

CoaT-RADS: Leveraging C-Scale Conv-attentional Transformers For Automated Mammography Classification

K. Chiranjeevi¹, Md. Sana Safoora², A. Poojitha², N. Vineetha², G. Deekshitha²

¹Assistant Professor, ²UG Student, ^{1,2}Department of Computer Science and Engineering (AI & ML)

^{1,2}Geethanjali Institute of Science and Technology, Nellore-Bombay Highway, S.P.S.R, Andhra Pradesh 524137, India

ABSTRACT

Breast cancer is one of the leading causes of mortality among women worldwide, and early diagnosis plays a critical role in improving survival rates. Globally, approximately 2.3 million new cases are reported each year, with nearly 685,000 deaths largely attributed to late-stage detection. In India, breast cancer constitutes more than 27% of all female cancers, emphasizing the urgent need for efficient and reliable diagnostic solutions. With the expansion of screening programs, automated mammography analysis has become increasingly important in hospitals, diagnostic centers, teleradiology services, and rural healthcare settings where access to expert radiologists is limited. Conventional manual interpretation of mammograms is often affected by inter-observer variability, fatigue-related errors, and challenges in identifying subtle abnormalities, especially in dense breast tissues with overlapping structures. This research presents a structured mammography evaluation framework that integrates Co-Scale Conv-Attentional Image Transformers (CoaT) with feature-driven representations derived from Extreme Gradient Boosting (XGB), Histogram Gradient Boosting (HGB), and Fast Interpretable Oblique Trees (FIOT). Each representation contributes uniquely to understanding mammographic patterns without depending solely on automated inference. XGB organizes features using gradient-based tabular structures, capturing variations in tissue density and lesion boundaries, while HGB represents grayscale and texture information through histogram-based distributions for improved intensity analysis. FIOT employs an oblique-tree structure using linear feature combinations, enabling enhanced interpretability of tissue irregularities. Comparative analysis within the COAT framework indicates that FIOT achieves superior performance due to its stable and interpretable feature interactions, followed by HGB, whereas XGB demonstrates comparatively lower consistency.

Keywords: Breast Lesion Classification, Mammography Image Analysis, Computer-Aided Diagnosis, Clinical Data Analytics, Intelligent Healthcare Systems.

1. INTRODUCTION

Breast cancer is the most frequent malignancy in women worldwide. In 2020, approximately 2.3 million new cases were diagnosed, and 685,000 women with breast cancer died. The global incidence of this disease is increasing with a 3.1% annual rate, beginning with 641,000 cases in 1980 and reaching more than 1.6 million in 2010. This trend is likely to continue. The process of the diagnosis of breast cancer starts with a mammography exam. Mammography is an imaging technique that uses low-energy X-ray beams to examine the human breast for diagnosis and screening. The goal of mammography is the early detection of breast cancer, typically through the identification of specific lesions like masses, calcifications, architectural distortions, or focal asymmetries. Early breast cancer is a type of cancer that has not spread to other parts of the body and is considered curable in around 70–80% of cases, whereas advanced metastatic cancer is not considered curable. For this reason, an early diagnosis is crucial to improve the life expectancy of patients. Many countries adopt population

policies. screening for breast cancer using mammography is aimed at detecting the disease at an early stage to allow effective treatment. A frequent issue with mammography screening is false positive recalls, which involve additional exams and would likely lead to overtreatment. Women often fear the screening process, the possibility of cancer diagnosis, and the waiting time for results, which creates significant psychological pressure. False positive findings can lead to unnecessary biopsies and additional tests, causing fear, trauma, and financial strain, while false negatives may delay diagnosis and result in advanced cancer, affecting survival and increasing treatment burden. Figure 1. shows the occurrence of breast cancer in females across different age groups by showing both the average number of cases per year and the incidence rate per 100,000 women. It reveals that breast cancer is extremely rare in early life and starts to rise significantly after the age of 40. The highest number of cases and the peak rate are observed in women aged 60– 64, indicating that the risk is greatest during middle and older age. Although there is a small decline between 70–74 years, the rate again increases in women aged 85 and above. The graph highlights that breast cancer risk increases with age, emphasizing the importance of regular screening for women over 40 to support early detection and better outcomes.



