A Review of Multi-Modal Cancer Detection Systems: Advances in Early Diagnosis

Review Paper on AI-Driven Multimodal Cancer Diagnosis Using Deep Learning and Machine Learning Frameworks

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Abstract—Early and accurate cancer detection continues to rely heavily on advances in artificial intelligence, particularly deep learning and machine-learning systems designed for multimodal imaging and clinical data analysis. Recent studies in breast cancer diagnosis highlight the growing efficiency of lightweight CNN architectures such as MobileNetV3, Xception, and hybrid CNN–SVM models in classifying ultrasound and histopathological images, with several approaches demonstrating high accuracy and robustness despite limited and variable datasets. Parallel developments in liver cancer research show significant improvements through CNN-based CT segmentation frameworks, multiparametric ultrasound techniques, and hybrid optimization-driven classifiers, all enabling better lesion characterization and early disease detection. Similarly, thyroid cancer diagnostics benefit from enhanced YOLO-based detectors, attention-guided CNNs, and classical ML models, which collectively improve nodule classification using ultrasound or biopsy images. Additionally, multi-cancer prediction frameworks using MRI and structured clinical datasets show the promising role of SVM and ensemble learning in generalized cancer risk assessment. Across all modalities, these studies emphasize the importance of integrating deep learning with IoT infrastructure, multi-source transfer learning, and optimization algorithms to address noise, data imbalance, and limited imaging quality. Together, the reviewed works demonstrate how multimodal AI-driven systems are driving a shift towards faster, more reliable and resource-efficient cancer detection technologies, ultimately supporting early diagnosis and broader accessibility in clinical and underserved settings.

Index Terms—*Convolutional Neural Network, Support Vector Machine, MobileNetV3, Xception, Hybrid CNN-SVM, YOLO, Deep Learning, Cancer Detection.*

I. INTRODUCTION

Cancer remains one of the leading causes of mortality worldwide, and its successful management relies heavily on early and accurate detection. Traditional diagnostic methods—such as ultrasound, CT scans, MRI, histopathology, and biopsy—continue to play a central role in clinical decision-making. However, these methods often face challenges related to limited imaging quality, operator dependency, low contrast, noise, and variability across patients and imaging devices. As a result, there has been a growing shift toward integrating artificial intelligence (AI) to enhance diagnostic precision and reduce clinical workload.

In recent years, deep learning and machine-learning models have shown remarkable potential in analyzing complex medical data across multiple cancer types. Convolutional Neural Networks (CNNs), lightweight architectures, hybrid learning systems, and advanced optimization frameworks have significantly improved image classification, segmentation, and lesion detection accuracy. These AI-driven systems offer the ability to automatically extract discriminative features from medical images, overcoming many of the limitations of traditional manual interpretation.

Breast, liver, and thyroid cancers—three of the most commonly diagnosed cancers globally—have particularly benefited from these technological advancements. Studies have demonstrated strong results using ultrasound-based CNN models for breast cancer, CT segmentation and multiparametric ultrasound for liver cancer, and YOLO-based detectors as well as biopsy-focused CNN models for thyroid nodules. At the same time, multimodal machine-learning frameworks using MRI, clinical parameters, and ensemble learning methods have further expanded the possibilities of generalized cancer prediction.

C. Thyroid Cancer Detection

This paper presents a computer system that helps doctors find thyroid nodules in ultrasound images using an improved YOLOv5 model. Key improvements include the Coordinate Attention (CA) module and the Label Smoothing Regularization (LSR) module. Tested on 191 ultrasound images, the system achieved an accuracy score of 95.3% and detection speed of 8.4 milliseconds, making it a viable tool for clinical use [11].

A further study looks at how machine learning (ML) can improve the diagnosis of thyroid cancer. The researchers tested ML methods such as Logistic Regression and Decision Trees with Stacking and Voting techniques. Results showed approximately 82% accuracy in detecting thyroid cancer, with Logistic Regression performing best among the models, suggesting ML can lead to better and more efficient thyroid cancer diagnostic systems [12].

