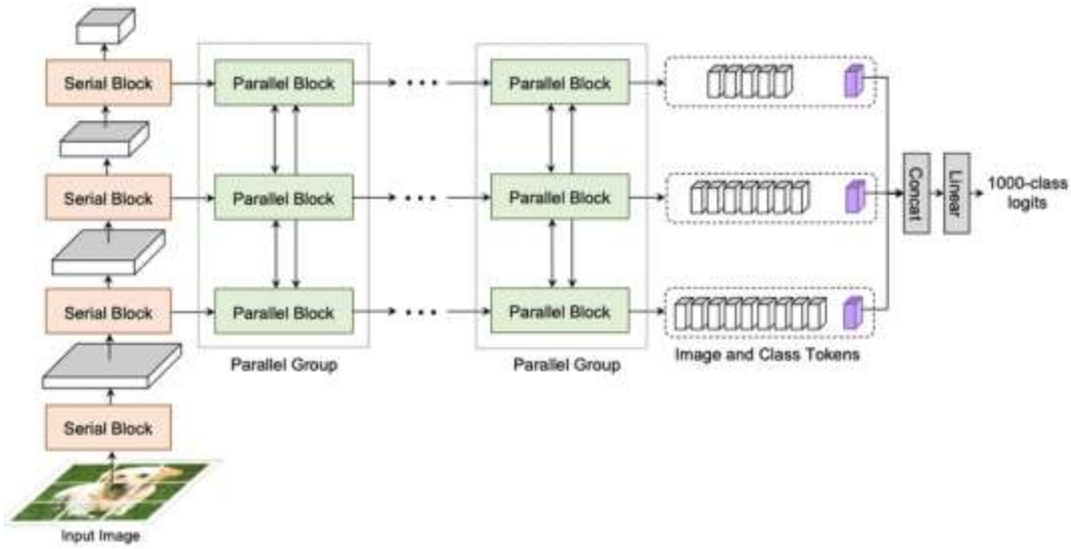

Figure 3: Generalized layered architecture of coaT model

Internal working of CoaT

Image Input and Preprocessing: In the first step, the mammography images from the dataset are loaded into the system and converted into a standardized format. Each image is resized to 224 × 224 pixels and normalized to maintain consistent pixel intensity values. This preprocessing ensures that the input images match the input requirements of the CoaT model and improves feature extraction performance.

Patch Embedding and Convolutional Encoding: After preprocessing, the image is passed through initial convolutional layers where the image is divided into smaller patches. These patches are converted into embedded feature representations using convolutional operations. This step captures local spatial patterns, edges, textures, and structural details present in mammography images.

Self-Attention Mechanism: In this stage, the transformer component of the CoaT model applies a self-attention mechanism to analyze relationships between different regions of the image. The attention mechanism allows the model to focus on important areas such as suspicious masses or calcifications. This helps the model capture global contextual information from the entire image.

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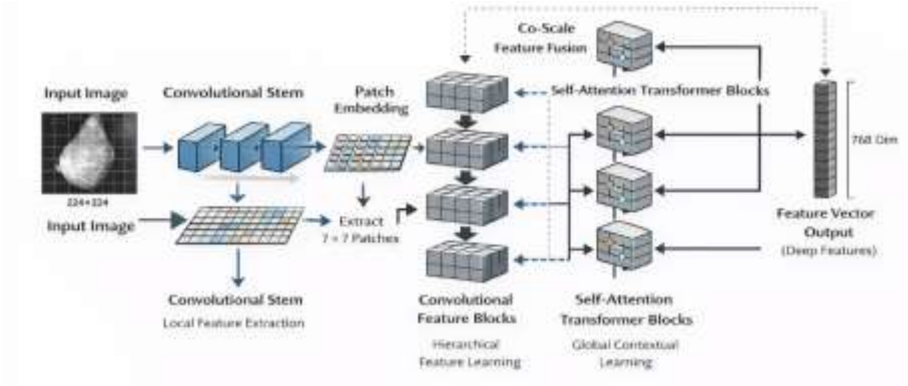

Figure 4: Internal workflow of coaT model

Hierarchical Feature Learning: CoaT uses a hierarchical architecture where features are progressively refined through multiple attention and convolutional layers. At each stage, the model combines local convolutional features with global attention features. This hierarchical learning enables the system to detect complex patterns associated with breast lesions.

Global Feature Representation: After passing through multiple transformer layers, the extracted information is aggregated into a compact feature representation. The CoaT model outputs a high-dimensional feature vector (approximately 768 features) that summarizes the important visual characteristics of the mammography image.

