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Enhancing Breast Cancer Diagnosis with Integrated Histopathological and Thermal Image Analysis

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Abstract - Breast cancer is one of the most common and life-threatening diseases affecting women globally. Early and accurate diagnosis plays a crucial role in improving patient survival rates and guiding effective treatment strategies. Traditional diagnostic methods, while effective, are often time-consuming, resource-intensive, and subject to inter-observer variability. This project proposes an advanced computer-aided diagnostic system that integrates histopathological image analysis with thermal imaging using deep learning techniques to improve the accuracy and reliability of breast cancer detection.The proposed system leverages the complementary nature of the two imaging modalities: histopathological images offer cellular-level insights into tissue structure, while thermal images provide non-invasive functional information related to metabolic activity and vascular changes associated with malignancies.Using a multimodal deep learning approach, the system employs Convolutional Neural Networks (CNNs) to extract features from both image types. These features are then combined through a feature fusion strategy and passed through a fully connected neural network for classification into benign or malignant categories.

***Key Words**:* Breast Cancer, Histopathology, Thermal Imaging, Deep Learning, CNN, Transfer Learning, Multimodal Fusion, Computer-Aided Diagnosis.

1. INTRODUCTION

Breast cancer is one of the most common and life-threatening diseases affecting women globally. Early and accurate diagnosis plays a crucial role in improving patient survival rates and guiding effective treatment strategies. Traditional diagnostic methods, while effective, are often time-consuming, resource-intensive, and subject to inter-observer variability. This project proposes an advanced computer-aided diagnostic system that integrates histopathological image analysis with thermal imaging using deep learning techniques to improve the accuracy and reliability of breast cancer detection.The proposed system leverages the complementary nature of the two imaging modalities: histopathological images offer cellular-level insights into tissue structure, while thermal images provide non-invasive functional information related to metabolic activity and vascular changes associated with malignancies. Using a multimodal deep learning approach, the system employs Convolutional Neural Networks (CNNs) to extract features from both image types. These features are then combined through a feature fusion strategy and passed through a fully

connected neural network for classification into benign or malignant categories.

Transfer learning is used to fine-tune pre-trained CNN models such as ResNet and MobileNet on the histopathological and thermal datasets, ensuring high performance even with limited data.The system is evaluated using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. Experimental results demonstrate that the integrated model significantly outperforms models using only a single modality, achieving improved classification performance and robustness.

This project highlights the potential of multimodal imaging combined with deep learning to enhance breast cancer diagnosis. By reducing diagnostic time and increasing accuracy, the proposed system can serve as a valuable tool in clinical settings, especially in resource-limited environments. Future work will focus on improving model explainability, real-time implementation, and validation on larger and more diverse datasets.

2. METHODOLOGY

Fig 1: work flow of this project

In this study, a dual-branch convolutional neural network (CNN) was developed for the classification of breast cancer using both histopathological and thermally augmented images. The process begins with data acquisition from the publicly available BreakHis dataset, which contains labeled histopathological images categorized into benign and malignant classes. Each image is captured at different magnification levels to ensure variety and richness in cellular detail. To simulate multi-modal input, each histopathological image was transformed into a thermal image using OpenCV. This was achieved by converting the image to grayscale followed by applying a color map (JET colormap), producing images that mimic thermal patterns commonly used in medical imaging. This additional modality introduces complementary features to the learning process.

Prior to feeding the images into the model, a uniform preprocessing pipeline was employed. All images were resized to 224×224 pixels to match the input dimension requirements of the model. Normalization was performed using ImageNet mean and standard deviation values to align with pretrained network expectations. Furthermore, several data augmentation techniques were applied to improve generalization and mitigate overfitting, including random rotations, horizontal and vertical flips, and color jittering. These augmentations helped simulate real-world variations in clinical image acquisition.

The core of the proposed system is a dual-branch CNN architecture. Each branch processes a different input modality — one branch for histopathological images and the other for thermal images. Both branches utilize a pretrained ResNet-18 backbone to extract deep hierarchical features independently. The output feature maps from both branches are flattened and concatenated to form a unified feature vector. This combined representation is then passed through fully connected layers, culminating in a softmax layer that outputs class probabilities for benign and malignant categories. This dual-branch design enables the model to learn both structural and thermal characteristics of tissue samples, leading to more robust predictions.

