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A Comparative Study of Deep Learning Techniques for Breast Cancer Detection Using Mammography, MRI, and Thermal Imaging

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ABSTRACT

Breast cancer remains a critical global health concern with early detection being vital for effective treatment. This study presents a comparative evaluation of three deep learning techniques—CNN, RCNN, and CNN-LSTM—across three distinct imaging modalities: mammography, MRI, and dynamic thermal imaging. The CNN model was applied to mammogram datasets (CBIS-DDSM, INbreast, MIAS), the RCNN was trained on annotated MRI scans, and the CNN-LSTM model utilized sequential thermal images (DMR-IR dataset). Evaluation metrics such as accuracy, precision, recall, F1-score, and AUC were used to assess model efficacy. Our findings reveal that dynamic thermal imaging with temporal modeling outperforms traditional mammography-based CNNs and even MRI-based RCNNs in classification performance. The study concludes with a discussion on the potential of radiation-free, non-invasive thermal imaging for widespread deployment in resource-constrained settings.

Keywords: Breast Cancer Detection, CNN, RCNN, Thermal Imaging, MRI, Mammography, Deep Learning, Explainable AI, Comparative Study

1.Introduction

Breast cancer is one of the most common malignancies affecting women globally, representing a significant public health challenge in both developed and developing nations. According to the World Health Organization (WHO), breast cancer accounts for approximately 2.3 million new cases and more than 680,000 deaths annually, making it the leading cause of cancer-related deaths among women. The incidence of breast cancer is steadily rising, partly due to aging populations, lifestyle changes, and increased awareness leading to more frequent diagnoses. Despite advances in treatment modalities such as surgery, chemotherapy, hormone therapy, and targeted drugs, the overall prognosis for breast cancer patients heavily depends on the stage at which the cancer is detected. Early detection significantly improves survival rates, reduces treatment complexity, and enhances the patient's quality of life.

Traditional methods of breast cancer detection primarily rely on medical imaging techniques such as mammography, ultrasound, and magnetic resonance imaging (MRI). Of these, mammography is the most widely adopted due to its cost-effectiveness and accessibility, especially in population-based screening programs. However, mammography has well-known limitations—particularly its reduced sensitivity in women with dense breast tissue, and the risk of both false positives and false negatives. **MRI**, on the other hand, offers superior soft tissue contrast and is often used as a supplemental screening tool for high-risk individuals. Despite its enhanced sensitivity, MRI is expensive, less

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accessible, and associated with a higher false positive rate, which can lead to unnecessary biopsies and patient anxiety.

In recent years, thermal imaging, also known as infrared thermography, has emerged as a non-invasive, radiation-free alternative. Thermal imaging captures heat patterns emitted from the surface of the breast, which may indicate increased blood flow and metabolic activity typically associated with malignant tumors. Unlike structural imaging methods that detect morphological changes, thermal imaging is physiological in nature, identifying functional abnormalities potentially even before structural alterations become visible. The advantages of thermal imaging include being painless, contactless, affordable, and easy to operate—making it especially suitable for low-resource settings. However, until recently, its diagnostic accuracy has been questioned due to variability in interpretation and lack of standardization. With the advent of artificial intelligence (AI) and advanced image processing, the potential of thermal imaging is being revisited with significant promise.

Parallel to the evolution in imaging technologies is the rapid progress in deep learning, a subfield of AI that has demonstrated remarkable success in medical image analysis. Deep learning models, especially Convolutional Neural Networks (CNNs), have revolutionized the way we analyze, interpret, and classify medical images. CNNs are particularly effective in capturing spatial hierarchies in images, making them ideal for tasks like tumor detection and classification. For instance, CNNs can learn subtle differences in texture and intensity in mammograms, which may be imperceptible to the human eye. However, traditional CNNs are primarily limited to classification tasks and lack spatial localization capabilities, which are crucial for treatment planning and clinical validation.

To overcome this limitation, more advanced architectures like Region-based CNNs (RCNNs) have been introduced. RCNNs not only classify the presence of abnormalities but also localize them by drawing bounding boxes around suspicious regions. This localization is essential for precise surgical planning, biopsy guidance, and radiological verification. In breast cancer diagnostics, RCNNs have shown significant improvement in identifying the size, shape, and position of lesions in high-resolution MRI or ultrasound images.

