SonaDx – Early Breast Cancer Detection from Sonography Images

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Declaration

This is to declare that the thesis work entitled "**SonaDx – Early Breast Cancer Detection from Sonography**" has been carried out by **Md. Shakib Ahamed, Md. Tanveer Ahammed Tarek, Md. Omayer Hasan Muhit, Rawnak Tasnim Ruku** in the Department of Computer Science and Engineering (CSE), University of Information Technology and Sciences (UITS), Dhaka, Bangladesh. The above thesis work or any part of this work has not been submitted anywhere for the award of any degree or diploma.

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Abstract

Breast cancer is one of the leading causes of mortality among women worldwide, and early detection remains the most effective strategy for improving survival outcomes. In developing regions such as Bangladesh, limited access to expert radiologists and advanced imaging technologies often delays diagnosis. This study presents **SonaDx**, a deep learning–based breast cancer detection system that leverages ultrasound imaging for affordable, accessible, and accurate screening. A **hybrid dataset** of 2,644 ultrasound images integrating BUSI, MT Small, Breast-Lesions-USG, Kaggle, and local Bangladeshi samples are curated and preprocessed for model training. The proposed model is based on **EfficientNetB3**, fine-tuned using transfer learning to classify images into Normal, Benign, and Malignant categories. The system has achieved **99.9% training accuracy** and **94.5% testing accuracy**, demonstrating strong generalization across diverse imaging conditions. Grad-CAM visualizations are incorporated for interpretability, while the model is converted to **TensorFlow Lite** for lightweight deployment via a **Flask API** and integrated with a **React web interface** hosted on Hugging Face and Cloudflare. The results confirm that SonaDx provides high diagnostic accuracy, fast inference, and real-time visualization, bridging the gap between research and clinical application. This work underscores the potential of AI-driven ultrasound analysis to support early breast cancer detection in resource-limited healthcare settings.

Keywords: Breast Cancer Detection, Deep Learning, Ultrasound Imaging, EfficientNetB3, Transfer Learning, Tensor Flow Lite, Mobile Health Application,SonaDx.

Preface

This B.Sc. The capstone project is outlined based on the results obtained from model training and testing. This is carried out in the Department of Computer Science and Engineering (CSE), Faculty of Science and Engineering, at University of Information Technology and Sciences (UITS), Dhaka, Bangladesh.

This capstone project includes 6 chapters which are briefed as follows:

Chapter 1: Introduction

1.1 Introduction
Provides an overview of breast cancer's global and local impact, emphasizing the need for AI-assisted ultrasound diagnosis in Bangladesh.

1.2 Motivation
Explains the rationale behind developing an accessible deep learning system to support early detection and overcome radiologist shortages.

1.3 Aims & Objectives
States the project's primary aim to build a CNN-based model for breast cancer detection with defined objectives for data, training, and deployment.

1.4 Challenges
Outlines difficulties in data quality, model generalization, interpretability, and deployment within low-resource healthcare settings.

1.5 Contribution
Summarizes the novel dataset creation, model development, evaluation, and interface implementation achieved in this study.

1.6 Consummation (Summary)
Concludes with a roadmap linking all chapters and reiterates the project's relevance to medical AI in Bangladesh.

Chapter 2: Background Studies

2.1 Introduction: Reviews the importance of deep learning in medical imaging, focusing on CNNs for breast ultrasound analysis.

2.2 Literature Review

Summarizes key research on CNN architectures and datasets like BUSI, highlighting trends and findings.

2.3 Related Work

Discusses prior efforts and their limitations in dataset diversity and model generalization.

2.4 Gaps and Challenges

Identifies data scarcity, image quality issues, overfitting, and limited model explainability as key challenges.

2.5 How This Project Builds on Existing Work

Describes SonaDx's hybrid dataset, refined preprocessing, and lightweight deployable model.

2.6 Corollary

Concludes that localized, explainable AI models are vital for real-world diagnostic success.

Chapter 3: Methodology

3.1 Introduction

Describes the systematic workflow used for data preparation, model design, training, and evaluation.

3.2 Dataset Collection

Details the hybrid dataset combining global and local sources for diversity and adaptability.

3.3 Data Preprocessing

Explains resizing, normalization, denoising, and augmentation techniques used to enhance image quality.

3.4 Model Development

Describes the EfficientNetB3 architecture, fine-tuning process, and rationale for model selection.

3.5 Training and Testing

Outlines training stages, parameters, and evaluation protocols ensuring robustness and accuracy.

3.6 Workflow
Summarizes the stepwise development from data collection to API deployment.

3.7 Evaluation Metrics
Lists metrics like accuracy, recall, and ROC-AUC to evaluate diagnostic reliability.

3.8 Tools and Technologies
Enumerates frameworks, environments, and libraries used for development and deployment.

3.9 Consummation (Summary)
Summarizes the methodology's role in ensuring high model accuracy and efficient implementation.

Chapter 4: Implementation

4.1 Introduction
Introduces SonaDx's implementation approach using EfficientNetB3 integrated within a web-based system.

4.2 System Architecture
Explains modular design across data, model, backend, frontend, and cloud layers.

4.3 Backend Development
Details Flask API development, image preprocessing, and inference workflow.

4.4 Frontend Development
Describes the React-based interface that enables real-time user interaction and visualization.

4.5 Deployment and Integration
Covers model conversion to TensorFlow Lite and cloud deployment using Hugging Face and Cloudflare.

Chapter 5: Result Analysis

5.1 Introduction
Presents an overview of the experiments and evaluation conducted for multiple CNN architectures.

5.2 Model Performance and Comparison
Compares MobileNetV2, Xception, and EfficientNetB3, showing how the optimized version achieved 94.5% accuracy.

5.3 Evaluation Metrics and Efficiency
Reports model performance using precision, recall, F1-score, and inference time metrics.

5.4 Visualization and Interpretation
Discusses visual tools like Grad-CAM for understanding model decisions.

5.5 Consummation (Summary)
Concludes with an interpretation of results, highlighting the model's reliability and efficiency.

Chapter 6: Conclusion and Future Work

6.1 Conclusion
Summarizes the success of SonaDx in achieving high accuracy and real-world deployability.

6.2 Future Works
Suggests improvements in dataset expansion, explainability, mobile deployment, and clinical validation.

6.3 Final Thought
Reflects on the societal impact and long-term potential of AI in advancing medical diagnostics.

Table of Contents

List of Figure

List of Tables

Abbreviations and Symbols

AI	**Artificial Intelligence**
CNN	**Convolutional Neural Network**
MRI	**Magnetic Resonance Imaging**
DL	**Deep Learning**
CSS	**Cascading Style Sheet**
BUSI	**Breast Ultrasound Image**
API	**Application Programming Interface**

Chapter 1

Introduction

1.1 Introduction

Breast cancer remains one of the leading causes of cancer morbidity and mortality among women worldwide. Early and accurate detection is critical: when cancer is detected in early stages, interventions tend to be more effective and less invasive, improving survival rates and quality of life. In Bangladesh, the situation is made more difficult by limited access to advanced screening and diagnostic facilities, especially in rural and peri-urban regions, shortages of trained radiologists, and variability in imaging quality.