Figure 1. Average cases per year analysis

Mammography, though an important tool for early breast cancer detection, presents several challenges that directly affect patients. One of the major concerns is the physical discomfort and pain caused during breast compression, which can make many women hesitant to return for regular screening. Along with physical pain, anxiety and emotional stress are very common. 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

Nour et al. [1] utilized the model combines a modified ResNet50 for feature extraction, positional encoding, transformer encoder blocks with multi-head self-attention, and channel attention to enhance feature representation, achieving an accuracy of 90.80% and an AUC of 92.58% on the UCHC dataset. By employing focal loss, it effectively reduces false positives and negatives, outperforming

baseline models like ResNet50, Siamese networks, and others in detecting abnormalities such as masses, calcifications, and architectural distortions. Future work aims to extend the model to include benign cases and integrate multi-view analysis for improved diagnostic accuracy.

Abdikenov et al. [2] utilized clinical application is necessarily based on multiple views: usually CC and MLO for each breast, i.e., four per patient. Building off of the aforementioned, Patheda et al. presents a hybrid deep learning model that integrates convolutional neural networks (CNNs) with vision transformers (ViTs). The CNN component captures fine-grained local features, while the ViT processes global contextual information, enabling more accurate differentiation between benign and malignant cases. Evaluated on a balanced dataset of 10,000 images, the model achieved 90.1% validation accuracy with minimal overfitting. Compared to conventional and pre-trained models, the hybrid approach demonstrated a strong balance between accuracy and generalization, making it promising for clinical applications. They proposed a CLAHE pre-processing-enabled CNN-ViT architecture for increasing the contrast in dense breast tissue. Alkurdi et al. [3] utilized the model was trained and evaluated on the Categorized ContrastEnhanced Spectral Mammography (CDD-CESM) dataset, consisting of approximately 600 mammograms. The results demonstrate state-of-the-art performance, achieving an accuracy of 87.21% and an AUC-ROC of 0.9676, outperforming prior methods applied to the same dataset. The integration of metadata proved beneficial, allowing the model to learn clinically relevant correlations between mammographic patterns and patient risk factors. Additionally, the multi view, multi-backbone approach provided a more comprehensive feature representation, leading to improved lesion characterization and class separability. Dhanalaxmi et al. [4] utilized One of the most prevalent cancers among women is breast cancer. The mortality rate of this cancer may be lowered with an early diagnosis. In the literature, a wide range of AI-based techniques have been proposed. Nevertheless, they face several difficulties, including inadequate training models, irrelevant feature extraction, and similarities between cancerous and non-cancerous regions. Therefore, we propose a novel improved deep learning-based model for the segmentation and classification of breast cancer in this research. An enhanced UNet++ (EUNet++) model is used to segment the affected part of the lesion region. The improved ResNet (IResNext) model classifies mammogram images into benign and malignant classes. The findings showed that the suggested framework outperformed other models trained on the same dataset, achieving an exceptional 99.56% classification accuracy for the CBIS-DDSM dataset and 99.64% for the IN-breast dataset. Zhu et al. [5] utilized Experiments on two public mammography datasets, CBIS-DDSM and INbreast, demonstrate that the proposed method achieves competitive performance. On the INbreast dataset, LEM improves classification accuracy to 96.3% with an AUC of 0.976.

Jubraeel et al. [6] utilized the model was implemented using the Keras API with TensorFlow as the backend. To overcome existing limitations, key parameters such as learning rate and dropout were optimized to reduce overfitting and enhance classification performance. Various data augmentation techniques, including flipping, rotation, and contrast adjustments, were applied to improve generalization across different cases. The dataset, collected from the hospital, includes images from 430 patients across different age groups, ensuring clinical relevance. After training and evaluation, the model achieved a high accuracy of 98%, along with high sensitivity, specificity, and precision, confirming its reliability in distinguishing between normal and abnormal breast tissue. Singh et al. [7] utilized experimental results confirmed that the proposed model achieved an accuracy score of 81% in correctly categorizing between benign and malignant. It outperformed the state-of-the-art methods using the same dataset and was able to correctly classify the complex case features with the help of DWT and XCiT network. Naik et al. [8] utilized the models were trained and optimized for robust performance, with results compiled for comparative analysis. We also deployed our model on Azure

