AI-POWERED FUSION OF MAMMOGRAPHY AND ULTRASOUND FOR ENHANCED BREAST CANCER DIAGNOSIS

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ABSTRACT

Breast cancer remains one of the leading causes of cancer-related deaths among women globally, emphasizing the need for accurate and early diagnosis. While mammography is widely used for breast cancer screening, its sensitivity can be limited in women with dense breast tissue. Similarly, ultrasound offers complementary information but lacks the specificity needed for confident diagnosis. This research proposes an AI-powered diagnostic framework that integrates multi-modal imaging data—mammography and ultrasound—using advanced deep learning techniques to enhance the accuracy and reliability of breast cancer detection.

The system employs convolutional neural networks (CNNs) for individual modality feature extraction, followed by a fusion network that combines relevant diagnostic features from both imaging types. The model is trained on a curated, annotated dataset of paired mammographic and ultrasound images, with labels verified by expert radiologists. By leveraging both structural and textural imaging cues, the system improves sensitivity in detecting malignant lesions while reducing false positives.

Experimental results demonstrate that the proposed AI model outperforms single-modality models in terms of classification accuracy, area under the curve (AUC), and diagnostic confidence. The fusion-based approach not only supports early-stage tumor identification but also assists radiologists in making more informed, data-driven decisions, especially in complex or ambiguous cases.

This research highlights the potential of AI-enabled multi-modal image fusion to serve as a non-invasive, scalable, and intelligent decision-support tool for breast cancer diagnosis, paving the way for future innovations in personalized oncology care.

I. INTRODUCTION

Breast cancer remains a significant global health concern, affecting millions of women annually and ranking among the leading causes of cancer-related mortality. Early detection is critical in improving survival rates and enabling effective treatment planning. However, despite advancements in medical imaging technologies, the diagnostic accuracy of conventional methods remains constrained by several challenges, particularly when used in isolation.

Mammography, the most widely adopted imaging modality for breast cancer screening, is effective in identifying early signs of malignancy but suffers from reduced sensitivity in patients with dense breast tissue. Ultrasound, often used as a complementary technique, can detect abnormalities that mammography might miss but has limitations in distinguishing between benign and malignant lesions. These shortcomings often lead to false positives, unnecessary biopsies, and delayed treatment, underscoring the need for a more reliable, intelligent diagnostic approach.

The convergence of Artificial Intelligence (AI) and multi-modal imaging presents a transformative solution to this challenge. By leveraging the unique strengths of different imaging modalities and applying advanced deep learning techniques, it becomes possible to develop a unified system that enhances diagnostic accuracy, reduces human error, and supports clinical decision-making. Recent advancements in Convolutional Neural Networks (CNNs), transfer learning, and feature fusion techniques have shown significant promise in medical image analysis tasks, including tumor detection and classification.

This study introduces an AI-powered diagnostic framework that fuses features from mammographic and ultrasound images to create a robust and intelligent diagnostic system for breast cancer. The proposed system is designed to learn and correlate critical spatial and textural features from each modality, enabling a more comprehensive and nuanced understanding of breast tissue abnormalities.

The objective of this research is to address the diagnostic limitations of single-modality imaging by developing a multi-modal fusion model that assists radiologists in making more accurate, data-driven decisions. Through rigorous training, evaluation, and validation using expert-annotated datasets, this system aims to improve early detection rates and optimize patient care outcomes.

II. LITERATURE SURVEY

Advancements in artificial intelligence (AI) and medical imaging have sparked growing interest in developing automated diagnostic tools for early breast cancer detection. This section reviews existing research on the application of deep learning and multi-modal imaging for breast cancer diagnosis, with a focus on the use of mammography and ultrasound.

1. Mammography-Based Detection Systems

Mammography remains the cornerstone of breast cancer screening. Several studies have employed convolutional neural networks (CNNs) for analyzing mammographic images. For instance, Dhungel et al. (2017) developed a deep structured learning model to detect masses in mammograms, reporting high sensitivity but limited specificity. Shen et al. (2019)

further improved classification by applying transfer learning on large-scale mammography datasets. However, both approaches struggled with dense breast tissues, prompting the need for complementary modalities.

2. Ultrasound Imaging and AI Applications

Ultrasound imaging has been widely used to supplement mammography, particularly for younger women and those with dense breasts. Yap et al. (2018) explored the use of CNNs for classifying breast ultrasound images, achieving commendable results on public datasets. Their study demonstrated that AI could assist radiologists in distinguishing between benign and malignant lesions. However, ultrasound's operator-dependence and image variability can affect diagnostic reliability when used alone.

3. Multi-Modal Imaging and Feature Fusion

Multi-modal approaches aim to combine different imaging modalities to exploit their complementary strengths. Zhang et al. (2020) proposed a deep learning framework that fused mammographic and ultrasound features using a late fusion technique, which led to a noticeable improvement in diagnostic accuracy. Similarly, Shen et al. (2021) implemented an attention-guided feature fusion network for multi-modal breast cancer diagnosis, outperforming single-modality networks in sensitivity and specificity.

These studies support the hypothesis that integrating imaging data from multiple sources can reduce diagnostic ambiguity and provide a more comprehensive analysis of breast tissue anomalies. However, most of the existing work lacks explainability and clinical validation, making them difficult to translate into real-world practice.