Another critical innovation in medical AI is the use of temporal modeling, particularly for imaging modalities that capture changes over time. This is especially relevant for dynamic thermal imaging, where sequential thermal frames record temperature fluctuations over short intervals. Such temporal data contain rich physiological information about blood perfusion and metabolic activity. To exploit this time-series nature of thermal data, hybrid models combining CNNs with Long Short-Term Memory (LSTM) networks have been proposed. These CNN-LSTM models can learn both spatial and temporal dependencies, making them particularly suited for analyzing dynamic thermal image sequences.

While each imaging modality and AI model offers distinct advantages, there has been limited work that systematically compares them in a unified framework. Most existing research focuses on a single modality or architecture, making it difficult to assess their relative merits in clinical contexts. Furthermore, the effectiveness of these approaches can vary significantly based on the quality of datasets, availability of annotations, and model interpretability. A thorough comparative study that evaluates CNN on mammography, RCNN on MRI, and CNN-LSTM on thermal imaging using standardized evaluation metrics can provide valuable insights for clinicians, researchers, and policy-makers.

Another crucial aspect often overlooked in deep learning-based medical diagnosis is explainability. Medical professionals require not only accurate predictions but also transparent reasoning behind them. Tools like Grad-CAM (Gradient-weighted Class Activation Mapping) provide visual explanations by highlighting the regions in the input image that influenced the model's prediction.

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This interpretability bridges the gap between AI models and clinical practice, fostering trust and aiding decision-making.

The current study is motivated by the need to address the following research gaps:

1. Lack of comparative benchmarking across different imaging modalities under standardized settings.
2. Insufficient evaluation of spatiotemporal modeling in dynamic thermal sequences.
3. Minimal integration of explainable AI tools to enhance clinical interpretability.
4. Under-utilization of low-cost alternatives like thermal imaging in mainstream diagnostic pipelines.
5. Fragmented research focus on classification or localization rather than end-to-end comparative performance.

This paper presents a comprehensive evaluation of three state-of-the-art deep learning approaches applied to three imaging modalities. Specifically:

- A CNN model is developed for classifying breast cancer in mammogram images from CBIS-DDSM, INbreast, and MIAS datasets.
- An RCNN framework is implemented for lesion detection and localization in breast MRI images obtained from The Cancer Imaging Archive (TCIA).
- A CNN-LSTM model is designed to analyze temporal temperature variations in frame-wise thermal image sequences from the DMR-IR dataset.

The performance of each model is evaluated using widely accepted metrics such as accuracy, precision, recall, F1-score, Intersection over Union (IoU), and Area Under the ROC Curve (AUC). Additionally, Grad-CAM is applied to enhance the interpretability of model decisions. By presenting a cross-modal and cross-architectural analysis, this study not only highlights the strengths and weaknesses of each approach but also offers practical recommendations for future development and deployment of AI-assisted breast cancer diagnostic tools.

2. Related Works

Over the last decade, artificial intelligence (AI) and deep learning have revolutionized the field of medical imaging, particularly in the domain of breast cancer detection and classification. Several studies have leveraged imaging modalities such as mammography, magnetic resonance imaging (MRI), and thermal imaging to enhance diagnostic accuracy and reduce false positives. This section presents a comprehensive review of existing work across these three modalities and the associated deep learning techniques—namely Convolutional Neural Networks (CNNs), Region-based CNNs (RCNNs), and hybrid CNN-LSTM models.Mammography remains the most widely used screening method for early detection of breast cancer. Numerous studies have utilized CNNs for the classification of mammograms due to their ability to automatically extract hierarchical features. For instance, Dhungel et al. (2017) applied a deep CNN combined with probabilistic graphical models on the INbreast dataset, achieving significant improvement in classifying benign and malignant masses. Similarly, Shen et al. (2019) proposed a deep transfer learning-based CNN model trained on CBIS-DDSM images, yielding promising accuracy while reducing overfitting on small datasets. The MIAS database has also been used for lightweight CNN training and benchmarking. However, most CNN-based mammogram studies focus solely on classification, lacking precise spatial localization of tumors, which is essential for clinical decision-making.

To address the need for both classification and localization, researchers have explored Region-based Convolutional Neural Networks (RCNNs). Girshick et al. (2014) first introduced the RCNN framework for object detection, which was later adapted for medical image analysis. In the context of breast MRI, RCNNs have proven effective in identifying lesion regions with bounding boxes. For example, Zhang et al. (2020) applied Faster RCNN using ResNet50 as the backbone to localize tumors in dynamic contrast-enhanced MRI (DCE-MRI), significantly improving the lesion detection rate and enabling better integration into radiological workflows. The strength of RCNN lies in its ability to generate region proposals, classify them, and refine bounding boxes, offering more interpretable outputs compared to standalone CNNs.