with an automated pipeline, enabling seamless integration with a user-friendly website with accuracy of 92%. Sharma et al. [9] proposed This approach was evaluated through two case studies focused on detecting microcalcifications and masses both of which present considerable diagnostic challenges. Validation was performed using the CBIS-DDSM public dataset, with the model achieving impressive detection accuracies of 95.4% for masses and 99.4% for microcalcifications, along with specificities of 96% and 100%, and corresponding AUCs of 0.96 and 0.996. Narayana et al. [10] utilized this approach was evaluated through two case studies focused on detecting microcalcifications and masses—both of which present considerable diagnostic challenges. Validation was performed using the DDSM public dataset, with the model achieving impressive detection accuracies of 95.4% for masses and 99.4% for microcalcifications, along with specificities of 96% and 100%, and corresponding AUCs of 0.96 and 0.496. Shankar et al [11] utilized the Our framework utilizes a modified DenseNet-121 model and transfer learning, resulting in the Intelligent Learning Based Breast Cancer Detection (ILB-BCD) algorithm. An empirical study with a benchmark dataset, known as CBIS-DDSM, demonstrates that our proposed model surpasses numerous existing deep learning models with an impressive 99.16% accuracy.

Charim et al [12] utilized Our framework utilizes a modified DenseNet-121 model and transfer learning, resulting in the Intelligent Learning Based Breast Cancer Detection (ILB-BCD) algorithm. An empirical study with a benchmark dataset, known as CBIS-DDSM, demonstrates that our proposed model surpasses numerous existing deep learning models with an impressive 99.16% accuracy. Nowakowska et al. [13] utilized the binary classification model includes two scenarios: noncancerous and malignant, while the multi-classification approach includes three scenarios: normal, benign and malignant. The average accuracy of the two classifications was evaluated and compared. The average accuracy of the binary and multi-classification models was 77.98% and 79.29%, respectively. Manigrasso et al. [14] utilized the dataset includes 524 women with screen-detected cancer, 217 with interval cancers, and 132 with prior images/other; based on the available annotations, approximately 50% of interval cancers are not visible. To reduce the number of ambiguous cases, all exams considered priors, i.e., examinations in which more than 730 days had elapsed between the date of screening and the date of diagnosis, were excluded. Sun et al. [15] utilized the proposed method goes with the feature extraction process with the vector, the Improved Butterfly Optimization algorithm (IBOA) for feature selection, deep adaptive spatial-based feature fusion, and finally the feature vector selection process. The numerical validation of the proposed method results in an accuracy of 99.98%, a sensitivity of 98.79%, a specificity of 99.50%, and an F1-score of 98.90%.

3. PROPOSED SYSTEM

3.1 Overview

The proposed system is designed for mammography classification by systematically processing breast image data through structured stages starting from dataset preparation to final user-facing classification output. The system integrates image preprocessing, CoaT-based feature extraction, basic feature formation, and multiple existing classification models to evaluate and compare performance. By employing HGB, XGB, and FIOT on the same extracted feature set, the system enables consistent comparison of classification behavior. The final prediction results are generated using test data and presented through a graphical interface developed using Tkinter, allowing clear visualization of mammography classification outcomes such as normal, benign, or malignant, as shown in figure 2.

