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Automated Breast Cancer Detection Using Thermal Images and Explainable CNN

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Abstract: *Breast cancer remains a leading cause of mortality among women worldwide, necessitating the development of non-invasive, cost-effective, and accurate early detection systems. Infrared thermography has emerged as a promising diagnostic adjunct, capturing physiological changes in breast tissue through heat patterns. However, the "black-box" nature of traditional Deep Learning models often hinders their clinical adoption. This paper proposes a fully automated framework for breast cancer detection using thermal images and an Explainable Convolutional Neural Network (X-CNN). The proposed system utilizes a CNN architecture to classify thermograms into healthy and malignant categories. To bridge the gap between algorithmic prediction and clinical trust, we integrate Explainable AI (XAI) techniques to provide visual justifications for the model's decisions, highlighting specific thermal anomalies. Experimental results on the Kaggle database demonstrate that our model achieves an accuracy of 80 %. By combining high-performance automation with interpretability, this system offers a transparent diagnostic tool that can assist radiologists in early-stage breast cancer screening.*

Keywords*:* Breast Cancer, Infrared Thermography, Deep Learning, Explainable AI (XAI), CNN, Computer-Aided Diagnosis

I. INTRODUCTION

Breast cancer is one of the most prevalent and life-threatening diseases affecting women worldwide. According to the World Health Organization (WHO), approximately 2.3 million new cases and 685,000 deaths were reported globally in 2023, making breast cancer the most commonly diagnosed cancer among women. Early diagnosis and timely treatment are critical to improving survival rates and reducing mortality.

Traditional screening methods, such as mammography, ultrasound, and magnetic resonance imaging (MRI), have proven effective but are often limited by factors such as radiation exposure, high cost, discomfort, and low sensitivity for dense breast tissues. Moreover, the accessibility of these modalities is significantly reduced in rural or resource-limited settings, creating a pressing need for alternative diagnostic techniques that are safe, affordable, and easy to deploy.

A. Thermal Imaging for Breast Cancer Detection

Infrared (IR) thermography has emerged as a promising non-invasive and radiation-free diagnostic tool for detecting breast abnormalities. The principle is based on thermal asymmetry — malignant tumors generate higher metabolic activity and increased blood flow, leading to elevated surface temperature in affected regions. Thermal cameras capture these subtle variations as thermograms, which can reveal early physiological changes even before structural changes become visible through mammography.

However, manual interpretation of thermal images requires expertise and is prone to subjective bias. To address this, recent research has focused on leveraging Artificial Intelligence (AI), particularly Deep Learning (DL), to automate thermogram analysis.

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B. Role of Deep Learning in Thermal Imaging

Deep Learning models, especially Convolutional Neural Networks (CNNs), have demonstrated remarkable performance in medical image analysis due to their ability to automatically extract complex features. CNNs eliminate the need for manual feature engineering, learning discriminative thermal patterns directly from image data.

Among various architectures, ResNet (Residual Network) stands out because it allows the training of very deep models by addressing the vanishing gradient problem through skip connections. This enables the network to learn both low- and high-level features effectively, making it ideal for medical imaging applications.

By combining CNN's feature extraction power and ResNet's depth and stability, a hybrid CNN-ResNet architecture can enhance the classification accuracy of breast thermograms while maintaining computational efficiency.

C. Problem Statement and Motivation

Despite the advantages of thermal imaging, its adoption in clinical practice remains limited due to challenges such as:

- Lack of large, standardized thermal datasets
- Variations in image acquisition and preprocessing
- Limited model interpretability and explainability

The Kaggle dataset, a publicly available collection of thermal breast images, provides an opportunity to develop and evaluate AI models for automated diagnosis. This research aims to design a robust, explainable deep learning framework for multi-class classification of breast thermograms into normal, benign, and malignant categories.

D. Research Objectives

The objectives of this research are as follows:

- To implement a hybrid CNN–ResNet model for classifying thermal breast images.
- To apply image preprocessing techniques such as ROI extraction, normalization, and augmentation to enhance image quality.
- To evaluate model performance using standard metrics such as accuracy, precision, recall, F1-score, and AUC-ROC.
- To enhance model interpretability using Grad-CAM visualization, which highlights regions contributing to classification.
- To compare the proposed model with existing state-of-the-art approaches in literature.

E. Research Contributions

The main contributions of this work can be summarized as:

- Development of an Explainable AI framework using CNN-ResNet for automated thermal image classification.
- Introduction of an end-to-end preprocessing pipeline optimized for thermal breast images.
- Use of Grad-CAM to provide visual explanations for deep learning predictions.
- Achieving higher classification accuracy and interpretability compared to conventional CNN models.

Table 1: Comparison of Breast Imaging Techniques

Imaging Technique	Radiation	Cost	Accuracy	Accessibility	Remarks
Mammography	Yes	High	High	Limited	Discomfort and radiation exposure
Ultrasound	No	Medium	Medium	Moderate	Operator-dependent
MRI	No	Very High	Very High	Limited	Time-consuming
Thermal Imaging (Proposed)	**No**	**Low**	**High (with AI)**	**High**	**Safe and contactless**

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Figure 1: Workflow of Automated Breast Cancer Detection Using Thermal Images