A CNN-based approach is proposed for thyroid nodule detection using ultrasound images, potentially comparable in accuracy to fine-needle aspiration biopsy (FNAB). The study evaluates key prediction aspects including preprocessing steps such as normalization, noise reduction, contrast enhancement, and data augmentation. The study concludes that the CNN method, tested with real clinical data, could significantly improve thyroid nodule detection in medical settings [13].

This study differentiates non-cancerous and cancerous thyroid nodules in ultrasound images using deep learning. The researchers tested an improved Xception network with the Convolutional Block Attention Module (CBAM) to focus the model on important image regions. The original Xception network achieved an accuracy of 95.058%, demonstrating that deep learning models can effectively and automatically classify thyroid nodules [14].

Despite these advances, gaps remain in building unified, scalable systems capable of working across multiple imaging modalities and diverse cancer types. Most existing models remain organ-specific or modality-dependent, limiting their broader clinical applicability. This review addresses these limitations by examining a wide collection of research studies focused on multimodal cancer detection using deep learning and machine learning. The goal is to highlight technological progress, identify existing challenges, and outline research opportunities toward creating more integrated and clinically adaptable AI-based diagnostic frameworks.

II. LITERATURE REVIEW

A. Breast Cancer Detection

New developments in lightweight deep learning have greatly improved how we diagnose breast cancer, especially through analyzing tissue images. A study by Kaushik and Sharma proposes a MobileNetV3 framework using transfer learning to classify tissue samples as benign or malignant. By using pre-trained ImageNet weights and specific data enhancement methods, the model improves feature extraction even with limited data. The results show a diagnostic ability with a ROC-AUC of 0.78 and an accuracy of 0.76, supporting the move towards better AI tools for early cancer screening [1].

Ultrasound imaging is very important for checking breast cancer because it is safe, easy to access, and effective at finding problems in dense breast tissue. A study applied MobileNetV3 for classifying ultrasound images in real-time diagnosis. By using transfer learning, the researchers improved feature extraction from low-contrast ultrasound images. The method shows strong results in differentiating benign and malignant lesions, highlighting how smaller CNN models are increasingly practical in clinical settings where speed is important [2].

CNN-based systems are being used more to help find breast cancer in areas with limited access to advanced imaging tools. This study shows how CNN models can work with ultrasound images and IoT technology to help diagnose cancer early in underserved areas. Using the BUSI ultrasound dataset, the system achieves 99.31% accuracy, outperforming older machine learning methods such as quadratic SVM. An important aspect of this work is its IoT integration, allowing ultrasound images to be transmitted remotely for real-time decision support [3].

Hybrid deep learning models combining feature extraction from pre-trained CNNs with traditional machine-learning classifiers are gaining popularity for breast cancer ultrasound diagnosis. The study compares seven CNNs—VGG-16, VGG-19, ResNet-18, ResNet-50, EfficientNet-B0, MobileNet-V3, and DenseNet—paired with an SVM classifier. Results show hybrid models outperform standard CNN classifiers, with EfficientNet-B0+SVM achieving the highest accuracy of 98.84% and MobileNet-V3+SVM reaching 98.41% [4].

A further study evaluates CNN models—MobileNet, MobileNetV2, Xception, VGG16, and VGG19—for automated classification of breast ultrasound images. The Xception model achieved the best results with 94% accuracy and an AUC of 0.98. The study demonstrates how deep learning methods are becoming more reliable in helping radiologists reduce misinterpretation and enable earlier diagnosis [5].

A CNN model is applied to thyroid cancer diagnosis using high-resolution biopsy images. These high-resolution images allow clearer examination of cells compared to low-resolution ultrasound images. The CNN model was trained to classify images as benign or malignant, achieving an accuracy of 84% with good sensitivity and specificity, showing potential to speed up the diagnosis process [15].

