EXISTING SYSTEM

Breast cancer diagnosis in current clinical practice primarily relies on manual interpretation of medical images such as mammograms and ultrasound scans by experienced radiologists. While these imaging techniques are effective, the diagnostic outcome is highly dependent on the expertise of the clinician, leading to inter-observer variability and potential diagnostic errors, especially in early-stage cases and dense breast tissues.

Traditional computer-aided diagnosis (CAD) systems were developed to assist radiologists by extracting handcrafted features such as texture, shape, and intensity from medical images, followed by classification using machine learning algorithms. Although these systems reduced manual effort, their performance was limited by the quality of handcrafted features and poor generalization across datasets.

With the advancement of deep learning, several existing systems employ convolutional neural networks (CNNs) for automated breast cancer detection. Most of these systems focus on **single-modality analysis**, predominantly mammography or ultrasound images. While CNN-based models have demonstrated improved accuracy, reliance on a single imaging modality often results in high false positive and false negative rates, particularly in ambiguous cases.

Some recent systems integrate clinical information such as age and BI-RADS score along with imaging data. However, in many cases, clinical data is either underutilized or combined using simple fusion strategies without dynamically learning the importance of each modality. This limits the adaptability of such systems across diverse patient profiles.

Additionally, the majority of existing AI-based breast cancer diagnosis systems function as **single-stage classifiers**, directly predicting benign or malignant outcomes without performing an initial screening step. This does not align well with real clinical workflows, where screening and diagnosis are treated as separate processes.

Another significant limitation of existing systems is the lack of **explainability**. Many deep learning models act as black boxes and do not provide visual or logical explanations for their predictions. This lack of transparency reduces clinical trust and limits the adoption of AI systems in real-world healthcare environments.

Limitations of the Existing System

- Heavy reliance on **manual interpretation** by radiologists
- Predominantly **single-modality** based systems
- High false positive and false negative rates
- Limited integration of **clinical data**
- Absence of **two-stage diagnostic pipelines**
- Lack of **explainable AI mechanisms**

Need for Improvement

The limitations of existing systems highlight the need for a robust breast cancer diagnosis framework that integrates multiple imaging modalities and clinical data, follows a clinically aligned two-stage workflow, and provides explainable outputs to support medical decision-making.

PROPOSED SYSTEM

The proposed system presents a **two-stage, multimodal, explainable deep learning framework** for breast cancer detection and diagnosis. The design of the system is motivated by the limitations identified in existing systems, particularly the reliance on single-modality analysis, lack of clinical workflow alignment, and absence of explainability.

The proposed approach mimics real-world clinical practice by separating the process into **screening** and **diagnosis** stages. In the first stage, the system performs a coarse screening to identify whether a mammogram image is normal or abnormal. In the second stage, only abnormal cases are further analyzed using a multimodal diagnostic framework to classify the lesion as benign or malignant.

Stage 1: Screening (Normal vs Abnormal Classification)

In the first stage, mammogram images are used to perform an initial screening. The input mammogram undergoes preprocessing steps such as resizing and normalization before being passed to a convolutional neural network. A pretrained deep learning model is employed to extract discriminative features and classify the image into either **normal** or **abnormal** categories.

This stage acts as a filtering mechanism to reduce unnecessary diagnostic analysis and computational overhead. By separating normal cases early, the system improves efficiency and reduces false positives, aligning with standard breast cancer screening workflows.

Stage 2: Multimodal Diagnosis (Benign vs Malignant Classification)

In the second stage, only images classified as abnormal in Stage 1 are forwarded for detailed diagnosis. This stage integrates **multiple data modalities**, including mammogram images, ultrasound images, and structured clinical information such as patient age and BI-RADS score.

Separate deep learning encoders are used for each modality to extract meaningful features. Imaging features are learned using convolutional neural networks, while clinical data is processed through a lightweight neural network. The extracted features from all modalities are combined using a **late fusion strategy**, which allows independent learning of modality-specific representations.

To further enhance performance, an **attention mechanism** is applied to the fused feature space. This mechanism dynamically learns the relative importance of each modality for a given patient case, enabling the model to emphasize the most informative inputs during decision-making.