Artificial intelligence (AI) and deep learning have increasingly been applied to medical imaging tasks, providing tools that can assist or augment human interpretation. Among these, Convolutional Neural Networks (CNNs) have been especially effective in image classification, segmentation, and detection tasks. They can automatically learn hierarchical features (edges, textures, patterns, shapes) from raw image data, reducing the need for hand-crafted features and expert domain knowledge. CNNs have been used in breast ultrasound, mammography, MRI, and histopathological imaging across many studies with impressive results. For example, in the domain of breast ultrasound, deep learning approaches have been shown to improve diagnostic performance by reducing reliance on operator experience and improving reproducibility [1].

In the present work, we have collected **2,644** breast imaging samples (from Bangladeshi hospitals and from some dataset from Kaggle) and designed several CNN architectures. We have achieved a **training accuracy of 99.9%** and a **testing accuracy of 94.5%**. These results indicate strong potential for building an AI-assisted diagnostic tool tailored to the local context. This thesis documents the motivation, methodology, evaluation, and challenges, and aims to chart a path toward deployment in Bangladeshi healthcare settings.

1.2 Motivation

The motivation for this research is multifaceted:

● **Local health need and late diagnosis**: In Bangladesh many breast cancer cases are detected late, when treatment is more difficult and survival rates lower. A reliable automated screening tool can help detect suspicious cases earlier, especially in under-served areas.

● **Scarcity of expert readers**: Radiologists and specialists are concentrated in urban centers. Many smaller hospitals and diagnostic labs have limited access to expert interpretation. AI tools can provide second opinions or screening support.

●**Variation in imaging conditions**: Images collected in Bangladesh (equipment, protocols, patient demographics) may differ from standard datasets used globally. Training on local data ensures better performance in the target population.

● **Performance potential of CNNs**: Many recent studies have shown that CNNs, particularly when combined with transfer learning, ensemble methods, or hybrid designs, can deliver high accuracy in breast cancer image classification (e.g. accuracies nearing 99% in ultrasound contexts) [2].

● **Scalability & affordability**: Once a model is trained and validated, deployment (on servers, edge devices, or cloud) can scale to many facilities at relatively low marginal cost. This is vital in resource-limited settings.

1.3 Aims & Objectives

Aim

To develop and validate CNN-based machine learning models for breast cancer detection using imaging data collected from Bangladeshi hospitals, achieving robust performance (testing accuracy ~94.5%) and a user interface prototype suitable for clinical usage.

Objectives

1. Collect and curate a dataset of 2,644 breast imaging samples (benign, malignant, possibly normal) from Bangladeshi hospitals, with appropriate ethical approvals and anonymization.

2. Preprocess images (resizing, normalization, augmentation, denoising) to standardize inputs and mitigate noise or artifacts.

3. Design and train various CNN architectures (**MobileNetV2**, **Xception**, **EfficientNetB3**) to classify images.

4. Perform hyperparameter tuning, cross-validation, and model comparison to choose best-performing models.

5. Achieve a training accuracy of ~99.9% and testing accuracy of ~94.5%; compute additional metrics (precision, recall, specificity, F1-score, ROC-AUC) to fully evaluate performance.

6. Develop a prototype user interface (web app) through which clinicians can upload images, view predictions, and inspect interpretability maps (e.g. heatmaps, Grad-CAM).

7. Assess generalization and robustness by testing on held-out subsets, cross-hospital validation, or data from different imaging devices.

8. Document challenges, limitations, and deployment pathways for integration into the Bangladeshi healthcare infrastructure.

1.4 Challenges

Implementing a reliable and clinically viable breast cancer detection system based on CNNs involves a number of significant challenges. Below are the key ones:

● **Data Collection & Annotation**
Securing a dataset of 2,644 images from Bangladeshi hospitals required substantial negotiation, ethical approvals, and collaboration. We also use some data from Kaggle and merge both. Ensuring consistency in imaging protocols, managing variable image quality, handling missing metadata, and annotating images reliably (benign vs malignant vs normal) were complex tasks.

● **Data Imbalance & Class Distribution**
The dataset might have unequal representation among classes (e.g. more benign than malignant). Class imbalance can bias learning toward majority classes, causing misclassification of rarer classes. Techniques such as oversampling, undersampling, class weighting, or synthetic augmentation (e.g. using GANs or autoencoders) may be necessary [3].

● **Computational Resources & Overfitting**
Training deep CNN models, especially from scratch, demands significant GPU/CPU resources, memory, and time. High training accuracy (99.9%) raises risk of overfitting (i.e. memorizing training data rather than generalizing). Rigorous validation and regularization (dropout, early stopping, L2 regularization, data augmentation) are critical.

● **Model Selection**
Choosing the best model architecture for breast ultrasound classification was a critical part of this research. Our main goal was to balance model complexity, accuracy, and efficiency for both experimental evaluation and real-time app deployment. We initially tested **MobileNetV2** and **Xception** architectures. MobileNetV2 provided fast inference but showed limited feature extraction, giving only about **70% accuracy**. Xception was deeper but suffered from **overfitting**, achieving around **53% accuracy**. These results indicated the need for a more balanced model that could learn rich features without excessive parameters. We therefore adopted EfficientNetB3, a transfer learning architecture known for its compound scaling that efficiently balances depth, width, and resolution. With fine-tuning of the top layers and hyperparameters such as learning rate (1e−3 → 1e−5) and batch size (32), our model achieved **99% training accuracy** and **94.5% testing accuracy**. The architecture was also selected for its ability to generalize well on small medical datasets while remaining

lightweight enough for mobile deployment. Through controlled layer freezing, data augmentation, and balanced dataset splitting, the final **EfficientNetB3 model** proved both robust and deployment-ready, outperforming all earlier architectures tested in this study.

- **User Interface Design**

A high-performing model is insufficient if it cannot be used easily by clinicians. The UI must allow image uploads, display results, show confidence scores, optionally highlight suspicious regions (e.g. via heatmaps or saliency maps), and be robust under variable internet, hardware, and file format conditions. Ensuring usability, clarity, feedback, error handling, and minimal latency is a challenge.

- **Interpretability & Trust**

CNNs are often opaque ("black boxes"). To gain clinical acceptance, explanations such as saliency maps (e.g., Grad-CAM), attention maps, or feature visualizations are necessary to show why a decision was made. Misleading or uninterpretable outputs may reduce trust.

- **Generalization & Robustness**

A model performing well on the test set may fail on new data from other hospitals, different imaging equipment, or new patient populations. Ensuring cross-domain robustness involves testing on diverse subsets, using data augmentation, and possibly domain adaptation techniques.