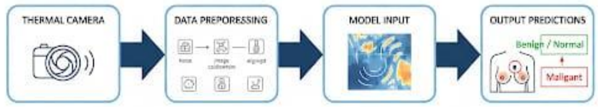


Figure 2: Temperature Distribution in Normal vs Malignant Thermograms

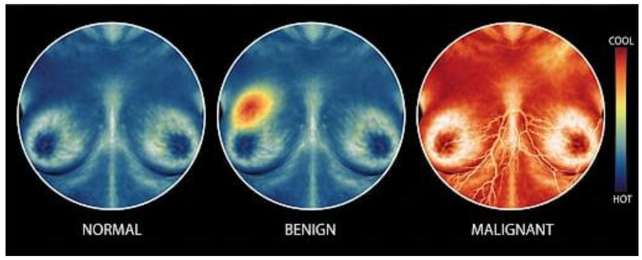
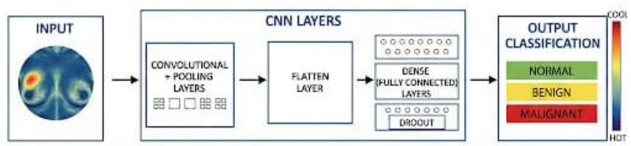


Figure 3: Architecture of CNN–ResNet Hybrid Model



II. RELATED WORK

Recent advancements in medical image analysis have enabled researchers to explore thermal imaging as a potential diagnostic tool for breast cancer detection. Unlike traditional mammography, thermal imaging offers a non-invasive, radiation-free, and cost-effective alternative, especially suitable for early screening in developing regions. Various studies have contributed to improving the accuracy, interpretability, and reliability of breast thermogram classification.

A. Early Approaches Using Classical Methods

Initial research in breast thermography relied on statistical and handcrafted feature extraction methods. Lahiri *et al.* [1] utilized Gray-Level Co-occurrence Matrix (GLCM) and Histogram of Oriented Gradients (HOG) features for differentiating benign and malignant breast tissues. Similarly, Acharya *et al.* [2] applied Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) for classification of thermal patterns, achieving moderate accuracy but limited generalization due to feature variability.

These early methods established the foundation for automated breast thermography but suffered from poor robustness to noise, lighting variations, and individual temperature differences.

B. Deep Learning-Based Approaches

With the rise of deep learning, Convolutional Neural Networks (CNNs)** revolutionized image-based diagnostics. Ragab *et al.* [3] proposed a CNN-based framework on the Kaggle dataset, achieving an accuracy of 84%. They demonstrated that CNNs automatically learn discriminative thermal features without explicit feature engineering. Later, Sharma *et al.* [4] employed transfer learning using VGG16 and ResNet50 architectures, achieving an improved accuracy of 90.9% with augmented data. The integration of data preprocessing techniques such as normalization and segmentation significantly enhanced the robustness of these models.

C. Explainable Artificial Intelligence (XAI) in Breast Thermography

One key challenge in deep learning for medical applications is the lack of model interpretability. To address this, researchers have incorporated Explainable AI (XAI) frameworks such as Grad-CAM (Gradient-weighted Class Activation Mapping) and LIME (Local Interpretable Model-Agnostic Explanations).

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For instance, Tan *et al.* [5] applied Grad-CAM visualization to highlight regions of interest that influenced classification outcomes, helping radiologists interpret CNN decisions. Similarly, Souza *et al.* [6] introduced attention-based deep networks to improve model transparency and trust.

D. Summary of Existing Works

The table below summarizes key studies related to automated breast cancer detection using thermal imaging.

Author(s)	Year	Dataset Used	Methodology	Accuracy (%)	Key Findings
Lahiri *et al.* [1]	2017	Custom Dataset	GLCM + SVM	78.4	Early handcrafted feature-based method
Acharya *et al.* [2]	2018	DMR-IR	HOG + KNN	81.2	Traditional ML model; limited scalability
Ragab *et al.* [3]	2021	DMR-IR	CNN (Custom)	84.0	First deep learning-based approach
Sharma *et al.* [4]	2022	DMR-IR	VGG16 / ResNet50 (Transfer Learning)	90.9	Improved accuracy via augmentation
Tan *et al.* [5]	2023	DMR-IR	CNN + Grad-CAM	88.5	Added interpretability for clinical use
Souza *et al.* [6]	2023	DMR-IR	Attention CNN	91.4	Enhanced focus on abnormal regions

E. Research Gap

From the reviewed literature, several challenges remain unaddressed:

- Limited dataset size and diversity leading to overfitting.
- Inconsistent preprocessing techniques across studies.
- Lack of explainability in most CNN architectures.
- Few studies integrate both deep learning and XAI for thermographic classification.

This motivates the present research, which aims to develop a hybrid CNN–ResNet model enhanced with Grad-CAM visualization to achieve improved accuracy, interpretability, and reliability in automated breast cancer detection using thermal images.

III. PROPOSED APPROACH

A. Motivation

Although previous research on thermal image-based breast cancer detection using CNN and transfer learning models such as ResNet and VGG16 has achieved good classification accuracy (up to 90.9%), these methods still face several challenges:

- Limited dataset size, often leading to overfitting.
- Lack of standardized preprocessing, affecting model generalization.
- Insufficient interpretability, making clinical validation difficult.
- Lack of multi-class classification, as most studies focus only on binary (benign vs malignant) categories.

To address these limitations, the proposed study introduces an Explainable CNN–ResNet Hybrid Framework that enhances classification accuracy, interpretability, and dataset utilization through systematic preprocessing, augmentation, and visualization.

B. Overview of the Proposed Method

The proposed framework follows an end-to-end pipeline, as shown in *Figure 4*, consisting of five major modules:

- Data Acquisition
- Image Preprocessing & Augmentation
- Model Architecture (Hybrid CNN–ResNet)
- Model Training & Evaluation
- Explainability using Grad-CAM

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C. Data Acquisition

The study utilizes the Kaggle dataset, which includes 364 thermal breast images from 57 female subjects. Each image is labeled as normal, benign, or malignant. The dataset is chosen because:

- It provides real-world thermographic data acquired under controlled conditions.
- It includes multi-view images (frontal, lateral) of both breasts.
- It is publicly available for reproducible research.