Explainability and Interpretability

To ensure transparency and clinical trust, the proposed system incorporates **explainable artificial intelligence (XAI)** techniques. Gradient-based visualization methods are applied to highlight the regions of mammogram and ultrasound images that contribute most to the model's predictions. Additionally, the attention weights provide insight into the contribution of each modality, offering clinicians an interpretable explanation of the diagnostic outcome.

Advantages of the Proposed System

- Implements a **two-stage diagnostic workflow** aligned with clinical practice
- Integrates **multimodal data** for improved diagnostic reliability
- Utilizes **attention-based fusion** to adaptively weigh modality importance
- Provides **explainable outputs** to support clinician trust
- Reduces false positives and unnecessary diagnostic processing

Outcome of the Proposed System

The proposed system aims to improve the accuracy, robustness, and interpretability of breast cancer diagnosis by combining multimodal deep learning with explainable AI techniques. This framework is intended to function as a **clinical decision support system**, assisting radiologists rather than replacing human expertise.

ALGORITHM / METHODOLOGY

The proposed breast cancer detection system follows a structured **two-stage methodology** combining deep learning, multimodal data fusion, and explainable artificial intelligence. The overall workflow is divided into two main phases: **Stage-1 Screening** and **Stage-2 Multimodal Diagnosis**. The detailed methodology is described below.

Algorithm 1: Stage-1 Screening (Normal vs Abnormal)

Input: Mammogram image
Output: Normal / Abnormal classification

Steps:

1. The mammogram image is acquired from the dataset and converted into a standardized RGB format.
2. Preprocessing is performed by resizing the image to a fixed resolution and normalizing pixel intensity values.
3. The preprocessed image is passed to a pretrained convolutional neural network to extract high-level image features.
4. The extracted features are forwarded to a fully connected classification layer.
5. The network outputs a probability score corresponding to normal and abnormal classes.
6. Based on the predicted class, the image is labeled as **normal** or **abnormal**.
7. Only abnormal cases are forwarded to the next diagnostic stage.

Algorithm 2: Stage-2 Multimodal Diagnosis (Benign vs Malignant)

Input: Mammogram image, Ultrasound image, Clinical data (Age, BI-RADS)
Output: Benign / Malignant classification

Steps:

1. Mammogram and ultrasound images are independently preprocessed through resizing and normalization.
2. Separate deep learning encoders extract modality-specific features from mammogram and ultrasound images.
3. Structured clinical data such as age and BI-RADS score are normalized and passed through a lightweight neural network to obtain clinical feature representations.
4. Features from all modalities are combined using a late fusion strategy by concatenating the learned representations.
5. An attention mechanism is applied to the fused feature vector to learn the relative importance of each modality.
6. The weighted fused features are passed to a classification layer to predict benign or malignant class labels.
7. The final diagnostic decision is generated based on the highest probability score.

Explainability Methodology

To enhance interpretability, gradient-based visualization techniques are applied to the imaging modalities. Activation maps are generated to highlight the regions of mammogram and ultrasound images that most influence the model's predictions. Additionally, attention weights are analyzed to understand the contribution of each modality in the diagnostic decision.

Overall Workflow Summary

1. Acquire mammogram, ultrasound, and clinical data.
2. Perform Stage-1 screening to filter normal cases.
3. Apply Stage-2 multimodal diagnosis to abnormal cases.
4. Generate explainable outputs for clinical interpretation.
5. Present the final diagnosis to the user.

Advantages of the Proposed Methodology

- Reduces unnecessary diagnostic processing through staged screening
- Improves diagnostic accuracy using multimodal data fusion
- Learns adaptive modality importance using attention mechanisms
- Provides interpretable and explainable outputs
- Aligns closely with real-world clinical workflows

3.4.2 Breast Cancer Detection System Modules

The breast cancer detection system is designed to assist in the early screening and diagnosis of breast cancer using medical imaging and clinical data. The system follows a two-stage deep learning-based approach and consists of several functional modules, including dataset handling, data preprocessing, feature extraction, model training, diagnosis, explainability, evaluation, and deployment. Below is a detailed description of each module.

Dataset Handling

The datasets used for training and evaluation consist of mammogram images, ultrasound images, and corresponding diagnostic labels. Publicly available datasets are utilized to ensure reproducibility and research validity. Mammogram images are labeled as benign or malignant, while ultrasound images are categorized into normal, benign, and malignant classes. Structured clinical information such as age and BI-RADS score is incorporated as auxiliary input. The datasets are organized into training and validation sets using an 80%–20% split to ensure balanced evaluation and prevent overfitting.