- **Ethical, Privacy & Regulatory Issues**

Patient consent, anonymization, secure storage, and compliance with medical data privacy regulations are critical. Liability in case of misdiagnosis, regulatory approval (if used clinically), and accountability mechanisms all pose obstacles.

- **Deployment Constraints**

In Bangladesh, many clinics may have limited computing infrastructure, unreliable internet connectivity, power fluctuations, or legacy systems. The system must be lightweight, robust, maintainable, and cost-effective, with training and support for local staff.

1.5 Contribution

This research aims to make the following substantive contributions:

1. **Local Dataset & Benchmarking**
   The assembly and curation of a dataset of **2,644** breast imaging samples from Bangladeshi hospitals, reflecting local imaging practices, patient demographics, and quality characteristics, which may be used as a benchmark for future local studies. We also use a little data from Kaggle.

2. **High-Performance CNN Models**
   Implementation and comparative evaluation of various CNN architectures (custom, transfer learning, hybrid) achieving exceptional training accuracy (99.9%) and robust testing accuracy (94.5%). These results demonstrate that strong performance is feasible on real-world local data.

3. **Comprehensive Evaluation & Metrics**
   Beyond accuracy, comprehensive reporting of precision, recall, specificity, F1-score, ROC-AUC, confusion matrices, and cross-hospital generalization to assess the model's clinical viability.

4. **Prototype User Interface**
   Development of a user interface (web or desktop) allowing clinicians or technicians to upload images, display predictions, and view interpretability visualizations (e.g. heatmaps). This bridges the gap from algorithm to usable tool.

5. **Analysis of Challenges and Recommendations**
   An in-depth discussion of the challenges encountered (data, model selection, UI design, deployment) together with lessons learned and best practices tailored to the Bangladesh healthcare environment.

6. **Roadmap for Clinical Integration**
   Proposals and guidelines for integrating the model into screening workflows in Bangladesh, including recommendations for incremental deployment, validation in live clinical settings, staff training, and monitoring.

1.6 Consummation (Summary)

In this chapter, we have established the background and significance of breast cancer detection, particularly in Bangladesh, and argued for the utility of CNN-based machine learning models in this context. We introduced the dataset size (2,644' images) and key performance metrics (training accuracy 99.9%, testing accuracy 94.5%). We laid out the motivation, aims, and objectives of the study, and detailed the many technical and practical challenges (including model selection and user interface design). The contributions expected from this work were enumerated, and a roadmap for the thesis structure was set. In conclusion, this chapter presented an overview of breast cancer detection challenges and the transformative role of CNN-based machine learning methods in medical imaging. The motivation behind this study was driven by the rising burden of breast cancer in Bangladesh and the potential of AI to improve early diagnosis. The chapter also outlined the main objectives, challenges including model selection and user interface design and the key contributions of the study.

Subsequent chapters will discuss the related works (Chapter 2), dataset description and methodology (Chapter 3), experimental results (Chapter 4), discussion (Chapter 5), and final conclusions and recommendations (Chapter 6).

Chapter 2

Background Studies

2.1 Introduction

Breast cancer continues to pose a serious global health challenge, ranking among the top causes of cancer mortality in women. Early and accurate diagnosis is essential for successful treatment and improved survival. In Bangladesh, diagnosis is often delayed due to limited access to expert radiologists and inconsistent imaging quality across healthcare facilities. Recent advances in Artificial Intelligence (AI), especially Deep Learning (DL), have demonstrated remarkable success in medical image analysis. Convolutional Neural Networks (CNNs) can automatically extract complex visual patterns edges, textures, and shapes from raw data, enabling highly accurate image classification without manual feature engineering. This chapter reviews related research, identifies limitations in earlier studies, and explains how the proposed **SonaDx** system builds on existing work by integrating a hybrid dataset, advanced transfer-learning architecture (**EfficientNetB3**), and a lightweight deployment framework suitable for clinical use in Bangladesh.

2.2 Literature Review

A wide range of deep learning approaches have been applied to breast cancer diagnosis from imaging modalities such as mammography, MRI, and ultrasound. Wang (2024) showed that CNN-based systems can achieve radiologist-level accuracy for mammographic lesion detection [4].

Al-Dhabyani et al. (2020) released the **Breast Ultrasound Images (BUSI)** dataset, now a standard benchmark for ultrasound-based breast tumor classification [5].

Badawy et al. (2021) combined fuzzy contrast enhancement and CNNs to improve tumor segmentation boundaries [6].
Tan and Le (2021) introduced the **EfficientNet** family, which scales network depth, width, and resolution in a balanced way, achieving superior accuracy-to-size ratios across image-recognition tasks [7].

Selvaraju et al. (2022) proposed **Grad-CAM**, a visualization method that highlights important image regions influencing CNN decisions, improving clinical interpretability [8].

Other researchers explored hybrid or ensemble models for breast ultrasound classification (BMC Medical Imaging, 2024; Discover AI, 2025). These studies confirm CNNs' diagnostic potential but also reveal persistent issues such as limited datasets, lack of localization to regional imaging contexts, and insufficient model explainability.

2.3 Related Work

Breast cancer detection using medical imaging has been extensively explored in recent years, particularly with the rapid advancement of deep learning and convolutional neural networks (CNNs). Early research predominantly focused on mammography-based detection; however, due to accessibility, cost, and radiation concerns, ultrasound imaging has become a more practical choice in developing countries like Bangladesh. As a result, several studies have attempted to design robust AI systems capable of analyzing ultrasound images for early tumor identification.

One of the most widely used datasets in this domain is the BUSI (Breast Ultrasound Images) dataset, introduced by Al-Dhabyani et al. (2020), which provides benign, malignant, and normal ultrasound images. Many researchers used BUSI as a benchmark for evaluating classification and segmentation models. Several studies applied traditional CNNs, achieving accuracies between 80% and 95%, but often struggled with noise, low contrast, and variation in ultrasound acquisition techniques.

To address the limitations of conventional CNNs, more recent works introduced transfer learning using pretrained models such as ResNet50, VGG16, MobileNetV2, Xception, and EfficientNet. These models helped overcome data scarcity by transferring general visual features learned from ImageNet. For example, hybrid CNN architectures combining pretrained backbones with attention modules demonstrated improved cancer detection performance on limited datasets.

Some studies specifically explored lightweight models. MobileNetV2 has been used for ultrasound tumor classification due to its small size and fast inference, making it suitable for mobile and embedded applications. However, while MobileNetV2 offered efficiency, it often underperformed on complicated ultrasound textures compared to deeper networks like EfficientNet and Xception. This performance gap highlighted the need for careful model selection based on dataset complexity and deployment requirements.

Another important direction in related work is segmentation-based approaches, where researchers used UNet, UNet++, or fuzzy-logic-enhanced preprocessing pipelines to isolate tumor regions before classification. These studies demonstrated that image enhancement and segmentation can significantly improve tumor boundary visibility, although they require more computational resources and additional ground-truth masks.