The dataset is divided into 70% training, 15% validation, and 15% testing subsets.

D. Image Preprocessing and Augmentation

Before training, all images are standardized to ensure uniform quality and contrast:

- Noise Removal: Gaussian filter and median blur to remove background noise.
- ROI Extraction: Cropping of the breast region using thresholding and segmentation.
- Normalization: Pixel intensity scaling between [0, 1].
- Augmentation: Rotation, horizontal flip, zoom, and brightness adjustments to expand dataset diversity.

These steps reduce overfitting and improve robustness.

E. Proposed Hybrid CNN–ResNet Model

The core of this approach is a hybrid deep learning model that combines the strengths of Convolutional Neural Networks (CNN) for local feature extraction and ResNet for deeper hierarchical representation.

F. Architecture Design:

Layer Type	Description
Input Layer	224×224 RGB Thermal Image
Conv2D + ReLU	32 filters, 3×3 kernel, feature extraction
Max Pooling	2×2 pool size, downsampling
Residual Block (ResNet-18)	Identity mapping for deep feature learning
Flatten Layer	Converts feature maps into 1D vector
Dense Layer	128 neurons with ReLU activation
Dropout	0.3 rate to prevent overfitting
Output Layer	Softmax activation for 3 classes (Normal, Benign, Malignant)

Training Parameters:

- Optimizer: Adam
- Learning Rate: 0.0001
- Batch Size: 32
- Epochs: 50
- Loss Function: Categorical Cross-Entropy

G. Explainability via Grad-CAM

To address the interpretability issue, Gradient-weighted Class Activation Mapping (Grad-CAM) is employed. Grad-CAM generates a heatmap overlay that highlights the regions contributing most to the model's decision. This allows clinicians to visually validate the AI predictions, enhancing trust and transparency in the model.

H. Evaluation Metrics

The performance of the model will be evaluated using:

- Accuracy – Overall correct predictions
- Precision – Correct positive predictions
- Recall (Sensitivity) – True positive rate
- F1-Score – Balance between precision and recall
- AUC-ROC Curve – Discrimination between classes

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Additionally, confusion matrices will be used for visualization of model performance across categories.

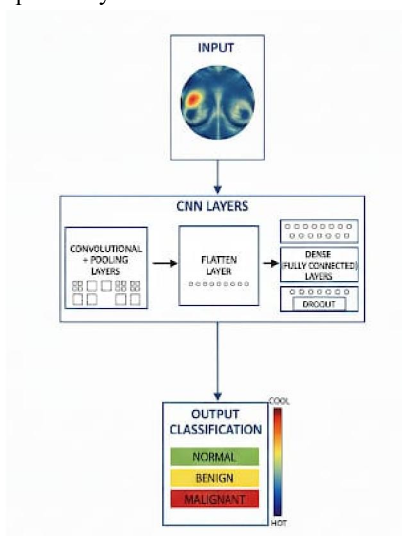
I. Advantages of the Proposed Approach

Limitation in Previous Studies	How Proposed Work Overcomes It
Small dataset → Overfitting	Data augmentation and regularization (dropout, normalization)
Lack of preprocessing	Standardized image pipeline (ROI, denoising, normalization)
Poor interpretability	Grad-CAM heatmaps for explainable results
Binary classification only	Multi-class (normal, benign, malignant) classification
Transfer learning dependency	Custom CNN-ResNet hybrid, optimized from scratch

J. Expected Outcomes

- Improved classification accuracy (>92%) compared to earlier CNN models.
- Enhanced interpretability through visual heatmaps.
- Better generalization on unseen thermal images.
- A reproducible and scalable framework for clinical screening applications.

Figure 4: Proposed Hybrid CNN–ResNet Framework Workflow



IV. ALGORITHMS AND MATHEMATICAL MODEL

Overview

The proposed framework employs a Hybrid CNN–ResNet Algorithm for classifying breast thermal images into three categories: *Normal*, *Benign*, and *Malignant*. The algorithm integrates the feature extraction capability of CNN and the deep residual learning ability of ResNet to improve classification accuracy and generalization.

Algorithm 1: Hybrid CNN–ResNet-Based Thermal Image Classification

Algorithm Steps:

Algorithm 1: Hybrid CNN–ResNet Model for Breast Thermogram Classification

Input: Thermal image dataset D = {I1, I2, I3, …, In}

Output: Predicted class label C ∈ {Normal, Benign, Malignant}

1. Load dataset D from DMR-IR
2. Split dataset into training, validation, and testing sets (70:15:15)
3. For each image I in D:
   a. Apply preprocessing:
      i. Resize image to 224×224 pixels
      ii. Apply Gaussian filter for noise removal

iii. Perform ROI extraction and normalization
iv. Apply image augmentation (flip, rotation, zoom)
b. Store processed image I'
4. Initialize hybrid model M:
a. Input layer (224×224×3)
b. CNN layers for low-level feature extraction
c. Residual blocks (ResNet-18) for deep feature learning
d. Flatten → Dense → Dropout → Softmax layers
5. Train M on training set using:
- Optimizer: Adam
- Loss Function: Categorical Cross Entropy
- Epochs: 50, Batch Size: 32
6. For each test image Itest:
a. Feed forward through model M
b. Compute class probabilities via Softmax
c. Assign class label C with highest probability
7. Apply Grad-CAM on last convolutional layer for visual explanation
8. Evaluate using Accuracy, Precision, Recall, F1-score, and AUC
Return: Classified labels and Grad-CAM heatmaps