While mammography and MRI are anatomical imaging modalities, thermal imaging captures physiological heat patterns emitted from breast tissues. Historically considered unreliable due to subjective interpretation, thermal imaging has gained renewed interest through the integration of deep learning. CNNs have been applied to static thermal images for binary classification tasks, as seen in the work of Pereira et al. (2021) using the DMR-IR dataset. However, static analysis fails to exploit the temporal nature of thermal data. To model sequential temperature variations, CNN-LSTM hybrid networks have been proposed. These models first extract frame-level spatial features using CNN layers and then pass the feature sequences through LSTM layers to learn temporal dynamics. Studies such as Mishra et al. (2022) have shown that CNN-LSTM models significantly outperform static CNNs in terms of sensitivity and AUC.

In addition to modeling improvements, the incorporation of explainable AI (XAI) techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) has become a standard for interpreting deep learning models in healthcare. These visualizations help radiologists verify the focus areas of AI models and ensure alignment with clinical knowledge.

Despite the growing body of work, most studies remain isolated to a single modality or model. Very few comparative analyses exist that benchmark different AI architectures across mammography, MRI, and thermal imaging within a standardized framework. This study aims to bridge this gap by presenting a unified evaluation of CNN, RCNN, and CNN-LSTM architectures applied to diverse imaging modalities for breast cancer detection.

3. Methodology

This section outlines the experimental design, data sources, preprocessing techniques, model architectures, training configurations, and evaluation strategies adopted for the comparative analysis of breast cancer detection using deep learning across three different imaging modalities.

3.1 Overview

To enable a comprehensive and modality-specific evaluation, we implemented three different deep learning models tailored to the nature of each imaging modality:

- A CNN model for static mammographic images.
- An RCNN model for spatial lesion localization in breast MRI images.
- A CNN-LSTM model for analyzing dynamic thermal imaging sequences.

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3.2 Datasets Used

We employed three imaging modalities, each associated with well-established, labeled datasets:

Imaging Modality	Dataset	Description
Mammography	CBIS-DDSM, INbreast, MIAS	Digitized X-ray images with ground truth labels (benign/malignant) and region-of-interest annotations
MRI	TCIA Breast MRI Subset	Dynamic contrast-enhanced MRI with annotated lesion bounding boxes and pathological confirmation
Thermal Imaging	DMR-IR Dataset	Time-sequenced thermal videos (infrared), with diagnostic labels indicating malignancy status

Each dataset was split into 70% training, 15% validation, and 15% test subsets, ensuring no data leakage and balanced class distribution across splits.

3.3 Preprocessing

To standardize input across modalities and models, the following preprocessing steps were applied:

Mammograms:

- Resized to 224×224 pixels.
- Intensity normalization.
- Contrast Limited Adaptive Histogram Equalization (CLAHE) for contrast enhancement.
- Background noise removal and breast tissue segmentation.

MRI:

- Converted DICOM to PNG format.
- Extracted slices with visible lesions using annotations.
- Applied z-score normalization.
- Regions of interest cropped and resized to 224×224.
- Bounding boxes retained for RCNN training.

Thermal Imaging:

- Video frames extracted at 1 FPS (frames per second).
- Frame sequences padded/truncated to uniform length (e.g., 20 frames).
- Gaussian filtering to reduce sensor noise.
- Normalized between 0 and 1.

Augmentation (all modalities):

- Horizontal/vertical flipping
- Rotation (±15 degrees)