D. Multi-Cancer Prediction

This paper uses SVM algorithms to classify three types of cancer—lung, breast, and liver—using MRI scans. The study focuses on improving diagnostic accuracy by using machine learning to analyze medical images through feature extraction and SVM model training. Results show that the SVM approach can be effective for cancer detection across multiple cancer types using a unified imaging method [16].

This research creates prediction models using machine learning to detect prostate, lung, and breast cancer early. The study uses Logistic Regression, Random Forest, and Gradient Boosting methods, incorporating SMOTE to address class imbalance. Each model is evaluated using accuracy, precision, and recall, with results showing that machine learning models can reliably predict these three cancers to support early screening [17].

III. CONCLUSION

In this review, we examined a wide range of multimodal cancer detection approaches used for breast, liver, and thyroid cancer diagnosis. The studies covered diverse imaging modalities—including histopathology, ultrasound, CT, MRI, and biopsy images—along with deep learning, traditional machine-learning models, hybrid frameworks, and optimization-based classifiers. Each method demonstrated distinct strengths in feature extraction, lesion classification, segmentation accuracy, and computational efficiency.

This review also summarized the different algorithms, performance metrics, preprocessing strategies, and architectures used across the literature, highlighting how advancements such as lightweight CNNs, transfer learning, hybrid CNN–SVM systems, and multiparametric imaging have contributed to improved early detection outcomes. Despite these improvements, several challenges persist, particularly related to dataset imbalance, imaging noise, modality-specific variability, and limited real-time deployment in resource-constrained settings.

A key research gap identified in this work is the absence of a unified, generalized diagnostic model capable of accepting any type of medical image and reliably predicting any cancer type. Current systems remain highly specialized and restricted to specific organs or imaging modalities, limiting their scalability and clinical applicability. This gap opens opportunities for future research to explore universal, multimodal frameworks integrating cross-domain learning, multi-task architectures, and large-scale standardized datasets.

Overall, this review provides valuable insights into existing multimodal cancer detection technologies while emphasizing the need for more holistic, interoperable, and clinically adaptable AI solutions for early cancer diagnosis.

B. Liver Cancer Detection

Machine learning tools for predicting liver cancer are becoming popular because they can analyze medical data to find patterns linked to cancer. This study uses different machine learning methods including decision trees and support vector machines for early detection. The study points out that simple machine learning methods are still valuable in real healthcare situations where advanced imaging may not be available [6].

Deep learning helps to accurately find liver tumors in CT images, especially when the tumors are hard to see. This study introduces a method combining image processing with U-Net and GoogleNet neural networks to identify and classify liver tumors. Using the 3D-IRCADb01 dataset, U-Net performs better than GoogleNet, achieving 98.65% accuracy and excellent results in identifying tumor boundaries [7].

Multiparametric ultrasound (mpUS) imaging is a promising non-invasive way to detect early liver steatosis, which can lead to liver cancer. The study uses contrast-enhanced ultrasound (CEUS), shear-wave elastography (SWE), and H-scan imaging to measure changes in liver stiffness and tissue structure. Results show important changes indicating early fat buildup in the liver, and mpUS proved to be a reliable early diagnostic tool, potentially replacing painful liver biopsies [8].

This paper proposes using deep learning to improve the process of liver cancer detection. The method uses the Haar wavelet transform to extract features, followed by the Extreme Learning Machine (ELM) for classification. The GWO algorithm is used to optimize the ELM settings, and the GWO-ELM method achieved a classification accuracy of 99.41% on a diverse dataset, demonstrating strong effectiveness for detecting liver tumors accurately [9].

This study aims to improve B-mode Ultrasound (BUS) for detecting liver cancer using information from Contrast-Enhanced Ultrasound (CEUS). The researchers use supervised transfer learning to share knowledge between the two ultrasound types, applying a Multi-Kernel Learning-based NHSVM+ (MKL-NHSVM+) algorithm. The final model showed an average accuracy of 88.18%, proving that multi-source transfer learning can significantly improve BUS-based liver cancer detection [10].

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