Feature Vector Generation for Classification: Finally, the generated feature vector is flattened and stored as numerical data. These deep features represent the meaningful patterns detected in the image and are used as input to machine learning classifiers such as NGB, HGB, XGB, and FIOT. This allows the classifiers to accurately distinguish between different breast lesion categories.

4. RESULTS ANALYSIS

The results section presents the key findings of a study in a clear and organized manner. It focuses on displaying the data collected through experiments, surveys, or analysis without interpretation. Typically, results are shown using tables, graphs, or charts to make patterns and trends easy to understand. This section highlights important outcomes, comparisons, and any significant relationships observed in the data. It avoids personal opinions and sticks strictly to factual information. The results section provides the foundation for discussion and conclusions in the research.

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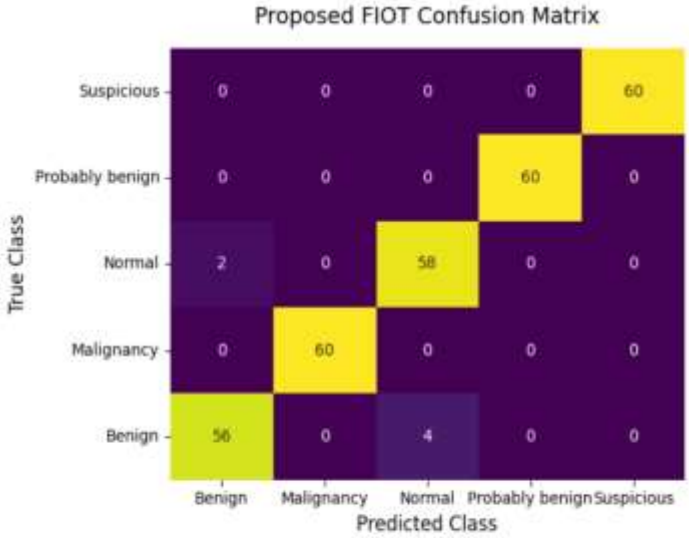

Figure 5: Illustration of confusion matrix using FIOT classifier

The figure 5 depicts the confusion matrix of the Proposed FIOT classifier used for breast lesion classification. The matrix compares the true class labels (rows) with the predicted class labels (columns) for the five categories: Benign, Malignancy, Normal, Probably Benign, and Suspicious. Most predictions appear along the diagonal, indicating correct classification such as 60 Malignancy cases, 60 Probably Benign cases, 60 Suspicious cases, and 58 Normal cases correctly identified by the model. In the Benign class, 56 images are correctly classified, while a small number are misclassified as Normal. Compared to the existing models, the proposed FIOT classifier demonstrates improved classification performance with fewer misclassifications, indicating better capability in distinguishing different breast lesion categories.

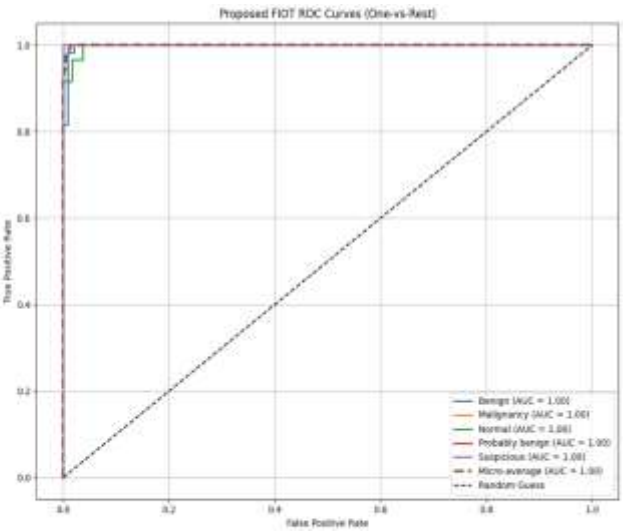

Figure 6: Illusutration of confusion matrix using FIOT model

The figure 6 shows illustrates the ROC curves of the Proposed FIOT classifier using the One-vs-Rest strategy for the five breast lesion classes: Benign, Malignancy, Normal, Probably Benign, and Suspicious. The ROC curves represent the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) for each class. The AUC (Area Under Curve) values for all classes are 1.00, indicating perfect classification performance. The micro-average AUC is also 1.00, showing that the proposed FIOT model achieves excellent discrimination capability across all lesion categories. Since

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all curves lie near the top-left corner and significantly above the random guess line, the results demonstrate that the proposed FIOT classifier provides superior and highly accurate performance in distinguishing different types of breast lesions compared to the existing models.