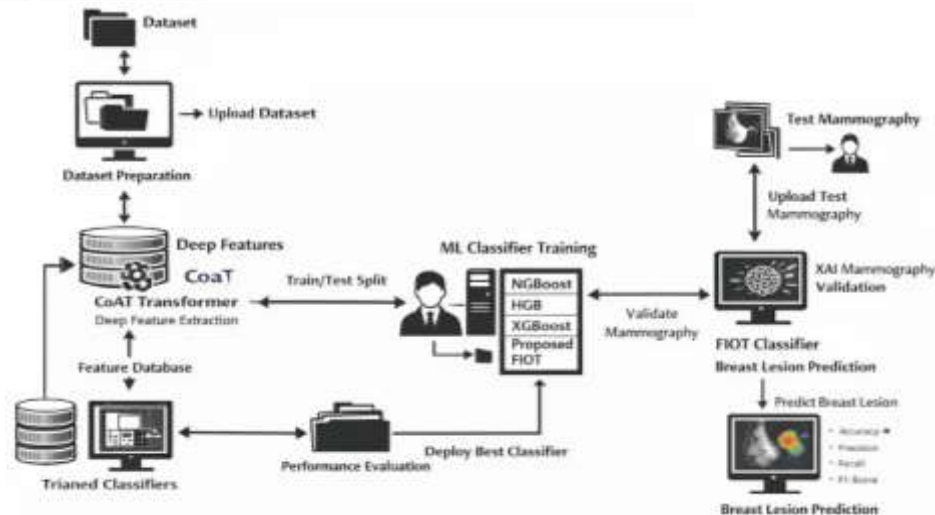


Figure 2. Proposed system architecture.

The proposed methodology begins with the selection of a labeled mammography dataset, which is systematically divided into training and testing subsets to ensure reliable model evaluation. The images undergo a comprehensive pre-processing stage that includes noise reduction, contrast enhancement, and intensity normalization to improve visual clarity and consistency across samples. Following this, CoaT feature extraction is applied to capture multi-scale breast tissue characteristics, including fine, intermediate, and coarse patterns through convolutional encoding and attention mechanisms. These extracted features are then refined into basic descriptive representations by summarizing texture, shape, and spatial attributes while eliminating redundancy, resulting in a compact and discriminative feature set suitable for classification.

Subsequently, a classification framework is developed using the processed feature set, where multiple advanced machine learning models are employed for comparative analysis. Histogram Gradient Boosting utilizes binned feature distributions to construct efficient decision structures, while Extreme Gradient Boosting focuses on gain-based optimization for enhanced feature separation. Fast Interpretable Oblique Trees further improve interpretability by forming linear combinations of features to generate oblique decision boundaries. The performance of these models is evaluated using standard metrics to determine their effectiveness in mammography classification. Finally, the trained models are applied to unseen test data to validate generalization capability, and the entire system is integrated into a TKInter-based interface, enabling users to upload mammography images and visualize classification results in an interactive and user-friendly environment.

3.2 CoaT Feature extraction

CoaT feature extraction begins with standardized mammography images to ensure uniform intensity and spatial resolution across all samples. The images are decomposed into multiple resolution levels, referred to as co-scales, where fine-scale representations capture localized texture and edge variations, mid-scale representations describe regional tissue organization, and coarse-scale representations summarize global breast structure. This co-scale decomposition allows the extraction process to retain both detailed and contextual information from the mammograms. At each co-scale, convolution-based spatial encoding is applied to preserve neighbourhood relationships and structural continuity within the breast tissue. Position-related information is integrated to maintain awareness of spatial location across the image, ensuring that similar tissue patterns from different regions remain distinguishable. Attentional relevance mapping (ARM) is then used to emphasize informative regions while

suppressing less significant background responses, improving the focus of the extracted features without losing spatial coherence. Following this, feature maps from fine, mid, and coarse scales are aligned through scale matching operations so that corresponding regions can interact across resolutions. The aligned maps are fused to form a unified representation that combines local texture details with broader structural context. Redundant feature responses are reduced during consolidation, resulting in a compact and structured COAT feature set (CFS). The final CFS encodes multi-scale texture, shape, and spatial relationships from mammography images and serves as the output for downstream breast analysis and classification task.