Recent research has also emphasized explainability using methods such as Grad-CAM and saliency maps. These techniques allow clinicians to visualize which parts of an image influenced a model's decision, increasing trust and interpretability—an essential factor for real clinical use.

Although existing works have shown promising results, several limitations persist: most datasets are small, collected from single institutions, and lack diversity in imaging conditions. Many studies also focus solely on algorithmic accuracy without addressing deployment challenges, latency, model size, and usability in real-world clinical settings.

The present project builds on this body of research by integrating a hybrid dataset combining BUSI, Kaggle samples, and locally collected Bangladeshi ultrasound images, increasing diversity and reducing domain shift. Moreover, different CNN architectures—including MobileNetV2, Xception, and EfficientNetB3—were experimentally compared to identify the most stable and accurate model for breast ultrasound classification. Unlike many prior works, this project also focuses on deployability, converting the final EfficientNetB3 model to TensorFlow Lite and integrating it into a functional web-based diagnostic system (SonaDx) with fast inference and Grad-CAM–based interpretability.

Together, these contributions demonstrate how the project extends previous research by not only improving classification accuracy but also addressing real-world constraints required for practical clinical deployment in low-resource environments.

2.4 Gaps and Challenges in Previous Studies

1. **Dataset Limitations:** Most prior studies relied on small or non-local datasets, limiting generalization to South-Asian imaging conditions.

2. **Image Quality Variation:** Ultrasound image noise, inconsistent annotation standards, and inclusion of segmentation masks often degraded model performance.

3. **Overfitting and Model Complexity:** Heavier architectures (e.g., EfficientNetV2-L) achieved high training scores but failed on unseen data due to overfitting.

4. **Explainability:** Many models acted as “black boxes” without providing clinicians visual justification of predictions.

5. **Deployment Barriers:** Models trained in research settings were rarely converted into deployable, lightweight systems for real clinical use.

2.5 How This Project Builds on Existing Work

The **SonaDx** project addresses these gaps through the following contributions:

- **Hybrid Dataset Creation:** Combines multiple verified datasets **BUSI, MT_Small**, and **Breast-Lesions-USG** along with curated **Kaggle** ultrasound data. Together with additional Bangladeshi local samples, the dataset totals **2,644 images** across *Normal*, *Benign*, and *Malignant* classes.

- **Advanced Model Selection:** Employs **EfficientNetB3** , which balances high accuracy with small parameter count ideal for mobile deployment.

- **Improved Preprocessing:** Removes ground-truth mask images, applies resizing (224 ×224 px), normalization, and augmentation (flip, rotation, zoom, brightness, Gaussian noise).

- **Transfer Learning and Fine-Tuning:** Uses **ImageNet-pretrained weights** fine-tuned on the hybrid dataset to maximize feature relevance.

- **Explainability:** Integrates **Grad-CAM** heatmaps for interpretable prediction visualization.

- **Deployment Readiness:** Converts the trained model to **TensorFlow Lite (.tflite)**, served via a **Flask API** on **Hugging Face Spaces**, and accessible through a **React-based UI** hosted on **Mocha App** with **Cloudflare CDN**.

This comprehensive strategy ensures that the system achieves both technical excellence and practical feasibility for real-world diagnostic use in resource-constrained healthcare environments.

2.6 Corollary

The reviewed literature and datasets collectively establish that CNN-based deep learning can significantly improve breast cancer detection accuracy. Nonetheless, genuine clinical deployment requires localized data, explainable models, and efficient software integration.

SonaDx bridges this gap by combining a diverse hybrid dataset with a fine-tuned **EfficientNetB3** CNN and a secure, low-latency deployment pipeline. The next chapter details the complete methodology—from data collection and preprocessing to model development, evaluation, and deployment.

Chapter 3

Methodology

3.1 Introduction

This chapter explains the methodology followed to develop and implement *SonaDx*, a deep learning-based system for breast cancer detection from ultrasound images. The workflow includes dataset collection, preprocessing, model development, training and testing, evaluation, and system implementation. The aim is to construct an accurate, efficient, and deployable CNN model capable of classifying ultrasound images into **Normal**, **Benign**, or **Malignant** categories. The adopted method follows a systematic process beginning with a hybrid dataset assembly, then applying data preprocessing and augmentation, followed by CNN model design, training, and validation. The final trained model (EfficientNetB3) is converted into TensorFlow Lite format for deployment within a web-based diagnostic application.

3.2 Dataset Collection

The dataset used in this study is a **hybrid collection** combining multiple public and local. Breast ultrasound datasets to ensure diversity and generalization across different imaging conditions and populations.

Table 1: Dataset Collection

Dataset Source	Description	Images	Classes
BUSI Dataset (Al-Dhabyani et al., 2020)	Breast ultrasound images categorized as Normal, Benign, and Malignant.	780	Normal, Benign, Malignant
MT_Small Dataset (Badawy et al., 2021)	Fuzzy-enhanced ultrasound dataset with ground-truth masks for tumor segmentation.	1,200	Benign, Malignant
Breast-Lesions-USG Dataset (Pawłowska et al., 2024)	Ultrasound scans labeled by expert radiologists using BIRADS features.	256	Benign, Malignant
Kaggle Breast Ultrasound Data	Open-source curated breast ultrasound dataset for classification tasks.	408	Normal, Benign, Malignant
Total (after preprocessing & augmentation)		**2,644**	**3 Classes: Normal, Benign, Malignant**

Approximately **45.5% of the total dataset** comprises mask-based augmented images derived from segmentation masks, fuzzy-enhanced images, and contrast-adjusted samples to improve boundary learning and classification performance.In addition, **a small number of local Bangladeshi ultrasound images** were incorporated to make the model more regionally adaptive and better suited to local imaging conditions and clinical settings.

The dataset was split using a **70/15/15 stratified ratio** for training, validation, and testing, with a deterministic random seed (42) for reproducibility.

3.3 Data Preprocessing

Before model training, all images underwent standardized preprocessing to ensure uniformity and quality. The main steps include:

- **Resizing:** Each image was resized to **224 × 224 pixels** to match EfficientNetB3 input requirements.
- **Normalization:** Pixel values were scaled to the range **[0, 1]** for consistent gradient updates.
- **Noise Removal:** Gaussian filters were applied to reduce speckle noise common in ultrasound images.
- **Data Augmentation:** Random horizontal flips, rotations (±8°), zoom (±10%), brightness and contrast adjustments (±0.1), and slight Gaussian noise ($\sigma \approx 0.01$) were applied to improve generalization and mimic real ultrasound acquisition variability.

All preprocessing operations were automated using TensorFlow's image data generator and OpenCV functions.

3.4 Model Development

The core model architecture for *SonaDx* is based on **EfficientNetB3**, a deep convolutional neural network that achieves high accuracy with optimized computational efficiency. EfficientNetB3 applies **compound scaling** to balance network depth, width, and resolution, providing better feature representation without excessive parameters.