Data Preprocessing

Data preprocessing is performed to standardize the input data and improve model performance. The preprocessing steps include:

- **Image Resizing:** All mammogram and ultrasound images are resized to a fixed resolution to ensure uniform input dimensions.
- **Normalization:** Pixel intensity values are normalized to a standard range to improve training stability.
- **Data Augmentation:** Techniques such as horizontal flipping are applied to increase dataset diversity and reduce overfitting.
- **Clinical Data Encoding:** Clinical features such as age and BI-RADS score are normalized to ensure consistent scale across samples.

Feature Extraction

Feature extraction is performed independently for each modality to preserve modality-specific characteristics:

- **Mammogram Feature Extraction:** A deep convolutional neural network is used to extract high-level spatial features from mammogram images.
- **Ultrasound Feature Extraction:** A lightweight convolutional neural network extracts texture and structural features from ultrasound images.
- **Clinical Feature Extraction:** A small neural network encodes structured clinical data into a compact feature representation.

Model Training

The system is trained using supervised learning techniques:

- **Stage-1 Training:** A convolutional neural network is trained to classify mammogram images into normal and abnormal categories.
- **Stage-2 Training:** A multimodal model is trained to classify abnormal cases into benign or malignant classes using fused multimodal features.
- **Optimization:** The model is trained using labeled data and optimized using gradient-based optimization techniques.
- **Validation Strategy:** Model performance is monitored on a validation set to ensure generalization.

Breast Cancer Diagnosis

Once the models are trained, the system performs automated diagnosis:

- **Screening Stage:** Mammogram images are first screened to identify abnormal cases.
- **Diagnostic Stage:** Abnormal cases are further analyzed using multimodal inputs to predict benign or malignant outcomes.
- **Prediction Output:** The system outputs the predicted class along with confidence scores for each case.

Explainability Module

To improve transparency and clinical trust, an explainability module is integrated:

- **Visual Explanation:** Gradient-based visualization techniques generate heatmaps highlighting regions of interest in mammogram and ultrasound images.
- **Modality Importance:** Attention weights are used to indicate the contribution of each modality in the final decision.

This module helps clinicians understand the reasoning behind model predictions.

Evaluation Metrics

The performance of the proposed system is evaluated using multiple metrics:

- **Accuracy:** Measures the overall correctness of the classification results.
- **Precision:** Evaluates the proportion of correctly identified malignant cases.
- **Recall:** Measures the ability of the system to detect actual malignant cases.
- **F1 Score:** Provides a balanced measure of precision and recall.
- **ROC AUC:** Assesses the trade-off between true positive and false positive rates.

Model Deployment & Storage

The trained models are stored and prepared for deployment:

- **Model Storage:** Trained models are saved in standard formats such as .pth for efficient loading and reuse.
- **Deployment Interface:** The system is integrated into a user-friendly interface that allows users to upload medical images and clinical data.
- **User Interface:** The interface displays diagnostic predictions, confidence scores, and explainability visualizations to support clinical decision-making.

ABSTRACT

Breast cancer is one of the most commonly diagnosed diseases among women, and timely detection plays a crucial role in improving treatment outcomes. In current clinical practice, diagnosis is largely based on the manual interpretation of medical images such as mammograms and ultrasound scans. While effective, this approach depends heavily on the experience of radiologists and may lead to variability in diagnosis, especially in early or complex cases.

Recent developments in deep learning have enabled automated systems for breast cancer detection; however, many existing methods rely on a single imaging modality and provide limited insight into how decisions are made. This reduces their reliability and acceptance in clinical environments. To address these challenges, this project proposes a two-stage breast cancer detection system that integrates multiple diagnostic sources and emphasizes interpretability.

In the first stage, mammogram images are screened to classify cases as normal or abnormal, allowing early filtering of non-suspicious cases. In the second stage, abnormal cases are further analyzed using a multimodal approach that combines mammogram images, ultrasound images, and basic clinical information such as age and BI-RADS score. The extracted features from different modalities are fused using an attention-based mechanism to support more informed diagnostic decisions. In addition, visual explanation techniques are employed to highlight important regions in medical images, helping users understand the model's predictions.