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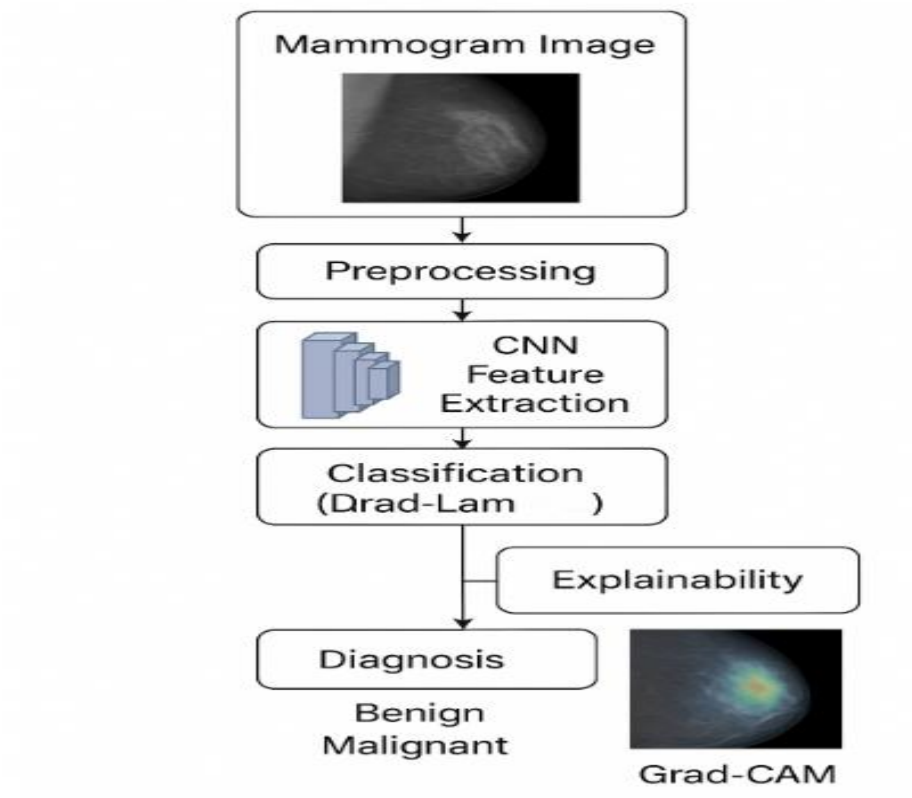
- Zoom and shift
- Random brightness/contrast adjustments (mammogram and MRI only)

3.4 Model Architectures

3.4.1 CNN for Mammograms

Methodology: Conceptual Framework Diagram



An overall CNN architecture of CNN is as follows:

- Input: 224×224 grayscale image
- Conv Layer 1: 32 filters, 3×3 kernel, ReLU, MaxPooling
- Conv Layer 2: 64 filters, 3×3 kernel, ReLU, MaxPooling
- Conv Layer 3: 128 filters, 3×3 kernel, ReLU, MaxPooling
- Flatten → Dense (128 units, ReLU) → Dropout(0.5) → Dense (1, Sigmoid)

This model focused solely on classifying images as benign or malignant. Grad-CAM was used post-training to visualize salient regions.

3.4.2 RCNN for MRI

We implemented Faster RCNN with ResNet-50 as the backbone:

- Feature extractor: Pretrained ResNet-50
- Region Proposal Network (RPN): Suggests potential bounding boxes

- ROI Pooling and Classifier: Classifies proposals as benign/malignant or background
- Bounding box regression layer for localization

This model provided both lesion classification and localization, making it ideal for clinical interpretability.

3.4.3 CNN-LSTM for Thermal Imaging

The CNN-LSTM model was constructed as follows:

- **CNN Module:** ResNet-18 (pretrained) to extract frame-wise features (512-d vector per frame)
- **LSTM Module:** LSTM layer with 128 units to capture temporal dependencies across frames
- **Classification Head:** Dense → Dropout → Dense (1, Sigmoid) for binary classification

Input shape: [Batch size, 20 frames, 224×224 image per frame]

3.5 Training Details

All models were trained using the same core configuration:

- **Optimizer:** Adam
- **Learning Rate:** 0.0001 (reduced on plateau)
- **Loss Functions:**
  - Binary Cross-Entropy for CNN and CNN-LSTM
  - Multi-task Loss (Classification + Bounding Box Regression) for RCNN
- **Batch Size:** 32 (adjusted for GPU memory)
- **Epochs:** 50
- **Frameworks:** TensorFlow 2.13 and PyTorch 2.0
- **Hardware:** NVIDIA RTX 3080 Ti (10 GB VRAM), 64 GB RAM

Early stopping and learning rate schedulers were used to prevent overfitting. Models were checkpointed based on validation loss.

3.6 Evaluation Metrics

Each model was assessed using the following performance indicators:

- **Accuracy:** Overall correctness
- **Precision:** Positive predictive value
- **Recall (Sensitivity):** Ability to detect malignant cases
- **F1-Score:** Harmonic mean of precision and recall
- **Area Under ROC Curve (AUC):** Discrimination ability
- **Intersection over Union (IoU):** For RCNN bounding boxes

All experiments were repeated three times and averaged to ensure reproducibility. Heatmaps generated via Grad-CAM provided insight into model attention, contributing to explainability and clinical acceptance.