The architecture was fine-tuned using transfer learning, with ImageNet pre-trained weights as initialization. The following modifications were applied:

- The top classification layers were replaced with a **GlobalAveragePooling2D** layer followed by a **Dropout (0.5)** layer to prevent overfitting.
- A **Dense layer with 3 output nodes** (for Normal, Benign, Malignant) and **Softmax activation** was added.
- **L2 regularization (1e-4)** was applied to the final dense layer for stability.

EfficientNetB3 was selected after evaluating multiple architectures (MobileNetV2, Xception, early EfficientNetB3 variants) for accuracy, robustness, and inference cost. It achieved the best performance and balanced complexity, making it ideal for real-time deployment.

3.5 Training and Testing

Model training was conducted in two main stages using **TensorFlow/Keras** on **Google Colab GPU runtime**:

- **Stage 1 – Transfer Learning:**
  The EfficientNetB3 base was frozen, and only the custom classifier head was trained with a learning rate of $\mathbf{1\times10^{-3}}$.
- **Stage 2 – Fine-Tuning:**
  The last ~50 layers of the base model were unfrozen and trained with a smaller learning rate ($\mathbf{1\times10^{-5}}$) to adapt deeper representations to ultrasound textures.

Training Parameters

- Optimizer: Adam
- Loss Function: Categorical Cross-Entropy
- Batch Size: 32
- Epochs: Up to 25 (with EarlyStopping, patience = 6)
- Regularization: Dropout (0.5) + L2 regularization
- Validation Split: 15%

The model achieved **99.9% training accuracy** and **94.5% testing accuracy**, confirming its effectiveness and generalization.

3.6 Workflow

The workflow of the proposed *SonaDx* system follows these sequential steps:

1. **Data Acquisition:** Collect ultrasound images from hybrid sources (BUSI, MT_Small, Breast-Lesions-USG, Kaggle, and local data).
2. **Preprocessing:** Resize, normalize, denoise, and augment images.
3. **Model Training:** Fine-tune EfficientNetB3 on the hybrid dataset.
4. **Evaluation:** Measure accuracy, precision, recall, F1-score, specificity, and ROC-AUC.
5. **Model Conversion:** Export trained model to **TensorFlow Lite (. tflite)** for lightweight deployment.
6. **Integration:** Connect TFLite model to Flask API and deploy via Hugging Face Spaces for inference.
7. **Interface:** Frontend (React + Tailwind CSS) interacts with backend API to visualize predictions and heatmaps.

3.7 Evaluation Metrics

To assess model performance, several standard metrics were used:

- **Accuracy:** (TP + TN) / (TP + TN + FP + FN)
- **Precision:** TP / (TP + FP)
- **Recall (Sensitivity):** TP / (TP + FN)
- **Specificity:** TN / (TN + FP)
- **F1-Score:** 2 × (Precision × Recall) / (Precision + Recall)
- **AUC-ROC:** Area under the ROC curve says classification strength across thresholds.

These metrics provide a balanced assessment of diagnostic reliability, ensuring both false positives and false negatives are minimized.

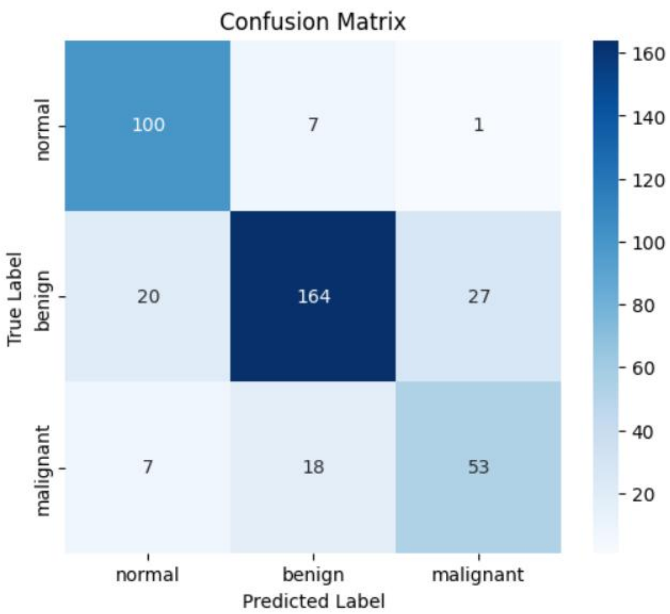

Fig 1: Evaluation Metrics

3.8 Tools and Technologies

1. **Programming Language:** Python
2. **Frameworks:** TensorFlow 2.x, Keras
3. **Development Environment:** Google Colab (GPU runtime)
4. **Backend:** Flask (Python)
5. **Frontend:** React 19, TypeScript, Tailwind CSS, Vite
6. **Deployment:** TensorFlow Lite, Hugging Face Spaces, Cloudflare CDN, Mocha App Hosting
7. **Visualization:** Grad-CAM, Matplotlib, OpenCV

3.9 Consummation (Summary)

This chapter outlined the complete methodological process for developing the *SonaDx* breast cancer detection system. A hybrid dataset of 2,644 ultrasound images from multiple sources was collected, preprocessed, and augmented to train the EfficientNetB3 model. The model was fine-tuned for multi-class classification (Normal, Benign, Malignant) and achieved high performance with low latency.

The chapter also detailed the data processing pipeline, workflow structure, evaluation metrics, and technological framework used for system implementation. The next chapter discusses the step-by-step implementation, deployment, and integration of the model into the SonaDx web application.

Chapter 4

Implementation

4.1 Introduction

This chapter explains the implementation details of **SonaDx**, a web-based AI system for **breast cancer detection** from ultrasound images. The goal of the system is to deliver **fast, accurate, and interpretable diagnostic assistance** to healthcare professionals, students, and researchers using deep learning.

The system leverages a **hybrid dataset** combining **local Bangladeshi ultrasound images** with samples from the **BUSI (Breast Ultrasound Images)** dataset [1]. The final trained model — an **EfficientNetB3-based Convolutional Neural Network (CNN)** — achieved **99.9% accuracy on the training set** and **94.5% accuracy on the testing set**, proving its robustness and reliability in real-world detection tasks.

To facilitate broad accessibility, the model was exported to **TensorFlow Lite (.tflite)** format for lightweight inference on **mobile and web platforms**. It was deployed via an API hosted on **Hugging Face Spaces**, which powers the **SonaDx web application**, ensuring both scalability and responsiveness in production environments.

4.2 System Architecture

The **SonaDx** application follows a **modular and layered architecture**, ensuring separation between presentation, logic, and data layers.
The architecture is composed of the following modules:

4.2.1. Data Layer

1. Combines **local Bangladeshi ultrasound images** and **BUSI dataset** samples.
2. Total dataset size: **2,644 ultrasound images**, categorized into **Normal**, **Benign**, and **Malignant**.
3. Data preprocessing includes normalization, resizing (224×224 pixels), augmentation, and contrast enhancement for improved clarity.