The proposed system is intended to function as a supportive decision-making tool rather than a replacement for medical professionals. By combining multimodal learning with explainable outputs, this work aims to contribute toward more reliable and transparent breast cancer diagnosis systems.

CHAPTER 1

INTRODUCTION

Breast cancer is one of the most prevalent and life-threatening diseases affecting women worldwide, accounting for a significant proportion of cancer-related morbidity and mortality. According to global health statistics, millions of new cases are diagnosed each year, making early detection and accurate diagnosis critical for improving survival rates and treatment outcomes. Breast cancer is characterised by the uncontrolled growth of abnormal cells in breast tissue, which can spread to other parts of the body if not detected at an early stage. The severity and progression of the disease vary across patients, highlighting the need for timely screening and effective diagnostic strategies.

Over the years, several screening and diagnostic techniques have been developed for the detection and analysis of breast cancer. Among these, medical imaging modalities such as mammography and ultrasound have emerged as the most widely used tools due to their non-invasive nature and ability to reveal structural abnormalities within breast tissue. Mammography is commonly used as a primary screening technique, while ultrasound is often employed as a complementary modality, particularly in cases involving dense breast tissue. The interpretation of these imaging modalities plays a crucial role in early diagnosis, treatment planning, and patient management.

Despite their effectiveness, traditional breast cancer diagnosis methods heavily rely on manual interpretation by experienced radiologists. This process can be time-consuming, labor-intensive, and prone to inter-observer variability. Radiologists must carefully examine medical images to identify subtle patterns that distinguish benign from malignant lesions. Such manual analysis can lead to inconsistencies in diagnosis and delays in clinical decision-making. Additionally, medical images often contain noise, low contrast regions, and complex visual patterns, which further complicate accurate interpretation.

To address these challenges, the integration of artificial intelligence (AI) and machine learning (ML) techniques has gained significant attention in recent years. Automated breast cancer detection systems leverage deep learning models to analyze medical images, extract meaningful features, and assist clinicians in diagnosis. These systems aim to reduce dependency on manual analysis, improve diagnostic consistency, and enhance detection accuracy. Recent advances in deep learning have demonstrated promising results in medical image analysis, enabling improved performance over traditional computer-aided diagnosis systems.

In this project, we focus on developing a two-stage, multimodal breast cancer detection system using deep learning techniques. The proposed approach integrates mammogram images, ultrasound images, and clinical information to improve diagnostic reliability and interpretability. By leveraging modern computational methods and explainable artificial intelligence techniques, this study aims to enhance diagnostic accuracy, reduce false positives, and support clinical decision-making. Through this work, we contribute to the growing field of AI-assisted medical diagnosis, offering a potential solution for more reliable and transparent breast cancer detection.

1.1 Overview

Breast cancer is one of the most prevalent and life-threatening diseases affecting women worldwide, accounting for a significant proportion of cancer-related morbidity and mortality. According to global health statistics, millions of new breast cancer cases are diagnosed each year, making it a major public health concern. Breast cancer is characterized by the uncontrolled growth of abnormal cells in breast tissue, which may invade surrounding tissues or spread to other parts of the body if not detected early. The progression and severity of the disease vary across individuals, ranging from slow-growing benign tumors to aggressive malignant forms. Due to this variability, early and accurate detection of breast cancer is essential for effective treatment planning, improved patient survival, and reduced mortality rates.

Various screening and diagnostic techniques have been developed to detect breast cancer, with medical imaging playing a central role in clinical practice. Among these techniques, mammography is the most widely used and recommended method for early breast cancer screening. Mammograms provide detailed images of breast tissue and help identify masses, calcifications, and other abnormalities that may indicate the presence of cancer. Ultrasound imaging is commonly used as a complementary diagnostic tool, particularly in cases involving dense breast tissue where mammography alone may be insufficient. By analyzing mammogram and ultrasound images, clinicians can assess lesion characteristics, determine disease severity, and make informed diagnostic decisions. However, accurate interpretation of these medical images requires substantial expertise and clinical experience.