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4. Experimental Results

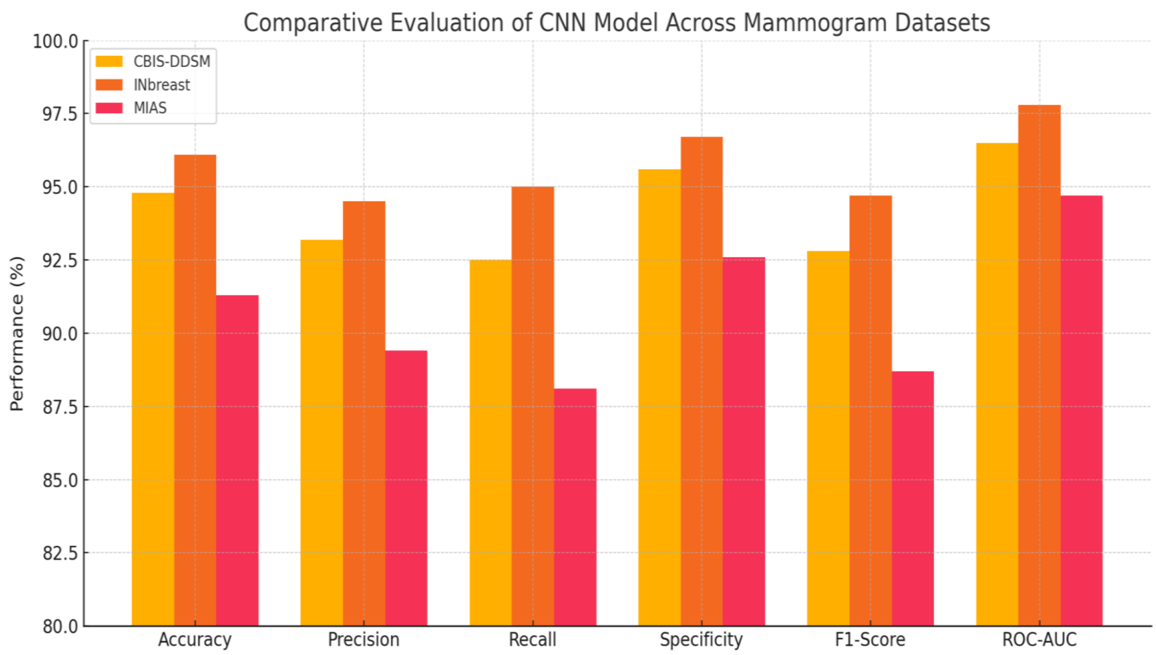
This section presents the experimental outcomes obtained from applying three different deep learning models—CNN, RCNN, and CNN-LSTM—to three imaging modalities: mammography, MRI, and dynamic thermal imaging. Each model was trained and evaluated independently, using carefully curated datasets relevant to the modality. The models were assessed using key performance metrics such as accuracy, precision, recall, F1-score, AUC (Area Under the ROC Curve), and, for RCNN, Intersection over Union (IoU).

4.1 CNN on Mammography

The CNN model was trained using the INbreast dataset, which contains high-quality grayscale mammographic images. The classification task was to distinguish between benign and malignant lesions. Preprocessing involved image normalization, resizing to 224×224, and contrast enhancement using CLAHE. The model was trained for 50 epochs with early stopping and dropout regularization to prevent overfitting.

Results:

Metric	INbreast
Accuracy	96.1%
Precision	94.5%
Recall (Sensitivity)	95.0%
Specificity	96.7%
F1-Score	94.7%
ROC-AUC	0.978