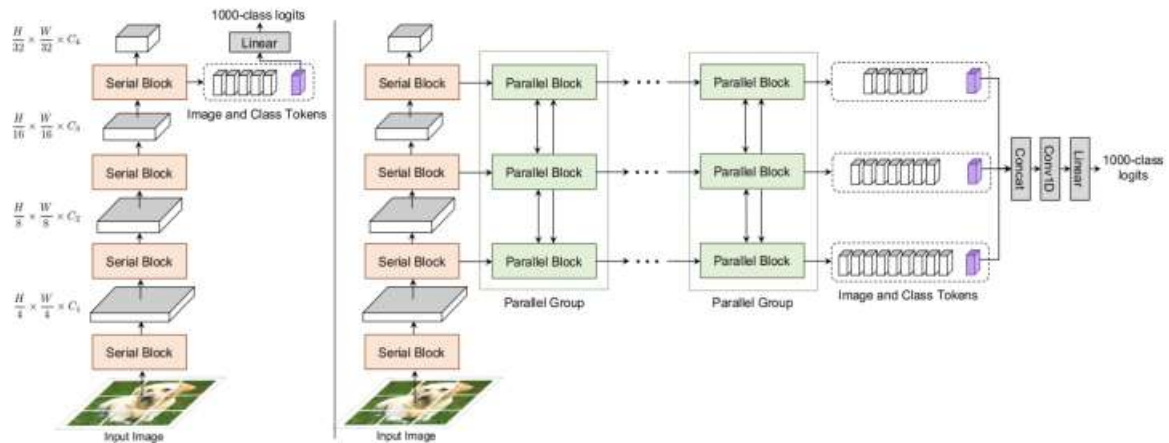


Figure 3. Generalized layered architecture of coaT model

Internal working of CoaT

The process begins with loading mammography images and performing preprocessing, where each image is resized to 224×224 pixels and normalized to ensure consistent intensity values and compatibility with the CoaT model. The preprocessed images are then passed through convolutional layers, where they are divided into smaller patches and transformed into embedded feature representations, enabling the extraction of local spatial details such as edges, textures, and structural patterns. Subsequently, the transformer-based self-attention mechanism analyzes relationships between different regions of the image, allowing the model to focus on critical areas like masses or calcifications while capturing global contextual information, thereby enhancing feature representation for accurate classification.

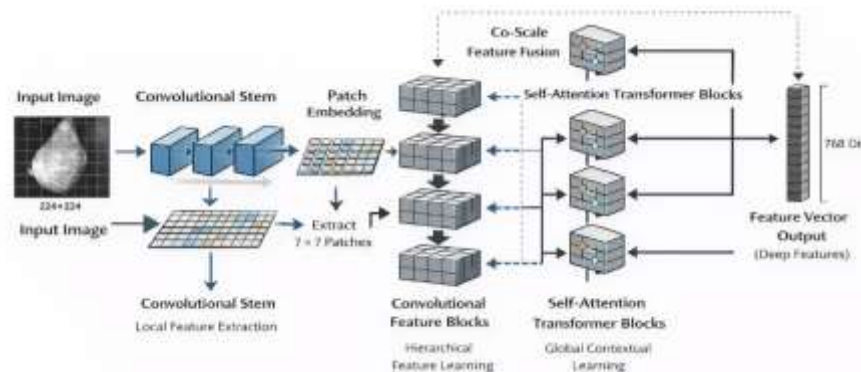


Figure 4. Internal workflow of coAT model

In the subsequent stages, the CoaT model performs hierarchical feature learning, where features are progressively refined through multiple layers combining convolutional operations and self-attention mechanisms. This integration of local and global feature learning enables the model to capture complex and subtle patterns associated with breast lesions. Following this, the extracted information is consolidated into a compact global feature representation, resulting in a high-dimensional feature vector (approximately 768 features) that effectively summarizes the critical visual characteristics of the mammography image. Finally, this feature vector is flattened and converted into numerical form, serving as input to machine learning classifiers such as NGB, HGB, XGB, and FIOT, enabling accurate and efficient classification of different breast lesion categories.

4. RESULT ANALYSIS

Figure 5 shows graphical user interface that displays the system control panel where the dataset is uploaded, the system automatically detects the available classes such as Benign, Malignant, Normal, Probably Benign, and Suspicious, and confirms that the dataset has been successfully loaded. The GUI then provides options for performing operations such as CoaT feature extraction, dataset splitting, training classifiers (NGB, HGB, XGB), and running the proposed FIOT classifier, allowing the admin to train and evaluate models through the interface before proceeding to prediction tasks.