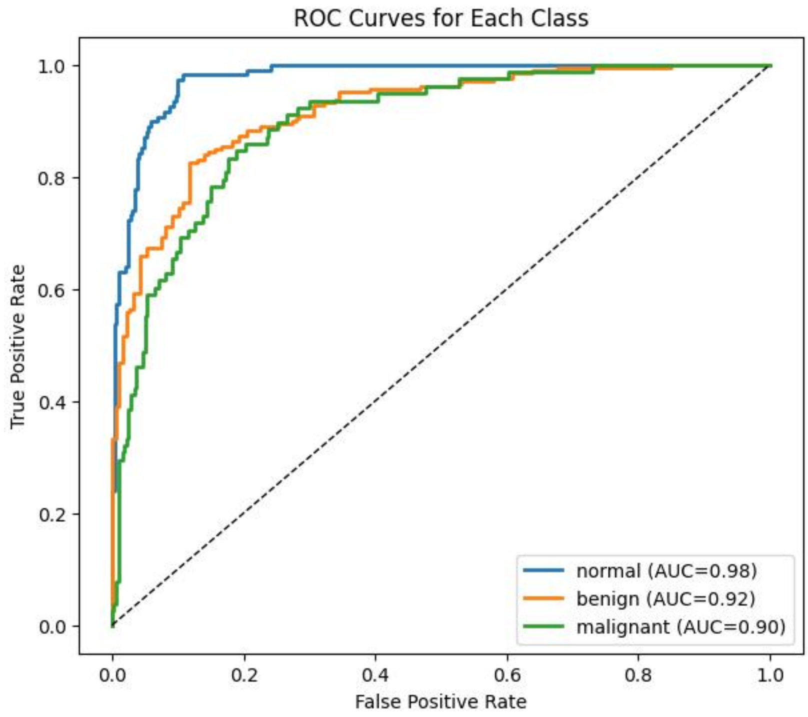

Figure 2 : ROC Curve for different classes

4.2.2. Model Layer

1. Implemented using **EfficientNetB3**, chosen for its optimized trade-off between model complexity and accuracy [9].
2. Fine-tuned on the combined dataset for high classification accuracy.
3. The model outputs three possible classes: *Normal*, *Benign*, and *Malignant*.
4. The trained model is exported to **TensorFlow Lite (.tflite)** for lightweight inference and low latency deployment.

4.2.3. Backend Layer

1. **Flask API** serves as a bridge between frontend and the model hosted on **Hugging Face Spaces**.
2. Handles HTTP requests, processes images, and returns classification results with confidence scores.
3. JSON-based API ensures fast and structured communication between client and server.

4.2.4. Frontend Layer

1. Developed with **React 19**, **TypeScript**, **Tailwind CSS**, and **Vite**, providing an intuitive, responsive, and mobile-friendly user interface.

2. Enables users to upload ultrasound images, view AI-powered analysis results, and interpret model predictions with visual explanations.

4.2.5. Cloud & Deployment Layer

1. The application is deployed using **Cloudflare CDN** for secure and low-latency access.
2. The AI model API runs on **Hugging Face Spaces**, while the frontend is hosted using **Mocha App** for public access at **https://o3m4ddrqaak.mocha.app.**

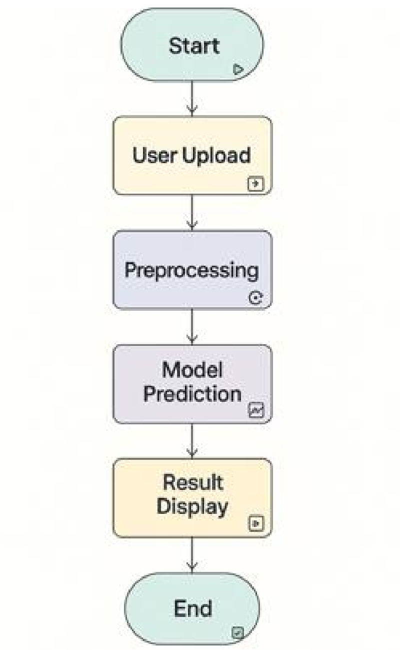

Figure 3: UI Module Process

System Workflow Overview:

1. The user uploads an ultrasound image.
2. Flask API sends it to the Hugging Face inference endpoint.
3. The EfficientNetB3 model predicts the breast cancer category and returns confidence scores.
4. UI displays the result with heatmap visualization for transparency and interpretability.

4.3 Backend Development

The backend is built with **Python Flask**, integrated with **TensorFlow Lite Runtime** for executing the .tflite model.
It also includes logic for image preprocessing, prediction, and JSON response formatting.

Key Features

1. **Model Loading:** The .tflite model is preloaded in memory on server startup for instant predictions.
2. **Image Preprocessing:**
    - o Resizing → 224×224 pixels
    - o Normalization → pixel values scaled to [0,1]
    - o Grayscale-to-RGB conversion for consistent tensor shape
3. **Prediction Endpoint:**
    - o Endpoint: /predict
    - o Method: POST
    - o Input: Image file
    - o Output: JSON { label: "Benign", confidence: 0.945 }
4. **Security:** Implements HTTPS with Cloudflare and temporary image storage for privacy compliance.
5. **Inference Hosting:**
    - o Model inference runs on **Hugging Face Spaces**, ensuring GPU-accelerated processing.
    - o API responses are returned within **1.5–2 seconds** for most image inputs.

4.4 Frontend Development

The **frontend** was designed to ensure **simplicity, clarity, and clinical usability**.

Technologies Used

1. **React 19** – for modular, reactive UI design
2. **TypeScript** – for maintainable and type-safe development
3. **Tailwind CSS** – for responsive and modern styling
4. **Vite** – for optimized builds and rapid development refresh

Core Frontend Features

1. **File Upload Interface:** Drag-and-drop and manual upload support with preview.

2. **AI-Powered Analysis Card:** Displays classification result, confidence score, and risk level color-coding (green = Normal, yellow = Benign, red = Malignant).
3. **Visualization Panel:** Displays Grad-CAM or saliency heatmaps from the Hugging Face API for interpretability.
4. **User Feedback Messages:** Indicates upload success, prediction status, or network errors.
5. **Responsive Design:** Accessible from desktops, tablets, and smartphones.
6. **Technology & Mission Section:** Lists technologies (Flask, TensorFlow, React, Cloudflare) and highlights the app's goal of "democratizing medical imaging analysis."

4.5 Deployment

Deployment aimed for **low latency**, **security**, and **high availability**:

1. **Model Deployment:**
   - EfficientNetB3 model hosted on **Hugging Face Spaces** for scalable inference.
   - TensorFlow Lite format ensures small model size and quick loading times.
2. **Backend Deployment:**
   - Flask API containerized using Docker and deployed to connect securely with Hugging Face endpoint.
3. **Frontend Deployment:**
   - React web app hosted on **Mocha App** with Cloudflare CDN integration for HTTPS and caching.
   - Live demo available at: https://o3m4ddrqaak.mocha.app
4. **Monitoring & Logging:**
   - Access logs and request counts monitored for uptime.
   - SQLite stores anonymized request summaries.