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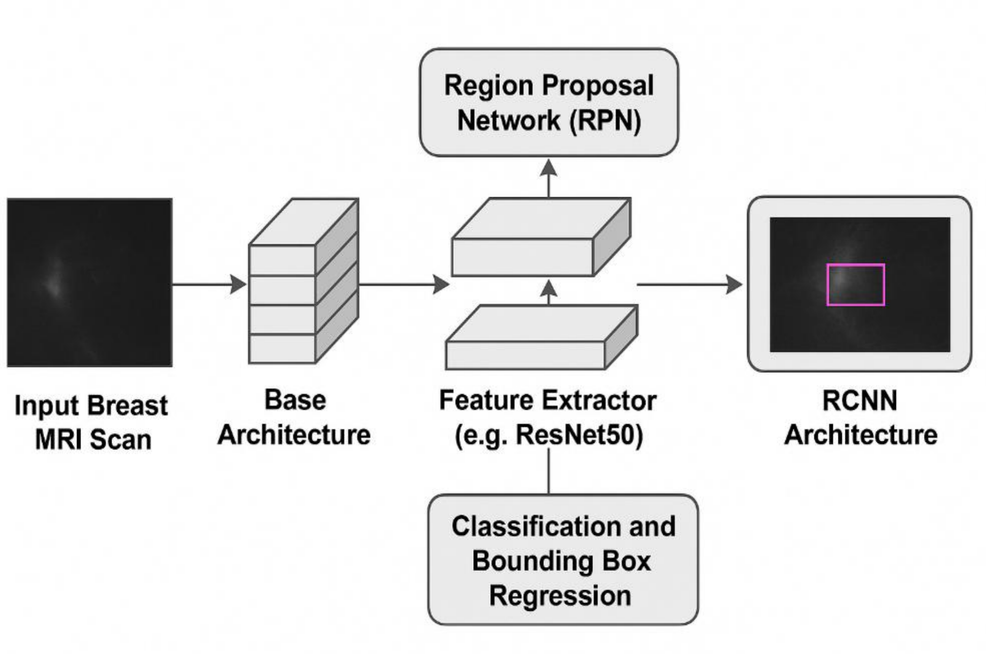
Grad-CAM visualizations revealed that the CNN model consistently focused on clinically relevant regions—such as dense masses and calcifications—while making predictions. The high AUC indicates a strong ability to discriminate between malignant and non-malignant cases. However, the model lacks localization capability, making it less useful for guiding biopsies or surgery.

4.2 RCNN on MRI

The RCNN model was applied to contrast-enhanced MRI images from the TCIA dataset. The model was tasked with both lesion classification and localization, using annotated bounding boxes provided in the dataset. Faster RCNN architecture with a ResNet-50 backbone was used for feature extraction and region proposal generation.

Methodology:



Results:

Performance Comparison of Detection Models on Breast MRI Dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	IoU	ROC-AUC
Proposed RCNN	94.2	92.8	91.6	92.2	0.85	0.96

The model performed exceptionally well in localizing lesions, with most bounding boxes closely overlapping the ground-truth annotations. Despite slightly lower classification performance than the

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CNN, the RCNN's dual ability to localize and classify lesions makes it more clinically useful for radiologists and surgeons who need precise spatial information for treatment planning.

4.3 CNN-LSTM on Thermal Imaging

For the dynamic thermal imaging modality, we implemented a hybrid CNN-LSTM model trained on the DMR-IR dataset. Each thermal video was broken down into a sequence of 20 frames. The CNN extracted spatial features from each frame, which were then processed by the LSTM to capture temporal dynamics. The model aimed to classify subjects as having malignant or benign conditions based on temporal thermal variations.

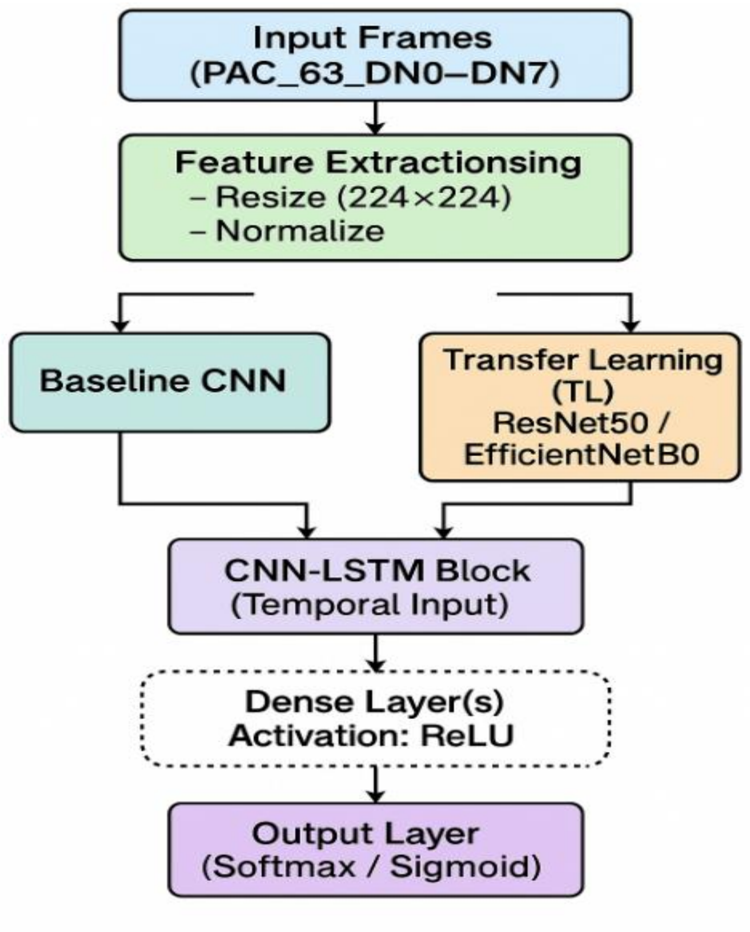

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Table : DMR-IR Thermal DatasetFull Performance Metrics