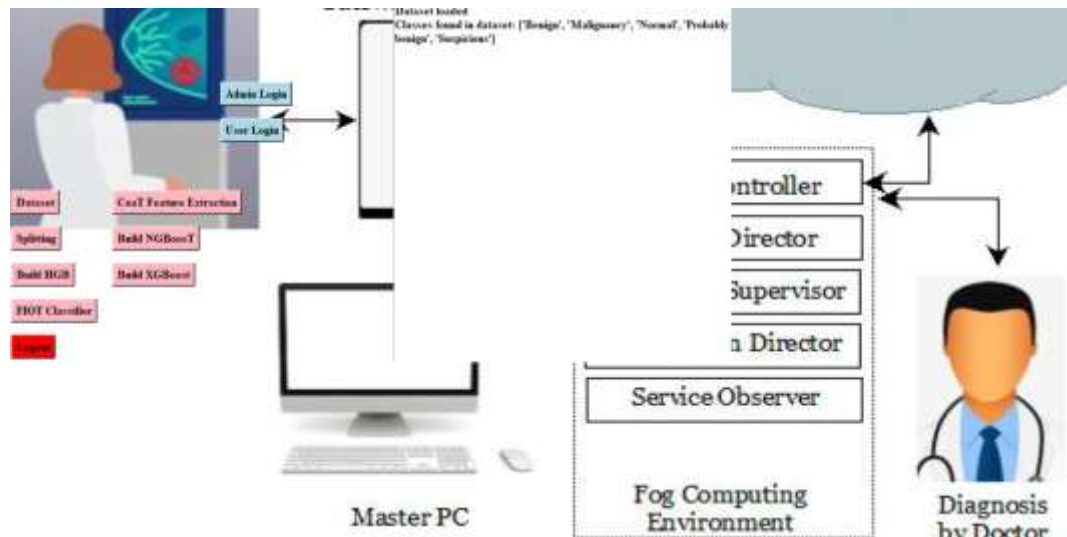


Figure 5. GUI for uploading dataset of breast lesion detection

The figure 6 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.

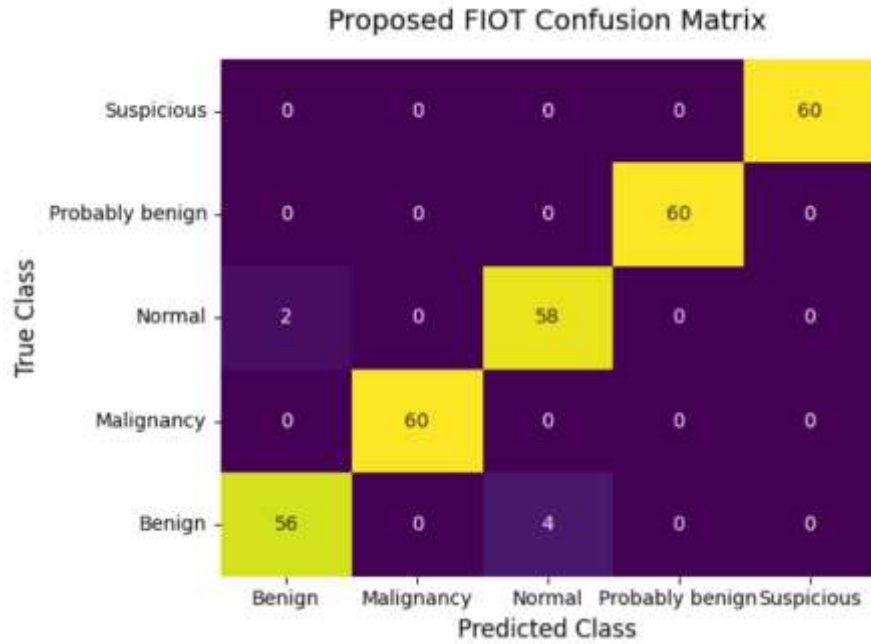


Figure 6. Illustration of confusion matrix using FIOT classifier

The figure 7. 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 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.