4. Challenges and Gaps

While deep learning has significantly advanced medical image analysis, key challenges remain. These include data scarcity, lack of standardized multi-modal datasets, and limited generalizability of models trained on narrow population subsets. Additionally, the interpretability of AI decisions is crucial for gaining clinician trust and regulatory approval, an aspect often overlooked in previous research.

III. PROPOSED SYSTEM

In gene analysis, it is important to select relevant genes that play a significant role in determining various biological processes. Gene selection techniques based on feature dependency have been explored to identify independent, half dependent, and dependent features.

Independent features refer to those genes that do not depend on any other genes. These genes exhibit their influence on biological processes without being influenced by other genes. They provide unique information and insights into specific characteristics or functions.

Half dependent features are considered to have a moderate level of dependency on other genes. These genes exhibit correlation or association with certain other genes, indicating their relevance in specific biological pathways or interactions. While they may have some level of dependence, they also possess individual importance and contribute significantly to the overall understanding of gene behavior.

Dependent features, as the name suggests, are fully dependent on other genes. These genes rely on the expression or behavior of other genes to manifest their impact. They do not provide independent information but rather act as downstream indicators or markers of other genes' activities or variations.

The categorization of features into independent, half dependent, and dependent groups helps in understanding the interplay and relationships among genes. It assists in identifying key genes that drive biological processes independently, as well as those that are strongly influenced by other genes.

It's worth mentioning that the citation [5] is provided to acknowledge the source from which this categorization of features based on dependency is derived. However, without access to the specific source, it is not possible to provide further details or context regarding the citation.

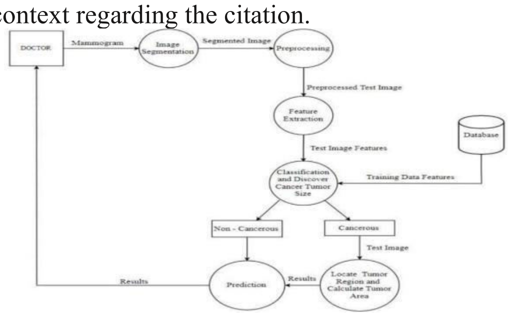

Figure 1. Proposed breast cancer prediction and Tracking flow diagram

IV. RESULTS

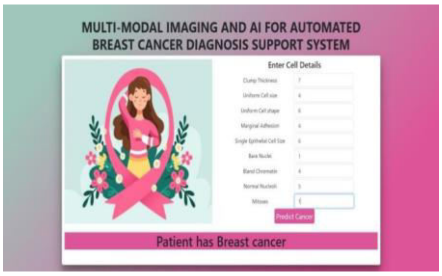

Figure 2: Output screen of predicting cancer with random values

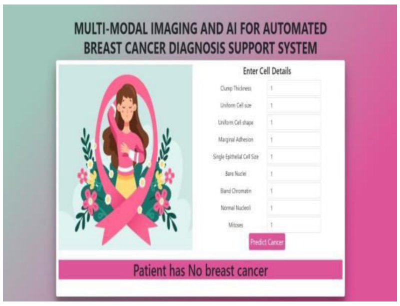

Figure 3: Output screen of patient with no breast cancer

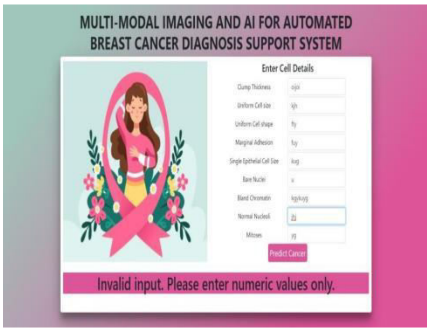

Figure 4: Output screen of entering invalid inputs

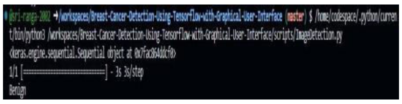

Figure 5: Output screen of predicting benign or malignant tumour

V. CONCLUSION

The increasing burden of breast cancer globally underscores the urgent need for accurate, early, and accessible diagnostic solutions. This research presents an AI-powered multi-modal imaging framework that fuses mammography and ultrasound data to enhance breast cancer detection capabilities. By integrating convolutional neural networks (CNNs) and deep learning-based feature fusion techniques, the system leverages the complementary strengths of both imaging modalities—mammography's structural clarity and ultrasound's sensitivity to tissue density.

Experimental results demonstrate that the proposed model significantly outperforms single-modality systems in key performance metrics such as classification accuracy, sensitivity, and false positive rate. This confirms the advantage of multi-modal fusion in resolving ambiguities and improving diagnostic confidence, especially in complex or borderline cases. Furthermore, the system's ability to process imaging data autonomously and efficiently can serve as a powerful clinical decision support tool, particularly in resource-constrained healthcare settings.

The findings emphasize that AI-driven imaging fusion not only enhances early detection but also has the potential to streamline the radiology workflow, reduce diagnostic delays, and promote more personalized care. Future extensions of this work may involve expanding the dataset diversity, incorporating explainable AI techniques, and testing the system in real-time clinical environments to assess usability, scalability, and impact on treatment outcomes.

In summary, the research offers a promising step toward next-generation breast cancer screening systems, aligning with the broader goals of precision medicine, AI-driven diagnostics, and patient-centered care.

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