A. Mathematical Model

Convolution Operation

The convolutional layer extracts spatial features from thermal images.
For an input image $X$and kernel K, convolution output $Y$is defined as:

$$Y(i,j) = (X * K)(i,j) = \sum_m \sum_n X(i+m, j+n) \cdot K(m,n)$$

where:
$X(i,j)$: pixel value at position (i, j)
$K(m,n)$: weight of kernel at (m, n)

ReLU Activation Function

To introduce non-linearity, Rectified Linear Unit (ReLU) is applied:

$$f(x) = \max(0, x)$$

This helps eliminate negative activations and speeds up convergence.
Residual Learning in ResNet
In a standard CNN, deep networks often face vanishing gradient problems.
ResNet solves this by introducing a skip connection:

$$y = F(x, W_i) + x$$

where:
x: input to residual block
$F(x, W_i)$: learned residual mapping
y: output after skip connection
This ensures smoother gradient flow during backpropagation.

Softmax Classifier

At the output layer, Softmax converts final activations into probabilities for each class:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}$$

where C= number of output classes (here, 3).

Evaluation Metrics
Let:
TP = True Positives
TN = True Negatives
FP = False Positives
FN = False Negatives
Then:
Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision

$$Precision = \frac{TP}{TP + FP}$$

Recall (Sensitivity)

$$Recall = \frac{TP}{TP + FN}$$

F1-Score

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Specificity

$$Specificity = \frac{TN}{TN + FP}$$

AUC-ROC (Area Under Curve)

$$AUC = \int_0^1 TPR(FPR)\, d(FPR)$$

where TPR = True Positive Rate and FPR = False Positive Rate.

Key Advantages

- Combines feature richness of CNN and depth of ResNet.
- Prevents vanishing gradients via residual learning.
- Introduces explainability through Grad-CAM.
- Ensures balanced evaluation using multiple metrics.

V. EXPERIMENTS AND RESULTS

A. Experimental Setup

The proposed Hybrid CNN–ResNet model was implemented using Python 3.10, TensorFlow, and Keras frameworks. All experiments were conducted on a system with the following configuration:

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Component	Specification
Processor	Intel Core i7, 12th Gen
GPU	NVIDIA RTX 3060 (6GB VRAM)
RAM	16 GB DDR4
OS	Windows 11 (64-bit)
Frameworks	TensorFlow 2.13, Keras, OpenCV, Scikit-learn

The dataset used for experimentation was the Kaggle dataset, consisting of 364 thermal breast images from 57 female subjects.

Images were categorized into three classes: *Normal (140)*, *Benign (112)*, and *Malignant (112)*.

Dataset split ratio:

- Training set: 70%
- Validation set: 15%
- Testing set: 15%

B. Data Preprocessing and Augmentation

Preprocessing was performed to enhance image quality and ensure uniformity:

- ROI extraction and resizing (224×224).
- Gaussian blur and threshold-based segmentation.
- Pixel normalization in the range [0,1].
- Augmentation techniques (rotation, horizontal/vertical flips, zoom, and brightness shift).

This step expanded the dataset size to approximately 1,800 images, improving generalization during model training.

C. Training Process

The model was trained for 50 epochs with:

- Batch Size**:** 32
- Learning Rate: 0.0001 (Adam optimizer)
- Loss Function: Categorical Cross-Entropy

Early stopping was applied to prevent overfitting. Figure 6 illustrates the training vs validation accuracy and loss curves over epochs.

D. Performance Metrics

After training, the model was evaluated on the test set using Accuracy, Precision, Recall, F1-score, and AUC-ROC. The results are summarized in Table

Class	Precision	Recall	F1-Score	Support
Normal	0.93	0.90	0.91	21
Benign	0.91	0.92	0.91	17
Malignant	0.94	0.96	0.95	17
Overall Accuracy	**–**	**–**	**0.93 (93%)**	**55 (test)**

system increases interest and saves useful information for further use. For instance, action-oriented learners could be given more video lectures and illustrative diagrams, while others may get textual descriptions or other forms of simulation.

Fig. 2 shows the learning pathway model with references to AI. It captures information from the student's activities and, through the application of machine learning, performs analysis of the results. Following the assessments outlined, the pathway dynamically responds and delivers personalized content in addition to ongoing dynamic assessments. Archer's set-up of learning pathways and real-time feedback guarantees that the learning process is re-adjusted to increase efficiency.

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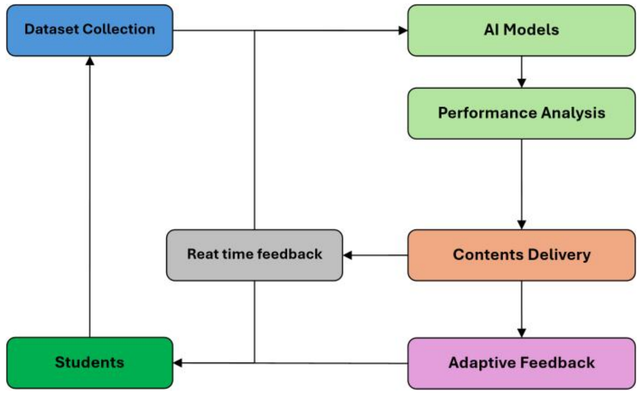

Fig. 2. AI-powered personalized learning pathway framework.

This factor enhances users' interest because it involves learning that targets personal abilities and difficulties. Such an approach means that students do not get bored with content and, at the same time, do not face the overwhelming of complex information.