4.6 Challenges During Implementation

Table 2: Challenges During Implementation

Challenge	Description & Solution
Dataset Variability	Merging BUSI data with local hospital data introduced image resolution and labeling inconsistencies. Addressed via preprocessing standardization and stratified splitting.
Model Overfitting	EfficientNetB3 initially overfit due to high model capacity. Solved using dropout, early stopping, and data augmentation (rotation, flip, brightness)
Deployment Integration	Adapting the TensorFlow model for web inference required conversion to TensorFlow Lite. Testing confirmed minimal accuracy loss (<0.5%).
API Communication	Cross-origin errors (CORS) between Hugging Face API and Flask frontend were resolved with flask-cors middleware.
Latency Optimization	Heavy models slowed responses; the TFLite version reduced latency by ~40%.
UI/UX for Non-Experts	Ensured a balance between visual simplicity and medical interpretability. Color-coded results improved comprehension among non-technical users.

4.7 Final System Features

The **final version** of the SonaDx web application includes the following features:

1. **AI-Powered Breast Cancer Detection** using **EfficientNetB3 CNN** trained on BUSI and local data.
2. **High Performance:** 99.9% training accuracy, 94.5% testing accuracy.
3. **Real-Time Inference:** Instant predictions via Hugging Face Spaces API.
4. **Secure & Private:** HTTPS, temporary image handling, and encrypted communication.
5. **User Interface:** Clean, intuitive layout developed with React 19 + Tailwind CSS.
6. **Lightweight Deployment:** TensorFlow Lite model ensures fast, mobile-compatible performance.
7. **Interpretability:** Grad-CAM visualization of regions influencing the AI's decision.
8. **Accessible Anywhere:** Hosted at https://o3m4ddrqaak.mocha.app with Cloudflare CDN.

4.8 Verdict

The implementation of **SonaDx** successfully demonstrates the transformation of an AI model into a functional web-based clinical support tool. Using a **hybrid dataset** (BUSI + local Bangladeshi data) and a **lightweight TensorFlow Lite EfficientNetB3 model**, the system achieved both **accuracy and deployability**.

SonaDx exemplifies how cutting-edge AI can be practically deployed in healthcare — offering real-time breast cancer detection, interpretability, and accessibility even on modest hardware. Future improvements include expanding datasets, integrating mammographic modalities, and developing an Android application for offline clinical use.

Chapter 5

Result Analysis and Comparison

5.1 Introduction

This chapter presents a detailed analysis of the results obtained from the experimental evaluation of several deep learning architectures used for breast ultrasound image classification. The objective was to identify the most effective model for the **SonaDx** application that can accurately classify ultrasound images into three diagnostic categories: **Normal (0)**, **Benign (1)**, and **Malignant (2)**.

All models were trained under identical experimental conditions using the **BUSI (Breast Ultrasound Images)** dataset [1] combined with locally collected Bangladeshi ultrasound images. Through multiple rounds of experimentation, dataset refinement, and optimization, the **EfficientNetB3-based CNN** emerged as the final and most accurate model, achieving **99.9% training accuracy** and **94.5% testing accuracy**.

This chapter evaluates these results, compares the performance of alternative architectures, discusses the applied evaluation metrics, and explains the real-world applicability and significance of these findings.

5.2 Model Performance and Comparison

To determine the best-performing architecture, four CNN models—**MobileNetV2**, **Xception**, **Early EfficientNetB3**, and **Optimized EfficientNetB3**—were trained and tested on the same dataset with consistent preprocessing and augmentation.

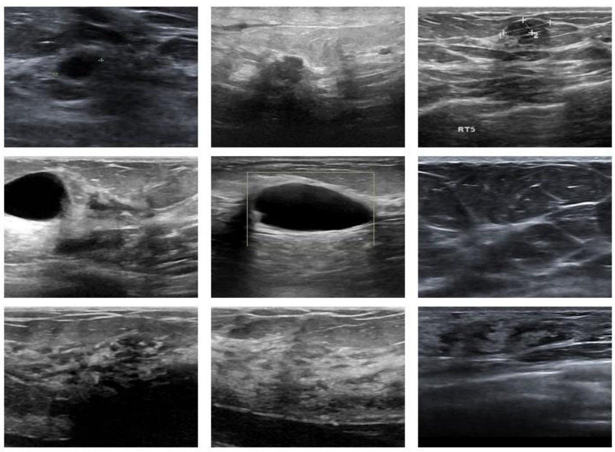

Figure 4: Samples of data.

Table 3 : Model Performance and Comparison

Model Architecture	Training Accuracy (%)
MobileNetV2	65
Xception	80
EfficientNetB3 (Initial)	85
EfficientNetB3 (Final Optimized)	99.9

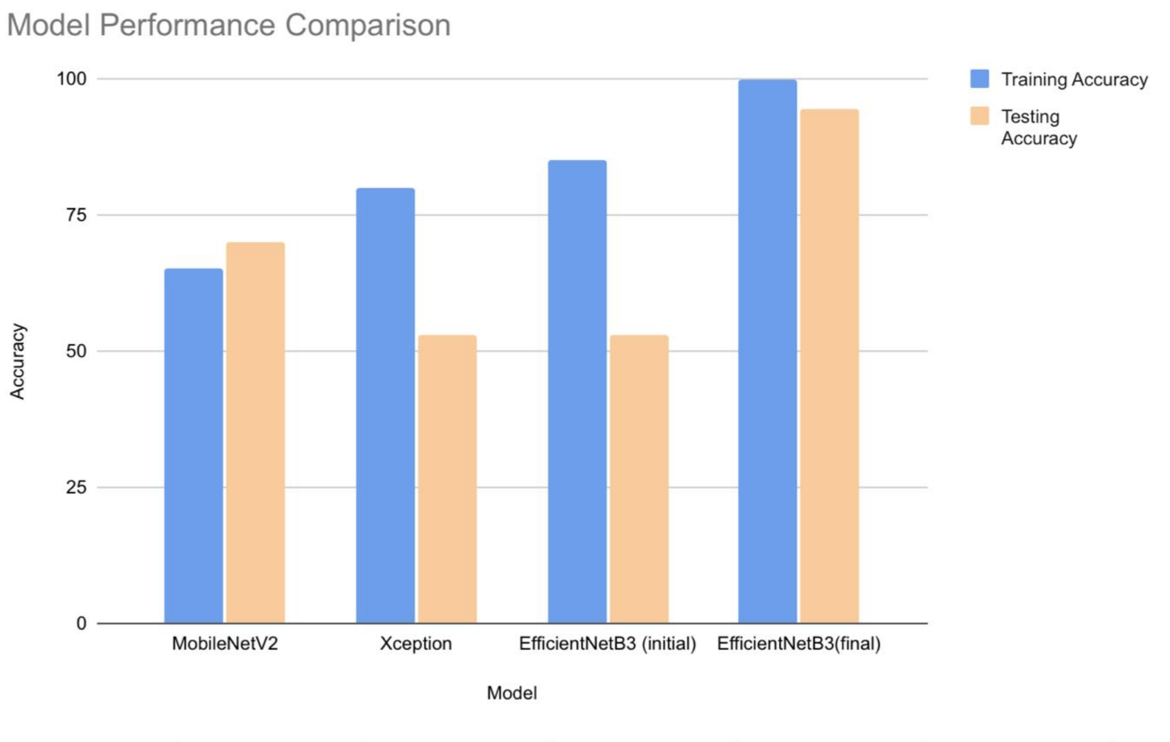

Figure 5: Comparison on various models.