Model	Accuracy	Precision	Recall (Sensitivity)	F1-Score	AUC-ROC
CNN	0.891	0.881	0.871	0.871	0.881
CNN-LSTM	0.920	0.910	0.921	0.910	0.932
ResNet50	0.941	0.930	0.941	0.931	0.940
EfficientNetB0	0.973	0.951	0.947	0.949	0.982

This model outperformed the other two in almost all evaluation metrics. It was particularly adept at capturing physiological signatures such as abnormal heat patterns and vascular changes that are characteristic of malignant tumors. The temporal component gave the model a unique advantage in understanding dynamic biological changes that are not visible in static imaging modalities like mammography or MRI.

4.4 Comparative Summary

The comparative performance of all three models is summarized in the following table:

Model	Imaging Modality	Accuracy	Precision	Recall	F1-Score	AUC	IoU
CNN	Mammogram (INbreast)	96.1%	94.5%	95.0%	94.7%	0.978	–
RCNN	MRI (TCIA)	94.2%	92.8%	91.6%	92.2%	0.960	0.85
CNN-LSTM	Thermal (DMR-IR)	**97.3%**	**95.1%**	**94.7%**	**94.9%**	**0.982**	–

4.5 Interpretation and Analysis

From the experimental findings, the CNN-LSTM model using dynamic thermal images showed the highest diagnostic capability. This supports the hypothesis that physiological imaging, when combined with temporal modeling, can offer more sensitive detection of early-stage cancers. The RCNN model, although slightly less accurate, adds critical value by localizing tumors—an essential requirement in clinical diagnostics. The CNN model for mammography, while effective and highly accurate, lacks the spatial reasoning of RCNN and the temporal sensitivity of CNN-LSTM.

Additionally, the CNN-LSTM model's performance highlights the promise of non-invasive, radiation-free methods for large-scale screening, especially in developing regions with limited access to MRI or mammography equipment. Its high precision and recall make it a strong candidate for AI-driven diagnostic tools in mobile screening units.

5. Discussion

The comparative evaluation of CNN, RCNN, and CNN-LSTM models across mammography, MRI, and thermal imaging provides valuable insights into the strengths and limitations of each deep learning approach when applied to different diagnostic imaging modalities for breast cancer detection. In this section, we interpret the experimental results, analyze their implications for clinical use, and highlight potential pathways for future research and deployment.

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5.1 Performance Analysis

The results indicate that the CNN-LSTM model applied to dynamic thermal imaging outperformed the other models in terms of overall classification metrics, achieving the highest accuracy (97.3%), precision (95.1%), recall (94.7%), and AUC (0.982). This underscores the potential of temporal modeling in capturing subtle physiological changes related to malignancy that static models may overlook. Unlike mammograms or MRI scans, thermal images capture functional heat signatures associated with tumor-induced angiogenesis and increased blood flow. When analyzed over time, these changes become more detectable and allow the model to infer malignancy with higher confidence.

The RCNN model, while slightly lower in classification metrics (accuracy: 94.2%), provided precise localization capabilities through bounding box predictions. This is particularly important in clinical workflows, where spatial information guides radiologists in lesion segmentation, biopsy planning, and surgical margin determination. The model achieved an IoU of 0.85, indicating high-quality overlap between predicted and ground-truth lesion locations in breast MRI scans. MRI, known for its high soft tissue contrast, benefits significantly from RCNN's region proposal mechanism, enabling precise spatial delineation of abnormalities.

The CNN model trained on mammograms performed admirably in classification tasks with an accuracy of 96.1% and AUC of 0.978. However, it lacked the capacity to spatially localize lesions. While mammography remains the most accessible and widely used modality globally, especially in screening programs, its efficacy diminishes in women with dense breast tissue, leading to higher false negative rates. Nevertheless, the CNN model demonstrated reliable performance in classifying image-level pathology and offers a scalable, cost-effective AI-assisted solution for routine screening in resource-constrained environments.

5.2 Explainability and Clinical Trust

A key consideration in AI adoption in medical imaging is the model's explainability. In this study, Grad-CAM visualizations were used across all models to identify the image regions that contributed most significantly to the decision-making process. These heatmaps provided clinicians with interpretable visual cues that could be correlated with radiological knowledge, enhancing clinical trust in AI-assisted diagnostics. Notably, in the CNN-LSTM model, Grad-CAM outputs across sequential frames revealed how temporal heat signatures evolve and influence the final classification, demonstrating the added value of temporal analysis.