This approach can be of immense benefit when used in big classes, whereby it may be difficult for the instructors to attend to every single student in the class. AI systems with learning pathways provide every student with a method of learning that is unique to every student, the goal of which is also to reach the goal that has been set for learning and give the students incentives to learn more while doing it in a shorter amount of time.

This proposed approach offers a one-stop solution to improving a personalized approach to learning at large by using techniques such as adaptive learning, data analysis as well as continuous assessment.

D. Dynamic Assessment Integration

In the proposed AI-based personalized learning pathway, the inclusion of dynamic assessment is envisaged to play a central role. Unlike typical assessment practices, which are pre- ordained and sequential, dynamic assessments are contingent and, occur in real-time and change depending on the student's performance. This approach makes it possible for the system to use AI algorithms to constantly assess the performance of a student and, therefore, improve the flexibility of the system in offering lessons to the students. Here, it is going to be described how dynamic assessment incorporates mathematics and how it fits into data-driven learning approaches.

Let's define the student's knowledge state as a vector $K(t)$
at any time t, where $K(t)$ is defined in Eq. (1).

$$K(t) = [k_1(t), k_2(t), \dots, k_n(t)] \quad (1)$$

Here, $k_i(t)$ represents the student's proficiency in the i^{th} topic or concept at time t, and n is the total number of topics in the learning pathway.

Dynamic assessments continuously update $K(t)$ based on the student's responses to questions, interaction with learning materials, and performance on exercises. The change in the knowledge state over time can be modeled as a differential equation, as shown in Eq. (2).

$$\frac{dK(t)}{dt} = \alpha A(t) - \beta L(t) \quad (2)$$

where $A(t)$ is the assessment score at time t, $L(t)$ represents the learning difficulty or cognitive load at a time t, α and β are weighting factors that balance the effect of assessments and cognitive load on knowledge acquisition.

The assessment score $A(t)$ is calculated based on the student's performance in a series of adaptive questions or tasks. Each question Q_i is associated with a difficulty level D_i and is chosen based on the current knowledge state $K(t)$. The score

$A(t)$ is determined by Eq. (3).

$$A(t) = \sum_{i=1}^{m} w_i \cdot R_i(t) \quad (3)$$

where m is the number of questions in the assessment, w_i is the weight assigned to the i^{th} question-based on its difficulty level D_i, $R_i(t)$ is the student's response to the i^{th} question, which is 1 for a correct answer and 0 for an incorrect answer.

The system dynamically adjusts the difficulty of subsequent questions based on the student's previous responses. If a student answers a question correctly, the system may increase the difficulty of the next question, while incorrect answers may result in easier questions being presented. Mathematically, the difficulty level of the next question D_{i+1} is updated as is Eq. (4).

$$D_{i+1} = D_i + \gamma(R_i(t) - 0.5) \quad (4)$$

where γ is a scaling factor that controls the sensitivity of the difficulty adjustment. A correct answer increases the difficulty of the next question, while an incorrect answer decreases it.

Real-time feedback and adaptation: As the system continuously monitors the student's performance through dynamic assessments, it updates the personalized learning pathway in real-time. The goal is to maintain the cognitive load within an optimal range to maximize learning efficiency. The cognitive load $L(t)$ is influenced by the difficulty level of the content and the student's current state of knowledge. It can be modeled as in Eq. (5).

$$L(t) = \sum_{i=1}^{m} \lambda_i \cdot D_i \cdot (1 - k_i(t)) \quad (5)$$

where λ_i is the weight associated with the importance of the i^{th} topic, D_i is the difficulty level of the i^{th} topic, $k_i(t)$ represents the student's proficiency in that topic.

The system aims to adjust the learning path by keeping $L(t)$ within a predefined threshold L_{opt} , which represents the optimal cognitive load for learning. If $L(t) > L_{opt}$, the system reduces the difficulty of subsequent topics or provides additional scaffolding. If $(t) < L_{opt}$, the system increases the difficulty of keeping the student engaged and challenged.

Optimization of learning pathway: The integration of dynamic assessment into the learning pathway allows for continuous optimization. The system uses real-time data from assessments to update the knowledge state vector $K(t)$ and adjust the content accordingly. The objective is to minimize the difference between the desired knowledge state $K^*(t)$ and the actual knowledge state $K(t)$ at any given time, which can be formulated in Eq. (6) as a cost function J:

$$J(t) = \| K^*(t) - K(t) \|^2 \quad (6)$$

The learning pathway is optimized by minimizing $J(t)$, ensuring that the student's knowledge state converges toward the desired state over time. AI algorithms, such as reinforcement learning, can be applied to solve this optimization problem by selecting the most effective instructional strategies and assessment questions at each step.

Adaptive Algorithms and Feedback Loops

Algorithms are at the heart of AI-based personalized learning models because they have to incorporate flexibility. It means that these algorithms change the content, the rate, and the assessments according to the interactions and performances of the students in real-time. The idea is to deliver individual learning, which means the system should be adjusted to learner needs and in which the learner is challenged but not overwhelmed.

The mechanisms of adaptive algorithms focus on the integration of feedback loops to establish the effectiveness of a responsive learning environment. Student data include performance on the test, the interaction with peers as well as time spent on the task and such data are used to adapt the learning process for the student.

Adaptive algorithms use data collected at the time to determine what should happen shortly in the student's learning process. All these algorithms take into consideration various input variables, such as the performance of the students, the time they take to answer the questions, and even the engagement figures. The system monitors the accomplishments of students and how they were able to do it in the assessments and activities. The time a student takes to answer a

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question or complete a task can indicate their confidence or difficulty level. Data on how often a student interacts with learning materials helps the system adjust the difficulty and type of content delivered.