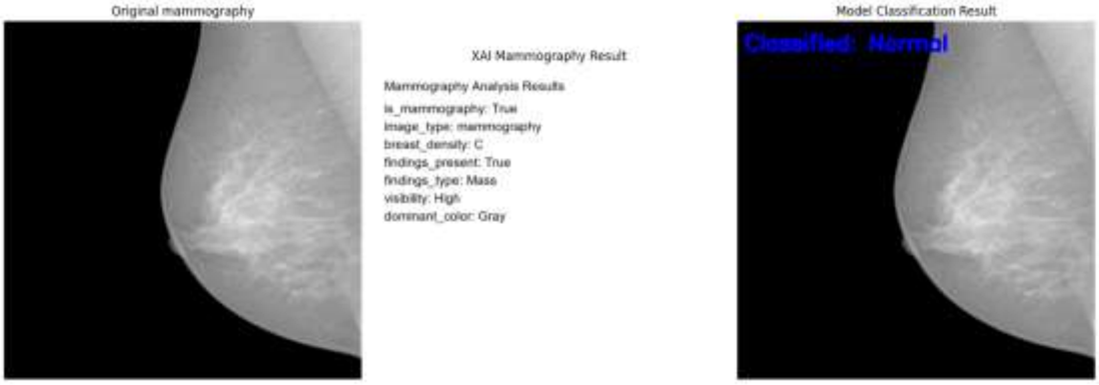

Figure 7: Prediction obtained on test image using FIOT and obtained XAI result

The figure 7 shows the final prediction output of the proposed breast lesion classification system. The left side displays the original mammography image, which is provided as input to the system. In the center panel, the XAI mammography analysis results are presented, confirming that the image is a mammography scan and providing additional diagnostic information such as breast density, findings presence, findings type, visibility, and dominant color. After feature extraction using the CoaT model and classification using the proposed FIOT classifier, the system displays the final classification result on the right side, indicating that the uploaded mammography image is classified as “Normal.” This output demonstrates how the system combines explainable analysis with machine learning classification to provide interpretable breast lesion prediction results.

Table 1: Performance comparison for the NGB, HGB, XGB and FIOT Model

Algorithms Name	Accuracy	Precision	Recall	F-score
NGB	92.33%	92.59%	92.33%	92.03%
HGB	96.0%	96.34%	96.0%	95.95%
XGB	96.92%	97.13%	96.03%	96.06%
FIOT	98.0%	98.02%	98.0%	98.99%

Table 1 presents the performance comparison of four classification models: NGB, HGB, XGB, and the proposed FIOT classifier for breast lesion classification using mammography images. The NGB model achieves an accuracy of 92.33%, with precision 92.59%, recall 92.33%, and F-score 92.03%, indicating a reasonable baseline performance. The HGB classifier improves the results with an accuracy of 96.0%, precision 96.34%, recall 96.0%, and F-score 95.95%, showing better classification capability compared to NGB. Similarly, the XGB model achieves slightly higher performance with 96.92% accuracy, 97.13% precision, 96.03% recall, and 96.06% F-score, demonstrating strong predictive ability due to its gradient boosting framework. However, the proposed FIOT classifier achieves the highest performance among all models, with 98.0% accuracy, 98.02% precision, 98.0% recall, and 98.99% F-score, indicating superior capability in accurately distinguishing between different breast lesion categories. These results demonstrate that the FIOT model outperforms the existing classifiers, providing more reliable and accurate breast lesion characterization from mammography images.

5. CONCLUSION

The research presents an intelligent system for automatic breast lesion characterization using mammography images by integrating deep learning–based feature extraction with advanced machine learning classifiers. In this work, mammography images belonging to five categories such as Benign, Malignancy, Normal, Probably Benign, and Suspicious were analyzed to develop an accurate classification framework. Deep features were extracted from the images using the CoaT transformer model, which effectively captures important visual patterns and structural characteristics present in breast tissue. These extracted features were then used to train several classification models including NGB, HGB, XGB, and the proposed FIOT classifier. The system also incorporated an XAI-based validation module to verify whether the uploaded image is a valid mammography image and to provide additional interpretability information before classification. Experimental evaluation demonstrated that while NGB, HGB, and XGB achieved strong performance, the FIOT classifier produced the best results with the highest accuracy, precision, recall, and F-score, indicating its superior capability in distinguishing different breast lesion categories. The developed system also includes a GUI-based interface that allows administrators to upload datasets, perform feature extraction, train models, and generate predictions easily. The proposed approach successfully combines transformer-based deep feature extraction with an optimized classification model to achieve highly reliable breast lesion detection, which can assist medical professionals in improving diagnostic efficiency and supporting early detection of breast abnormalities.

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