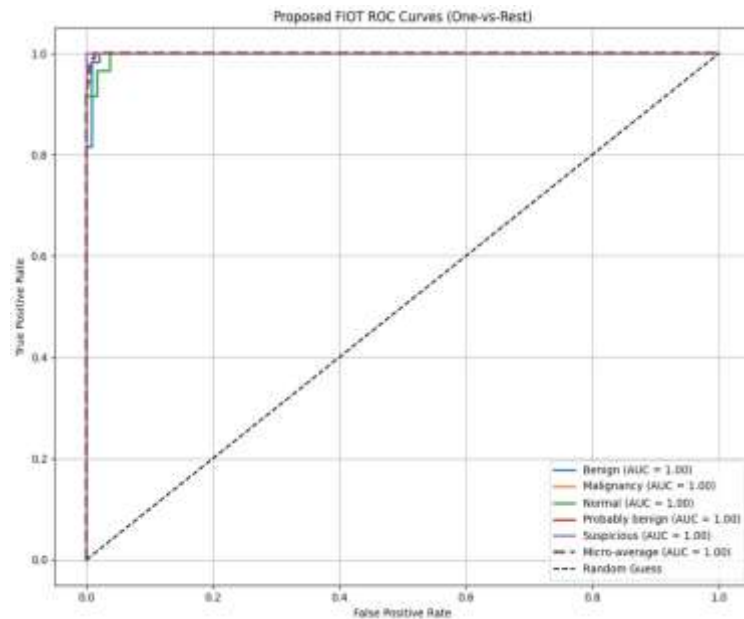


Figure 7. Illustration of confusion matrix using FIOT model

Figure 8 shows, the predictive capability of the system is demonstrated through a real-world test case where the model successfully processes a raw mammogram to provide a diagnostic label. The figure shows the "Original Image" alongside the "Model Classification Result," where the system has accurately identified the tissue as Classified: Benign. This outcome validates the effectiveness of the entire 11-step pipeline—from the initial image preprocessing and COAT feature extraction to the final decision made by the Fast Interpretable Oblique Tree (FIOT). By rendering the result in a clear, high-contrast blue text overlay, the system provides an immediate and interpretable visualization for medical professionals, confirming that the mathematical patterns learned during training can be reliably applied to individual patient scans to distinguish non-cancerous benign masses from healthy or malignant tissue.

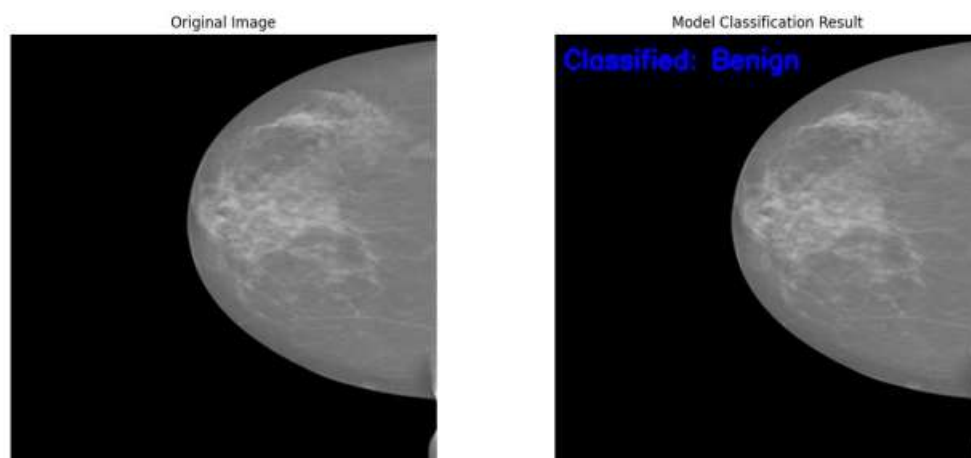


Figure 8. Prediction on sample test image using proposed FIOT model

Figure 9. shows the diagnostic capability of the system is further validated through a critical test case involving high-risk tissue. The figure displays the "Original Image" alongside the corresponding "Model Classification Result," where the system has successfully identified the presence of cancerous patterns, yielding a result of Classified: Malignancy. This accurate detection highlights the practical significance of the integrated COAT feature extraction and the Fast Interpretable Oblique Tree (FIOT) logic, demonstrating that the system can distinguish the complex, irregular architectural distortions characteristic of malignant tumours from benign masses. The clear blue text overlay provides an immediate, high-confidence notification for the clinical user, confirming that the 11-step methodology is effective in detecting lifethreatening abnormalities during the automated screening process.