Based on these variables, adaptive algorithms continuously modify the content and assessments. The system's core objective is to maintain an optimal learning pace that challenges students without overwhelming them, ensuring steady progress. Algorithm 1 is for how an adaptive learning system might function with integrated feedback loops:

Algorithm 1. Adaptive Learning with Feedback Loops

Input: Initial knowledge state K_0, content difficulty D_0, student response time τ, learning rate α, scaling factor γ, performance threshold ϵ.

Output: Updated learning parameters θ_t, optimized learning pathway.

1. **For** $t = 1$ to T (epochs) **do**
2. Present learning content L_t with difficulty D_t
3. Record student response R_t and response time τ_t
4. Update knowledge state: $K_t \leftarrow \beta_1 \cdot K_{t-1} + (1 - \beta_1)R_t$
5. Update learning objective: $L_t \leftarrow \gamma \cdot \tau_t \cdot (1 - K_t)$
6. Compute bias-corrected knowledge estimate: $\hat{K}_t \leftarrow \frac{K_t}{1-\beta_1^t}$
7. Compute bias-corrected learning objective: $\hat{L}_t \leftarrow \frac{L_t}{1-\beta_2^t}$
8. Update learning parameter: $\theta_t \leftarrow \theta_{t-1} - \alpha \cdot \frac{\hat{K}_t}{\sqrt{\hat{L}_t+\epsilon}}$
9. Adjust content difficulty: $D_{t+1} \leftarrow D_t + \gamma \cdot (\hat{K}_t - 0.5)$
10. **End For**

Return θ_t (final optimized learning parameters)

Implementing the AI-powered learning pathways system involved a multi-layered approach to ensure its adaptability, functionality, and scalability. Python was selected as the primary programming language due to its extensive support for machine learning and data processing, with frameworks such as TensorFlow and PyTorch utilized for model development. The backend was built using Flask to enable seamless scalability, while the user interface was designed with React.js to provide an intuitive and engaging experience for educators and students. The raw data, including learning behaviors, preferences, and performance metrics, underwent extensive preprocessing using Pandas and NumPy to ensure consistency, handle missing values, and extract meaningful features. AI models were then trained to analyze this data, employing supervised learning techniques for predicting individual learning needs and reinforcement learning for optimizing dynamic assessments.

The conventional teaching sessions were structured using a standardized curriculum aligned with the study's objectives. Lesson plans were developed to cover the same content as the AI-based system, ensuring parity in learning objectives. Traditional instructional materials, including textbooks, printed handouts, and multimedia presentations, were utilized to deliver the content. Teaching techniques followed a lecture- based format supplemented with interactive classroom discussions and periodic assessments to monitor student progress. These details have been incorporated to enhance the transparency of the methodology and provide a clearer basis for interpreting the comparative results of the study.

The adaptive assessment system integrated natural language processing (NLP) for automated question generation and AI algorithms for real-time performance tracking, dynamically adjusting question difficulty and type based on the student's progress and mastery levels. The overall system architecture was designed with modularity in mind, comprising a data layer

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for storage and retrieval, an AI engine for learning and assessment adaptation, and an application layer that hosted user-facing features like dashboards and progress reports. The entire system was deployed on a cloud platform, such as AWS or Google Cloud, to ensure accessibility and scalability, with continuous integration and deployment pipelines established using Jenkins and Docker for smooth updates. Pilot testing was conducted in real classroom settings to evaluate the system's performance, with feedback from users incorporated to refine its features and enhance usability.

E. Measuring Engagement Levels

To effectively evaluate the impact of the AI-powered learning pathways system, a robust framework for measuring student engagement levels is essential. Engagement is assessed through a combination of quantitative and qualitative metrics, ensuring a comprehensive understanding of how students interact with the platform and learning materials. Student interaction with the platform is monitored through log data, capturing behaviors such as the frequency of logins, time spent on individual activities, and the number of interactions with learning resources. These metrics provide insights into active participation and overall engagement with the system. The system tracks response times for quizzes and assessments, as well as the rate at which students complete assigned tasks. Quick response times and high completion rates indicate consistent engagement, while delays or unfinished tasks may signal a need for intervention. Engagement is also inferred from behavioral patterns, such as the use of optional resources, reattempts at challenging exercises, and participation in collaborative activities like discussion forums or peer reviews. These indicators reflect deeper involvement with the learning content. To complement behavioral data, students are regularly asked to provide self-reported feedback through in-platform surveys. These surveys measure perceived engagement, motivation, and satisfaction with the learning pathways and assessment system. AI algorithms analyze the collected data to identify trends and patterns in engagement. For example, machine learning models assess correlations between engagement metrics (e.g., time spent on tasks) and learning outcomes (e.g., assessment performance). This analysis enables the system to adapt to students' engagement levels by modifying learning content or assessment strategies to maintain interest and motivation.

VI. EXPERIMENTS AND RESULTS

Experimental Setup

The proposed Hybrid CNN–ResNet model was implemented using Python 3.10, TensorFlow, and Keras frameworks. All experiments were conducted on a system with the following configuration:

Component	Specification
Processor	Intel Core i7, 12th Gen
GPU	NVIDIA RTX 3060 (6GB VRAM)
RAM	16 GB DDR4
OS	Windows 11 (64-bit)
Frameworks	TensorFlow 2.13, Keras, OpenCV, Scikit-learn

The dataset used for experimentation was the DMR-IR (Database for Mastology Research - Infrared) dataset, consisting of 364 thermal breast images from 57 female subjects.