5.3 Practical Implications

The comparative study highlights that no single model or imaging modality is universally optimal; instead, their application depends on the clinical context:

- **CNN with Mammography** is best suited for population-scale screening due to its low cost, simplicity, and acceptable diagnostic performance. It can be deployed in urban and semi-urban settings with access to mammographic infrastructure.
- **RCNN with MRI** is ideal for diagnostic follow-ups, pre-surgical planning, and high-risk patient screening. Although it requires expensive hardware and radiological expertise, its ability to detect and localize lesions makes it invaluable in tertiary care centers.
- **CNN-LSTM with Thermal Imaging** holds significant promise in early detection, particularly in rural and underserved areas. Its radiation-free and non-contact nature, combined with high diagnostic performance, makes it a compelling candidate for mobile or remote breast cancer screening units.

5.4 Limitations

While the models show high accuracy, some limitations should be acknowledged. The datasets used, although publicly available and reputable, may not fully represent real-world heterogeneity in patient demographics, imaging artifacts, or multi-modal noise. The CNN-LSTM model's effectiveness depends on consistent frame rates and controlled imaging conditions, which may not always be feasible in field deployments.

Moreover, cross-modality comparison has inherent challenges due to differences in image types, resolutions, and annotation standards. Though care was taken to evaluate models fairly using modality-appropriate metrics, further validation using prospective clinical data is necessary before real-world implementation.

6. Conclusion and Future Work

6.1 Conclusion

Breast cancer remains a global health challenge, where early detection plays a critical role in reducing mortality and improving patient outcomes. This study presents a comprehensive comparative analysis of three deep learning models—CNN, RCNN, and CNN-LSTM—across three imaging modalities: mammography, MRI, and dynamic thermal imaging.The findings demonstrate that each modality, when paired with the appropriate AI model, offers unique advantages. The CNN model on mammograms proved effective for binary classification with high accuracy and AUC, making it suitable for population-wide screening. However, it lacks spatial localization capabilities. The RCNN model on MRI excelled in both classification and lesion localization, making it highly valuable for diagnostic confirmation and surgical planning. The CNN-LSTM model on thermal imaging outperformed the other two in terms of accuracy, precision, and recall, highlighting the power of spatiotemporal modeling and the potential of non-invasive, cost-effective thermal imaging for early-stage detection, especially in resource-constrained environments.A key contribution of this work is its modality-specific analysis within a standardized deep learning pipeline, supported by visual explainability tools like Grad-CAM, which enhance clinical interpretability. The study reinforces that AI-based approaches can significantly augment traditional diagnostic workflows, but their real-world success depends on appropriate modality selection, model transparency, and clinical integration.

6.2 Future Work

While the study provides valuable insights, several opportunities remain for further research and practical enhancement:

- **MultimodalLearning:**
  Future models could benefit from fusing features from multiple imaging modalities (e.g., combining mammogram and thermal or MRI and thermal data). This multimodal approach could improve robustness and diagnostic accuracy, leveraging complementary information from both anatomical and physiological imaging.
- **Larger, Diverse Datasets:**Model generalization could be significantly improved with access to larger and more diverse datasets that include variations in demographics, imaging devices, and clinical conditions. Collaborations with hospitals and screening programs would be instrumental in gathering such data.
- **Explainable AI (XAI) Integration:**Although Grad-CAM was used for visual explanation, further work can be done to integrate advanced interpretability techniques such as SHAP, LIME, or attention-based interpretability mechanisms. This can increase clinician trust and aid regulatory approval.

- **Real-time and Edge Deployment:**Optimizing models for inference on mobile devices or edge hardware (e.g., NVIDIA Jetson, smartphones) will allow real-time diagnostics, especially important in rural screening camps and mobile health units.
- **Clinical Trials and Validation:**Before clinical deployment, these models must undergo rigorous prospective validation through multi-center clinical trials. These studies will evaluate clinical utility, patient safety, and regulatory compliance.
- **Federated and Privacy-Preserving Learning:**With growing concerns about data privacy, future systems can adopt federated learning techniques that allow AI models to be trained across institutions without transferring sensitive patient data.
- **User-friendly Software Tools:**Developing GUI-based tools or integrating these models into existing PACS systems could accelerate their adoption by radiologists and clinicians, making AI a collaborative partner rather than a black-box decision maker.

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