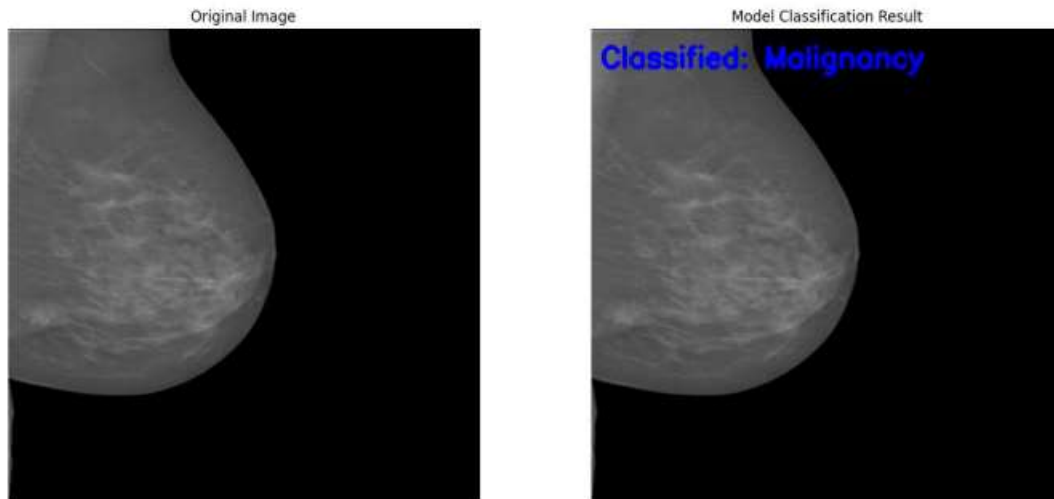


Figure 9. Prediction result obtained on malignancy image

Figure 10, shows the classification system that demonstrates its precision in identifying high-risk clinical scenarios by accurately flagging a mammogram for further investigation. The figure displays the side-by-side comparison of the "Original Image" and the "Model Classification Result," where the system has definitively assigned the label Classified: Suspicious. This outcome is a critical component of the 11-step methodology, proving that the Fast Interpretable Oblique Tree (FIOT) can effectively isolate tissue patterns that, while not yet confirmed as malignant, exhibit significant architectural irregularities that warrant immediate medical attention. By clearly rendering the diagnostic result in a blue text overlay, the system provides an essential early-warning signal, ensuring that potentially dangerous anomalies are prioritized for clinical review

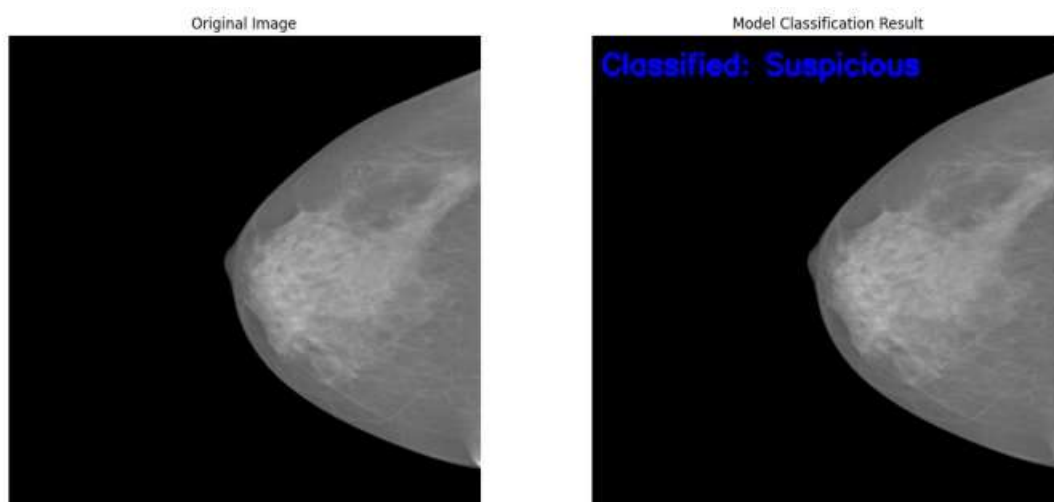


Figure 10. Prediction result obtained as benign using proposed FIOT model

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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