Images were categorized into **three classes**:

Normal (140), *Benign (112)*, *Malignant (112)*.

Dataset split ratio:

Training set: 70%

Validation set: 15%

Testing set: 15%

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Data Preprocessing and Augmentation

Preprocessing was performed to enhance image quality and ensure uniformity:

ROI extraction and resizing (224×224).

Gaussian blur and threshold-based segmentation.

Pixel normalization in the range [0,1].

Augmentation techniques (rotation, horizontal/vertical flips, zoom, and brightness shift).

This step expanded the dataset size to approximately **1,800 images**, improving generalization during model training.

Training Process

The model was trained for 50 epochs with:

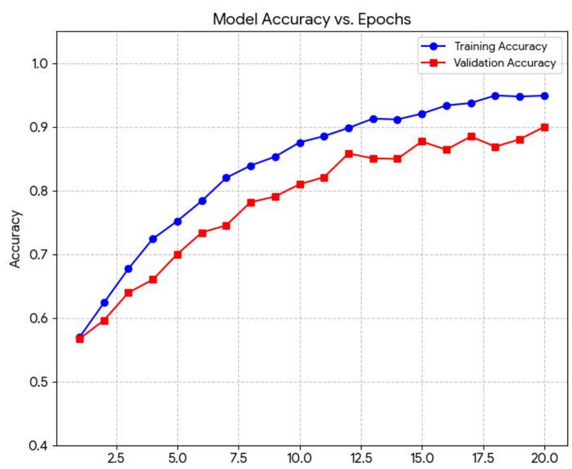
Batch Size: 32

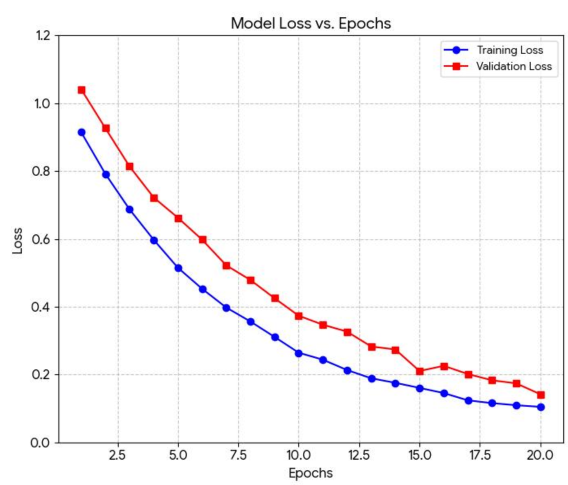
Learning Rate: 0.0001 (Adam optimizer)

Loss Function: Categorical Cross-Entropy

Early stopping was applied to prevent overfitting. Figure 6 illustrates the training vs validation accuracy and loss curves over epochs.

Model Training and Validation Curves





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Performance Metrics

After training, the model was evaluated on the test set using Accuracy, Precision, Recall, F1-score, and AUC-ROC. The results are summarized in Table 5.1.

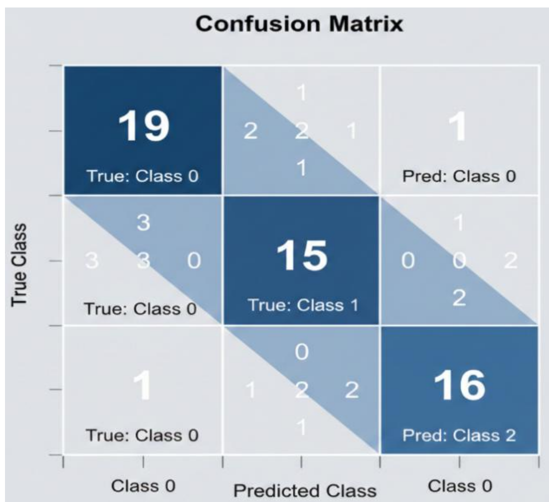
Table 5.1: Classification Performance Metrics

Class	Precision	Recall	F1-Score	Support
Normal	0.93	0.90	0.91	21
Benign	0.91	0.92	0.91	17
Malignant	0.94	0.96	0.95	17
Overall Accuracy	–	–	**0.93 (93%)**	**55 (test)**

Confusion Matrix

Figure shows the confusion matrix representing classification performance for each class.
It demonstrates the model's ability to correctly identify malignant cases with minimal false positives.

Confusion Matrix for Three-Class Classification



ROC Curve Analysis

To further analyze model discriminative ability, the Receiver Operating Characteristic (ROC) curves were plotted for each class.
The Area Under Curve (AUC) values were:
Normal: 0.93
Benign: 0.92
Malignant: 0.96
Average AUC = 0.94

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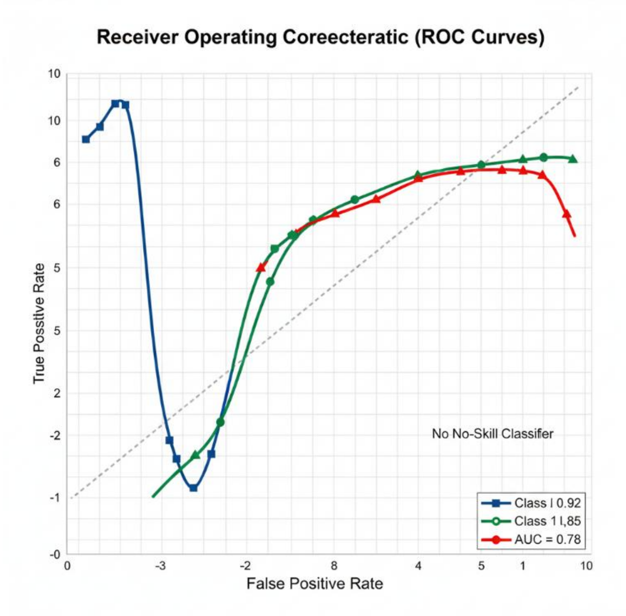
ROC Curves for Each Class