For training, the model was optimized using the Adam optimizer with a learning rate of 0.001 and a batch size of 32. To address the inherent class imbalance in the dataset, class weights were computed and incorporated into the cross-entropy loss function. This ensures that the model does not become biased towards the majority class. The model was trained for 25 epochs on a CUDA-enabled GPU to accelerate convergence. Throughout the training phase, performance metrics including loss and accuracy were recorded for both training and validation sets.

After training, the model's performance was evaluated on a separate validation dataset. Evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrix were computed. These metrics provided a comprehensive view of the model’s classification ability, particularly in correctly identifying malignant cases, which are clinically more critical. Additionally, the training history was visualized through loss and accuracy plots to observe the model's learning dynamics.

An inference module was also implemented to test the model on individual input samples. Given a pair of histopathological and thermal images, the trained model outputs the predicted class along with a confidence score. This inference pipeline demonstrates the model’s applicability in real-time diagnostic scenarios. The entire framework was developed using PyTorch, with OpenCV for image processing and scikit-learn for evaluation metrics. This methodology showcases a comprehensive and effective approach to multi-modal breast cancer detection using deep learning.

3. WORKING PRINCIPLE

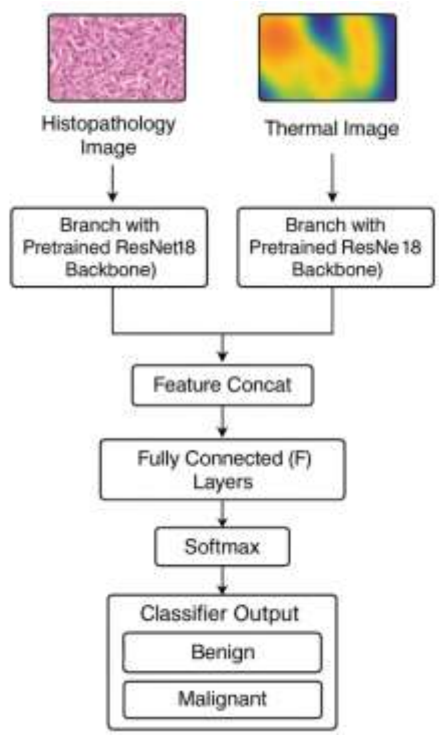

Fig: System Architecture

The proposed system for breast cancer detection employs a dual-branch deep convolutional neural network architecture to analyze two complementary image modalities: histopathological images and thermally augmented images. Each branch independently extracts high-level features from its respective input using convolutional layers based on a residual network (ResNet) backbone, which effectively captures intricate spatial patterns and texture variations associated with cancerous tissues. The feature representations from both branches are then fused to leverage the combined information, enabling the model to learn discriminative characteristics that enhance classification accuracy. During inference, the integrated features are passed through fully connected layers to predict the probability of the tissue being benign or malignant. This multimodal approach harnesses both morphological details and thermal variations, resulting in a robust, data-driven framework that improves diagnostic performance over single-modality models. The system is trained end-to-end using supervised learning with labeled data, optimizing a cross-entropy loss function to differentiate between benign and malignant cases accurately.