Traditionally, breast cancer detection and diagnosis rely heavily on manual analysis performed by trained radiologists. Radiologists examine medical images to identify suspicious regions and differentiate between benign and malignant lesions based on visual patterns and clinical guidelines. Although effective, this manual process is time-consuming, subjective, and prone to inter-observer variability. Subtle abnormalities may be overlooked, especially in early-stage cases or complex imaging conditions. In addition, medical images often contain noise, low-contrast regions, and overlapping tissue structures, which further complicate reliable interpretation. As screening programs generate large volumes of imaging data, manual analysis becomes increasingly challenging and resource-intensive.

Before the widespread adoption of deep learning techniques, conventional machine learning approaches were explored to assist in breast cancer detection. Traditional machine learning models such as support vector machines, decision trees, and k-nearest neighbors relied on handcrafted features extracted from medical images. These features typically included texture, shape, intensity, and statistical attributes designed by domain experts. While such methods demonstrated moderate success, their performance was highly dependent on the quality of manually engineered features. Since breast cancer exhibits significant variability in appearance across patients, handcrafted features often fail to capture the full complexity of tumor characteristics, leading to limited generalization and reduced diagnostic accuracy.

Deep learning has emerged as a powerful alternative by enabling automatic feature extraction and classification directly from raw medical images. Deep learning architectures such as convolutional neural networks can learn hierarchical representations of breast tissue patterns without the need for manual feature engineering. These models are capable of identifying subtle visual cues and complex spatial relationships that may not be easily detected through traditional methods. Recent advancements in deep learning have led to significant improvements in breast cancer detection accuracy, enabling automated screening, multimodal analysis, and enhanced diagnostic support. In this study, we aim to leverage deep learning techniques to develop a two-stage, multimodal breast cancer detection system that integrates mammogram images, ultrasound images, and clinical information. The proposed approach seeks to improve diagnostic reliability, reduce false positives, and support clinicians through accurate and interpretable decision-making.

1.2 Description

Breast cancer detection is crucial for early diagnosis and effective treatment planning, as the disease affects millions of women worldwide. This project focuses on analyzing medical imaging data to identify breast cancer using deep learning techniques. By leveraging convolutional neural networks (CNNs), the proposed system efficiently analyzes mammogram and ultrasound images to distinguish between normal, benign, and malignant cases, thereby improving diagnostic accuracy and reliability.

The system follows a two-stage detection framework, where the first stage performs screening to identify abnormal cases from mammogram images, and the second stage carries out detailed diagnosis using multimodal inputs. In addition to imaging data, basic clinical information such as age and BI-RADS score is incorporated to support more informed decision-making. The deep learning models are trained using publicly available breast cancer datasets, with emphasis on robust feature extraction, multimodal fusion, and generalization across different imaging conditions.

1.3 Objective

The primary objective of the Breast Cancer Detection System is to develop an efficient and reliable deep learning–based framework that assists in the early screening and diagnosis of breast cancer using medical imaging and clinical data. Given the increasing prevalence of breast cancer and the challenges associated with accurate diagnosis, this system aims to provide an automated, interpretable, and clinically supportive solution that can assist radiologists and healthcare professionals in identifying breast abnormalities. By leveraging advanced deep learning techniques, the proposed system seeks to enhance diagnostic accuracy, reduce false positives, and contribute to the integration of artificial intelligence into medical imaging and healthcare.

To achieve these goals, the system is designed with the following key objectives:

- **Accurate Detection of Breast Abnormalities** – Develop a robust deep learning–based screening model to classify mammogram images into normal and abnormal categories. This ensures reliable early detection and reduces unnecessary diagnostic procedures.

- **Classification of Breast Lesions** – Implement a diagnostic model capable of distinguishing between benign and malignant breast lesions using multimodal inputs. Accurate lesion classification supports early intervention and appropriate treatment planning.

- **Integration of Multimodal Data** – Combine mammogram images, ultrasound images, and structured clinical information such as age and BI-RADS score to improve diagnostic reliability and decision-making.

- **Optimization of Feature Extraction and Model Performance** – Train the system using publicly available breast cancer datasets and optimize feature extraction and model parameters to achieve high accuracy and generalization across diverse imaging conditions.

- **Explainable Diagnostic Output** – Incorporate explainable artificial intelligence techniques to provide visual and quantitative insights into model predictions, enabling clinicians to understand and trust the diagnostic results.
- **Improved Healthcare Support and Accessibility** – Assist healthcare professionals by providing automated diagnostic support that reduces workload and improves efficiency, while supporting timely identification of suspicious cases and facilitating early medical intervention.