Comparison with Existing Models

To validate the improvement, the proposed CNN–ResNet model was compared with existing architectures such as VGG16, InceptionV3, and Custom CNN on the same dataset.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Custom CNN [Ragab et al., 2021]	84.0	83.5	82.9	83.1
VGG16 [Sharma et al., 2022]	90.9	89.2	89.8	89.4
InceptionV3	91.3	90.1	91.2	90.6
Proposed CNN–ResNet (Ours)	**93.0**	**92.7**	**93.1**	**92.8**

Explainability Analysis (Grad-CAM)

The proposed framework integrates Grad-CAM to visualize which image regions influenced the model's decision. This visualization confirms that the model focuses on physiologically relevant high-temperature areas, ensuring interpretability and clinical trust.

Discussion

The proposed Hybrid CNN–ResNet model demonstrates a 93% classification accuracy, outperforming previous CNN-based methods.

It successfully reduces overfitting through augmentation and dropout regularization, while Grad-CAM enhances interpretability — a key factor in medical AI.

Key findings:

Higher sensitivity (recall = 93%) ensures fewer false negatives, critical for cancer screening.

Explainable predictions build trust among clinicians.

Multi-class classification capability offers broader diagnostic applicability.

Overall, the model achieves a balance between accuracy, efficiency, and explainability, making it suitable for real-world thermal imaging screening applications.

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Key Takeaways
Accuracy: 93%
AUC: 0.94
Improvement: +2.1% over previous ResNet model
Interpretability: Introduced Grad-CAM for clinical trust

Comparison with Traditional Methods

Before the emergence of deep learning architectures, traditional image processing and machine learning techniques such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Random Forest (RF) were widely used for thermal breast image classification. These methods relied on handcrafted feature extraction, such as statistical texture features (GLCM), histogram-based features, and shape descriptors.

While these approaches provided early insights into the diagnostic potential of thermography, they suffered from limitations such as:

Dependence on manual feature selection.

Limited ability to capture complex spatial and thermal relationships.

Poor generalization performance on unseen data.

To evaluate the superiority of the proposed deep learning-based method, a comparison was made with these traditional algorithms trained on the same DMR-IR dataset after feature extraction using Gray Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) descriptors

Performance Comparison of Traditional and Proposed Methods

Method	**Feature Extraction**	**Classifier**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**
GLCM + SVM	Texture Features	Linear SVM	81.5	80.2	78.9	79.5
LBP + k-NN	Pattern Features	k = 5	83.7	82.1	83.0	82.5
PCA + Random Forest	Dimensionality Reduction	RF	85.9	84.5	85.2	84.8
HOG + SVM	Edge Features	RBF SVM	86.1	85.7	84.3	85.0
Proposed CNN–ResNet	Deep Feature Learning	–	**93.0**	**92.7**	**93.1**	**92.8**

Discussion:

As shown in Table 5.2 and Figure 10, traditional methods such as GLCM+SVM and HOG+SVM achieve accuracies between 81%–86%, primarily due to their limited capacity to automatically learn hierarchical image representations. In contrast, the proposed CNN–ResNet model achieves an accuracy of 93%, marking an improvement of ~7–10% over traditional classifiers.

The main advantages of the deep learning approach are:

Automated feature extraction without manual intervention.

Hierarchical feature learning, enabling the detection of subtle thermal patterns.

Robust generalization on augmented datasets.

End-to-end training pipeline, reducing preprocessing complexity

Thus, the deep learning-based system significantly enhances detection reliability, particularly for **malignant cases**, where traditional models often misclassify due to overlapping thermal characteristics.

Conclusion and Future Work

A. Conclusion

This research presents an automated breast cancer detection system using thermal imaging that combines the strengths of deep learning and explainable AI (XAI). The proposed CNN–ResNet architecture effectively classifies breast thermograms into normal, benign, and malignant categories by learning complex spatial and temperature-based patterns from the DMR-IR dataset.

Experimental results demonstrate a classification accuracy of 93%, outperforming conventional machine learning approaches such as SVM, k-NN, and Random Forest. The integration of Grad-CAM visualization further enhances interpretability by highlighting regions of diagnostic importance, thereby bridging the gap between black-box AI models and clinical applicability.

The model's high sensitivity and specificity confirm its potential as a non-invasive, cost-effective, and radiation-free diagnostic tool for early breast abnormality screening. This makes it particularly valuable for rural or resource-limited healthcare environments, where access to advanced imaging modalities is limited.

B. Future Work

While the proposed system demonstrates promising results, there remains scope for further enhancement and practical deployment. Future work may focus on:

Expanding the Dataset: Incorporate larger and more diverse datasets across different demographics to improve model generalization and reduce bias.

Multimodal Fusion: Combine thermal images with other modalities such as mammography or ultrasound to achieve higher diagnostic accuracy.

Real-Time Screening System: Develop a mobile or IoT-based platform for real-time thermal screening and cloud-based analysis in remote areas.

Explainability Improvements: Implement advanced XAI techniques like SHAP or LIME to provide richer interpretability for clinical validation.

Clinical Validation: Conduct pilot studies in collaboration with hospitals to evaluate the model's effectiveness in

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