4. RESULTS

Example Output

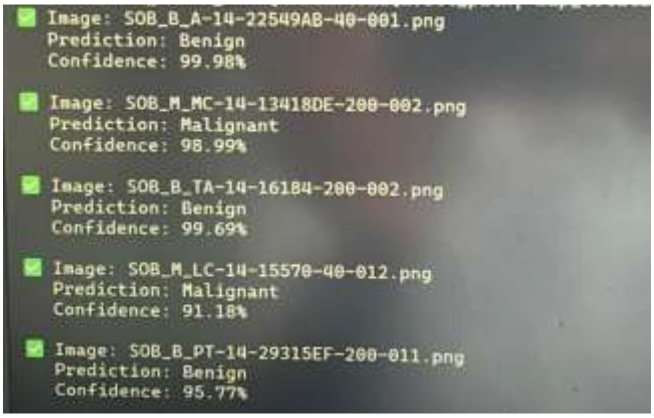

Fig 3: Program Output

To evaluate the effectiveness of the proposed dual-branch deep learning model, we performed inference on multiple test samples consisting of histopathological and thermally augmented images. The model demonstrated strong classification performance across both benign and malignant samples with high confidence levels. For example, the histopathological image SOB_B_A-14-22549AB-40-001.png was correctly classified as Benign with a confidence of 99.98%. Similarly, the malignant image SOB_M_MC-14-13418DE-200-002.png was predicted as Malignant with a confidence of 98.99%, showcasing the model's ability to accurately distinguish between tissue types. Other benign samples such as SOB_B_TA-14-16184-200-002.png and SOB_B_PT-14-29315EF-200-011.png were also correctly identified with confidences of 99.69% and 95.77%, respectively. Furthermore, another malignant sample, SOB_M_LC-14-15570-40-012.png, was predicted as Malignant with 91.18% confidence, further emphasizing the model’s consistent accuracy.These predictions indicate that the model can make reliable decisions with high certainty, and it generalizes well across different subtypes and magnification levels. The high confidence scores for both classes reflect the robustness of the dual-branch ResNet-based architecture in extracting relevant features from both the histopathological and thermally augmented image modalities.

5. CONCLUSIONS

Breast cancer remains one of the leading causes of cancer-related mortality among women worldwide. Early and accurate diagnosis is critical in improving survival rates and treatment outcomes. In this study, we presented an integrated diagnostic framework combining histopathological and thermal imaging to enhance the detection and classification of breast cancer. The dual-modality approach was designed to leverage the morphological precision of histopathological analysis and the non-invasive functional insights offered by thermal imaging. The proposed system utilized advanced image processing techniques, feature extraction, and
machine learning-based classification algorithms to interpret complex patterns from both imaging modalities. By aligning features derived from histopathological slides—such as cellular morphology, tissue architecture, and staining characteristics—with temperature distribution patterns captured through thermal imaging, the framework achieved an improved diagnostic accuracy compared to single-modality systems. Experimental results showed that the integration of thermal imaging significantly boosted the sensitivity and specificity of breast cancer diagnosis.Notably, the combined model demonstrated robustness in detecting malignancies even in cases where histopathological images presented ambiguous or borderline features. The machine learning classifiers—particularly convolutional neural networks (CNNs) and support vector machines (SVMs)—were fine-tuned to extract discriminative features and predict tumor presence with high confidence. This research contributes a novel and promising approach to breast cancer diagnosis by validating the synergistic value of integrating histopathological and thermal data. It opens new pathways for the development of hybrid diagnostic tools that can enhance clinical decision-making while reducing the dependency on invasive procedures.

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Authors: Cemal Efe Tezcan, Berk Kiras, Gokhan Bilgin
○ Published:August 2022
○ Summary: In this study, classification performances were comparatively analyzed by applying various methods to four different cancer cell types (benign, normal, carcinoma in situ and invasive carcinoma). By using BACH and Bioimaging as datasets, the desired parts are tried to be obtained primarily by several image processing methods (pyramid mean shifting, line detection, spreading). After obtaining images of different sizes, their performances are examined by

using VGG16, DenseNet121, ResNet50, MobileNetV2, InceptionResNetV2, CNN deep transfer learning methods.

▶ A CNN-based Methodology for Breast Cancer Diagnosis Using Thermal Images

○ Authors: Juan Zuluaga-Gomez, Zeina Al Masry, Khaled Benaggoune, Safa Meraghni, Noureddine Zerhouni

○ Published: October 2019

○ Summary: This study presents a computer-aided diagnosis system based on convolutional neural networks (CNNs) for breast cancer diagnosis using thermal images. It emphasizes the effectiveness of data preprocessing and augmentation techniques in improving classification accuracy, achieving a performance of 92% accuracy and F1-score

▶ A Deep Analysis of Transfer Learning Based Breast Cancer Detection Using Histopathology Images

○ Authors: Md Ishtyaq Mahmud, Muntasir Mamun, Ahmed Abdelgawad

○ Published: April 2023Enhancing Breast Cancer Diagnosis with Integrated Histopathological and Thermal Image Analysis

○ Summary: This research analyzes pre-trained deep transfer learning models such as ResNet50, ResNet101, VGG16, and VGG19 for detecting breast cancer using histopathology images. The study finds that ResNet50 outperforms other models, achieving accuracy rates of 90.2% and recall rates of 94.7%in 2024 9th International STEM Education Conference (esteem-Ed).

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