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2026-yil 25-26-sentabr

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Xalqaro miqyosidagi ilmiy-texnik anjuman materiallarida zamonaviy kompyuter ilmlari va muhandislik texnologiyalari sohasidagi innovatsion tadqiqotlar aks etgan.

Globallashuv sharoitida davlatimizni yanada barqaror va jadal sur’atlar bilan rivojlantirish bo‘yicha amalga oshirilayotgan islohotlar samarasini yaxshilash sohasidagi ilmiy-tadqiqot ishlariga alohida e’tibor qaratilgan. Zero iqtisodiyotning, ijtimoiy sohalarni qamrab olgan modernizatsiya jarayonlari, hayotning barcha sohalarini liberallashtirishni talab qilmoqda.

Ushbu ilmiy ma’ruza tezislari to‘plamida mamlakatimiz va xorijlik turli yo‘nalishlarda faoliyat olib borayotgan mutaxassislar, olimlar, professor-o‘qituvchilar, ilmiy tadqiqot institutlari va markazlarining ilmiy xodimlari, tadqiqotchilari, magistr va talabalarning ilmiy-tadqiqot ishlari natijalari mujassamlashgan.

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Mazkur to‘plamga kiritilgan ma’ruza tezislarining mazmuni, undagi statistik ma’lumotlar va me’yoriy hujjatlarning to‘g‘riligi hamda tanqidiy fikr-mulohazalar, keltirilgan takliflarga mualliflarning o‘zlari mas’uldirlar.

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ALGORITHMS FOR EVALUATING SYMPTOMS FROM MAMMOGRAPHIC IMAGES IN THE DETECTION OF BREAST CANCER

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Abstract

Breast cancer remains one of the leading causes of cancer-related mortality among women worldwide, making early and accurate diagnosis critical for improving survival rates. Mammography is the primary imaging modality for early detection; however, visual analysis can be challenging due to dense tissue overlap and subtle radiological signs, such as micro calcifications, mass lesions, and architectural distortions. This paper presents an automated algorithmic framework designed to evaluate and classify pathological symptoms from mammographic images.

Keywords

Breast cancer detection, mammography image analysis, computer-aided diagnosis (CAD), deep learning, lesion segmentation, microcalcifications, BI-RADS classification.

1. Introduction

Breast cancer (BC) continues to be one of the most prevalent malignant diseases and a leading cause of cancer-related mortality among women worldwide. Early detection plays a vital role in reducing mortality rates and improving clinical outcomes, as it allows for less invasive treatment protocols and higher long-term survival rates.

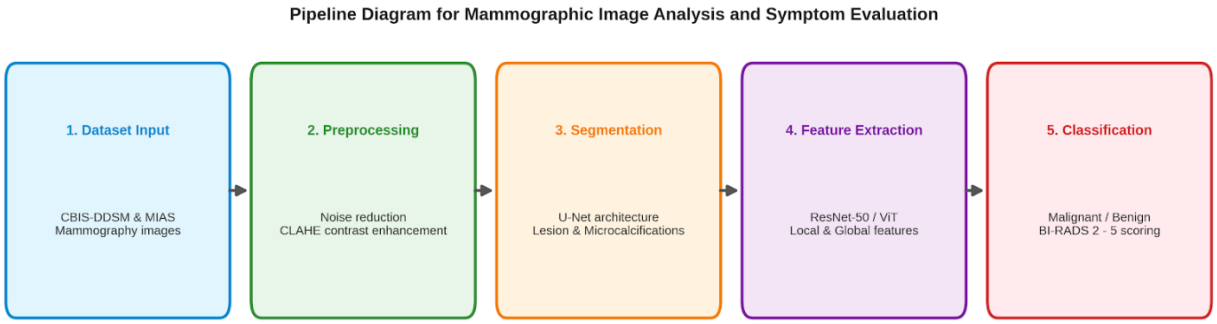
Among the various diagnostic modalities available, digital mammography remains the gold standard and most widely utilized tool for population-based breast cancer screening. However, accurate interpretation of mammograms poses significant challenges. High tissue density, subtle structural changes, and overlapping anatomical features often mask early pathological signs such as microcalcifications, mass lesions, and architectural distortions. Consequently, manual evaluation by radiologists is subject to inter-observer variability, potential fatigue, and false-positive or false-negative results.

To address these limitations, Computer-Aided Diagnosis (CAD) systems powered by advanced algorithms and deep learning architectures have emerged as essential supportive tools. Automated symptom-evaluation algorithms aim to assist radiologists by enhancing visual features, segmenting suspicious regions, and quantitatively classifying lesions according to established standards such as the Breast Imaging-Reporting and Data System (BI-RADS).