1.4 About the Project

The Breast Cancer Detection System is an innovative, AI-driven framework designed to assist in the early screening and diagnosis of breast cancer using deep learning techniques applied to medical imaging data. Given the critical importance of early detection in improving breast cancer survival rates, this project aims to bridge the gap between traditional image-based diagnosis and modern, intelligent decision-support systems. By integrating mammogram images, ultrasound images, and clinical information, the system supports timely diagnosis and improved patient outcomes.

Challenges in Breast Cancer Detection

Breast cancer diagnosis traditionally relies on manual interpretation of mammograms and ultrasound scans by experienced radiologists. While effective, this process can be time-consuming, subjective, and prone to inter-observer variability. Access to expert radiological analysis may be limited in under-resourced or remote healthcare settings, leading to delays in diagnosis and treatment. Additionally, the increasing volume of medical imaging data places a significant workload on healthcare professionals, increasing the risk of missed or delayed detection of subtle abnormalities. These challenges highlight the need for automated, AI-powered solutions capable of assisting clinicians in accurate and efficient breast cancer detection.

Project Goals and Approach

This project addresses these challenges by leveraging deep learning algorithms to automate breast cancer screening and diagnosis. The proposed system follows a two-stage approach, where mammogram images are first screened to identify abnormal cases, and subsequently analyzed using a multimodal framework that incorporates ultrasound images and clinical data. By extracting meaningful features from each modality and employing attention-based feature fusion, the system improves diagnostic accuracy and robustness. The model is trained on publicly available breast cancer datasets, ensuring that it learns representative patterns associated with benign and malignant lesions.

Key Features of the System

- **User-Friendly Interface:** The system is designed to support easy interaction, allowing users or healthcare professionals to input medical images and clinical information with minimal complexity.
- **Accurate and Efficient Diagnosis:** The two-stage deep learning framework enables reliable screening and classification, supporting early detection and timely medical intervention.
- **Optimized Deep Learning Performance:** Through effective feature extraction, multimodal fusion, and model optimization, the system achieves robust and generalized performance across diverse imaging conditions.
- **Accessibility and Scalability:** Unlike conventional hospital-centric diagnostic methods, the proposed system supports broader accessibility and can be extended to assist healthcare providers in resource-limited or remote settings.

1.5 Organisation of the Project Report

This project report is structured into multiple chapters, each covering essential aspects of the Breast Cancer Detection System. The chapters are organized as follows:

- Chapter 2 - Literature Survey: This chapter presents a comprehensive review of existing research works, methodologies, and technologies related to breast cancer detection and diagnosis. It includes an analysis of traditional diagnostic approaches and modern deep learning–based systems, highlighting research gaps and the motivation for the proposed work.
- Chapter 3 - System Requirements and Design: This chapter discusses the problem statement, identifies the limitations of existing breast cancer diagnostic systems, and introduces the proposed system along with its objectives. It also outlines the hardware and software requirements and describes the system architecture, design framework, and overall workflow.
- Chapter 4 - System Methodologies: This chapter provides a detailed explanation of the methodologies and algorithms used in the project. It includes descriptions of dataset preparation, image preprocessing techniques, feature extraction methods, model training procedures, multimodal fusion strategy, and explainability techniques employed in the system.

- Chapter 5 - Implementation: This chapter focuses on the practical implementation of the proposed system. It includes implementation details, system modules, sample inputs and outputs, performance evaluation results, and screenshots of the user interface developed for breast cancer detection.
- Chapter 6 - Conclusion and Future Enhancements: This chapter summarizes the key contributions and outcomes of the project. It also discusses the significance of the proposed system and outlines potential future enhancements, such as integration with real clinical data, deployment in healthcare environments, and further optimization of diagnostic performance.
- References: This section contains a well-documented list of research papers, journals, conference articles, and online resources cited throughout the report to support the methodologies and technologies used in the project.
- Appendix: This section includes supplementary materials such as source code, additional results, figures, and supporting documents relevant to the project.
- By following this structured organization, the report ensures clarity, logical flow, and detailed technical insight, enabling readers to clearly understand the scope, design, implementation, and significance of the proposed breast cancer detection system.