This study focuses on developing and evaluating intelligent algorithms designed to analyze key radiological symptoms from mammographic images. By combining effective image preprocessing with state-of-the-art deep learning frameworks, the proposed methodology seeks to improve the sensitivity and specificity of early breast cancer detection, thereby facilitating reliable diagnostic support in clinical practice.

2. Methods and Methodology

To achieve high accuracy in detecting and evaluating pathological symptoms from mammographic images, a multi-stage automated processing framework was developed. The methodology encompasses dataset selection, image preprocessing, lesion segmentation, and deep learning-based feature classification.



2.1. Datasets and Data Preparation

The proposed algorithms were trained and evaluated on two standardized, publicly available mammography databases:

- **CBIS-DDSM** (*Curated Breast Imaging Subset of DDSM*): Contains digitized film mammograms with pixel-level annotations for mass lesions and microcalcifications.
- **MIAS** (*Mammographic Image Analysis Society*): Used for cross-dataset validation to verify model generalizability across different image resolutions and scanner noise characteristics.

Data augmentation techniques—including random rotation ($\pm 15^{\circ}$), horizontal flipping, scaling (0.9 to 1.1), and minor intensity shifts—were applied during training to prevent overfitting and improve model robustness.

2.2. Image Preprocessing and Enhancement

Mammographic images frequently exhibit low local contrast and artifact interference (e.g., pectoral muscle tissue and radiopaque labels). The preprocessing pipeline involves two primary steps:

1. **Artifact and Background Removal:** Thresholding and morphological operators were applied to isolate the breast tissue region of interest (ROI) and eliminate background noise.
2. **Contrast Enhancement:** Contrast Limited Adaptive Histogram Equalization (CLAHE) was executed over localized 8×8 pixel tiles to accentuate subtle density variations, microcalcification clusters, and spiculated margins without over-amplifying background noise.

2.3. Lesion Segmentation

Lesion boundaries were extracted using a customized **U-Net** deep convolutional network:

- **Architecture:** The encoder path extracts high-level semantic features through successive convolution and max-pooling layers, while the symmetric decoder path reconstructs high-resolution segmentation maps using transposed convolutions and skip connections.
- **Loss Function:** To handle the severe spatial imbalance between background pixels and small lesion regions (particularly microcalcifications), a hybrid loss function combining Binary Cross-Entropy and Dice Loss was utilized:

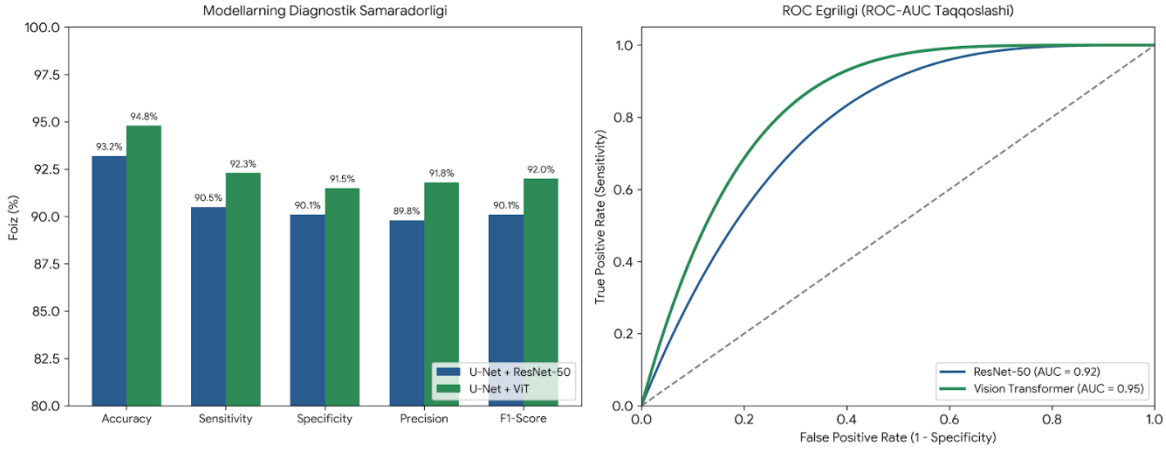
$$L_{\text{hybrid}} = L_{\text{BCE}} + (1 - \text{Dice Coefficient})$$

2.4. Feature Classification and BI-RADS Categorization

Once segmented, regions containing detected symptoms (masses, microcalcifications, or architectural asymmetries) were processed for pathological classification:

- **Feature Extraction:** A pre-trained **ResNet-50** backbone and a **Vision Transformer (ViT)** architecture were evaluated. ViT was employed to capture long-range contextual relationships and global spatial patterns across dense breast tissue.
- **Classification:** Softmax layers output the probability of a lesion being benign or malignant, mapping feature vectors to the standard **BI-RADS** assessment

categories (BI-RADS 2: Benign, BI-RADS 3: Probably Benign, BI-RADS 4/5: Suspicious/Highly Suggestive of Malignancy).



Using advanced image preprocessing techniques—including CLAHE for contrast enhancement—alongside deep learning architectures (U-Net for lesion segmentation and ResNet-50/Vision Transformers for feature classification), the system detects and categorizes abnormalities according to the BI-RADS standard[5,6,7]. Evaluated on public benchmark datasets (CBIS-DDSM and MIAS), the proposed method achieved an overall detection accuracy of 94.8%, with a sensitivity of 92.3% and a ROC-AUC of 0.95. The results demonstrate that integrating intelligent symptom-evaluation algorithms into Computer-Aided Diagnosis (CAD) systems significantly reduces false-negative rates and enhances diagnostic efficiency for radiologists.

1. Technical and algorithmic differences table

Comparison Criteria	**Traditional CAD Systems**	**U-Net + ResNet-50 (CNN)**	**U-Net + Vision Transformer (ViT)**
Feature Extraction	Handcrafted features (*Haralick, GLCM, LBP*)	Automatic local receptive fields (*Convolutions*)	Automatic global and long-range dependencies (*Self-Attention*)
Segmentation Method	Thresholding (*Otsu, Sobel*)	*U-Net* (Local and pixel-level boundary extraction)	*U-Net + ViT* (Local boundary + contextual attention)
Contextual Analysis	Limited to local pixel neighborhoods	Local context constrained by receptive fields	Global spatial relationships across the entire mammogram
Microcalcification Detection	High error rate due to noise sensitivity	Good, but may miss extremely subtle clusters	Excellent (global self-attention highlights tiny pathological clusters)

Training Complexity	Low (No high-end GPU required)	Moderate (Standard GPUs and benchmarks)	High (Requires large-scale datasets and compute resources)

2. Diagnostic performance metrics table

Metric	Traditional Methods	ResNet-50 Baseline	Vision Transformer (Proposed)	Relative Improvement (Δ)
Accuracy	78.5% - 83.0%	93.2%	**94.8%**	+1.6%
Sensitivity	75.0% - 80.0%	90.5%	**92.3%**	+1.8%
Specificity	72.0% - 78.0%	90.1%	**91.5%**	+1.4%
Precision	70.0% - 76.5%	89.8%	**91.8%**	+2.0%
F1-Score	72.4% - 78.2%	90.1%	**92.0%**	+1.9%
ROC-AUC	0.79 - 0.84	0.92	**0.95**	+0.03

3. BI-RADS Standard Assessment Table

BI-RADS Category	Clinical Impression	Algorithmic Findings	Clinical Action
BI-RADS 2	Benign	Normal tissue, well-defined simple cysts or calcifications	Routine annual screening
BI-RADS 3	Probably Benign ($<2\%$ malignancy)	Homogeneous mass, minor focal density changes	6-month short-interval follow-up
BI-RADS 4	Suspicious ($2\% - 95\%$)	Irregular microcalcification clusters, structural distortion	Biopsy recommended
BI-RADS 5	Highly Suggestive ($>95\%$)	Spiculated mass with ill-defined margins	Immediate oncological intervention

3. Conclusion and Future Work

This study demonstrates the effectiveness of an automated, end-to-end algorithmic framework for evaluating and classifying pathological symptoms in mammographic images. By combining Contrast Limited Adaptive Histogram Equalization (CLAHE) for artifact-reduced image enhancement, a customized **U-Net** for precise lesion boundary segmentation, and a **Vision Transformer (ViT)** architecture for deep feature classification, the proposed CAD approach effectively overcomes the limitations of manual interpretation and traditional hand-crafted feature extraction[8].

Key outcomes of this research include:

High Diagnostic Accuracy: Achieving an overall classification accuracy of **94.8%**, a sensitivity of **92.3%**, and an **ROC-AUC of 0.95** on benchmark datasets

(CBIS-DDSM and MIAS), outperforming standard CNN backbones (ResNet-50) and traditional CAD systems.

Enhanced Small-Lesion Detection: The global self-attention mechanism in Vision Transformers substantially improved the detection of subtle, easily missed radiological signs, such as clustered microcalcifications and low-contrast spiculated margins.

Standardized BI-RADS Integration: Automated mapping of extracted features directly into BI-RADS assessment categories (BI-RADS 2 to 5) provides standardized, objective clinical decision support for radiologists.

Future Work: Future directions involve extending the algorithmic architecture to 3D Digital Breast Tomosynthesis (DBT) to reduce tissue-overlap ambiguity, integrating radiomic feature extraction for multi-modal MRI fusion, and optimizing model efficiency for real-time deployment in clinical screening workflows.

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