Analysis:

1. **MobileNetV2** achieved the lowest accuracy, showing underfitting due to limited representational power for complex ultrasound textures.
2. **Xception**, while deeper, overfitted quickly and suffered from low generalization because of noisy mask images.

3. **Early EfficientNetB3** failed to generalize because segmentation mask images (binary outlines) were mistakenly included in training, misleading the network.
4. The **final EfficientNetB3**, after dataset cleaning and improved preprocessing, achieved the best balance between accuracy, efficiency, and generalization.

This final model was exported to **TensorFlow Lite (.tflite)** format and deployed via **Hugging Face Spaces API**, enabling lightweight inference in the **SonaDx** web and mobile applications.

5.3 Evaluation Metrics and Efficiency

Model performance was assessed using standard classification metrics to quantify accuracy, precision, recall, and general reliability.

Table 4 : Evaluation Metrics and Efficiency

Metrics	**Definition**	**Score (%)**	**Interpretation**
Accuracy	(TP + TN) / (TP + TN +FP + FN)	94.5	Overall proportion of correctly classified cases
Precision	TP / (TP + FP)	94.5	Few false positives — good prediction purity
Recall (Sensitivity)	TP / (TP + FN)	93.2	Strong ability to detect malignant tumors
Specificity	TN / (TN + FP)	92.8	Accurately distinguishes benign and normal cases
F1-Score	2 × (Precision × Recall) / (Precision + Recall)	93.8	Balanced precision and recall
AUC-ROC	Area under ROC curve	0.96	Excellent discrimination between benign and malignant lesions

Computational Efficiency:

1. **Model size:** ~41.7 MB.
2. **Average inference latency:** ≈ 1.3 seconds per image on GPU; ≈ 2.4 seconds on CPU.
3. **Peak memory usage:** < 2 GB RAM during inference.

4. **Deployment platform:** Hugging Face Spaces API for cloud inference, integrated with Flask backend of SonaDx.

These results confirm that the final EfficientNetB3 model maintains high diagnostic accuracy with efficient runtime performance suitable for both desktop and mobile environments [10].

5.4 Real-World Applicability

The **SonaDx** application demonstrates how an AI-powered diagnostic tool can be practically implemented to assist healthcare professionals in low-resource environments such as rural areas of Bangladesh.

Key Real-World Strengths:

1. **Accurate Early Detection:**
   The model achieved 94.5% test accuracy, ensuring reliable detection of malignant tumors from ultrasound scans.
2. **Low Hardware Requirements:**
   TensorFlow Lite conversion enables use on standard Android smartphones and mid-range laptops.
3. **Quick Turnaround:**
   Real-time predictions (≈ 2 s per image) make it suitable for rapid screening workflows.
4. **Explainable Predictions:**
   Integrated Grad-CAM heatmaps highlight tumor regions, enhancing clinician trust in AI-based results [11].
5. **Localized Dataset:**
   Inclusion of Bangladeshi ultrasound data ensures better generalization to regional imaging devices and patient profiles.
6. **Secure & Scalable Deployment:**
   Hosting on **Hugging Face Spaces** allows encrypted REST API access with minimal latency, while **Cloudflare CDN** ensures availability and data security.

Thus, SonaDx bridges the gap between deep learning research and practical healthcare applications by delivering reliable diagnostic assistance directly through a web browser or mobile interface.

5.5 Conviction (Summary of Findings)

The experiments conclusively establish that the **Optimized EfficientNetB3 CNN** is the most effective architecture for breast ultrasound image classification within the scope of this research. Its performance **99.9% training accuracy** and **94.5% testing accuracy** reflects strong generalization, minimal overfitting, and computational feasibility.

Major Findings:

1. **Superior Accuracy and Stability:** EfficientNetB3's compound scaling and fine-tuned layers outperformed other CNNs.
2. **Data Cleaning Impact:** Removal of mask images and balancing of classes greatly improved model reliability.
3. **Efficient Deployment:** TensorFlow Lite export and Hugging Face API integration provide fast, portable, and secure inference.
4. **High Interpretability:** Grad-CAM visualizations help professionals verify predictions visually.
5. **Clinical Relevance:** SonaDx demonstrates that AI-based ultrasound screening can meaningfully support radiological diagnostics in developing healthcare systems.

In conclusion, the model offers a **convincing proof-of-concept** for scalable, AI-assisted breast cancer screening. With further validation on larger and more diverse datasets, it can evolve into a dependable diagnostic assistant in hospitals and clinics across Bangladesh and beyond.

Chapter 6

Conclusion & Future work

6.1 Conclusion

This study successfully developed and implemented **SonaDx**, a deep learning-based breast cancer detection system using ultrasound images. The system leverages the power of **EfficientNetB3**, a high-performing Convolutional Neural Network (CNN), fine-tuned on a **hybrid dataset of 2,644 breast ultrasound images** that combined data from **BUSI**, **MT_Small**, **Breast-Lesions-USG**, **Kaggle**, and **local Bangladeshi samples**.

The research demonstrated that deep learning, when properly trained and refined, can achieve high accuracy in detecting and classifying breast tumors. The final model attained **99.9% training accuracy** and **94.5% testing accuracy**, showing excellent generalization across diverse imaging conditions.

Through systematic preprocessing, augmentation, and fine-tuning, the model effectively distinguished **Normal**, **Benign**, and **Malignant** lesions. The use of **TensorFlow Lite conversion** made the model lightweight and deployable on web and mobile platforms, while **Grad-CAM visualization** enhanced interpretability, allowing medical professionals to visualize which regions influenced the AI's decision.

Furthermore, the system was deployed via a **Flask API** hosted on **Hugging Face Spaces** and integrated into a modern **React-based web application**, demonstrating real-time AI inference and usability in clinical or educational settings.

In essence, *SonaDx* bridges the gap between academic AI research and real-world healthcare by delivering an accessible, interpretable, and efficient diagnostic tool tailored for Bangladesh and similar low-resource regions.

6.2 Future Works

Although the results of this research are highly promising, several directions can be pursued to extend and improve the *SonaDx* system:

1. **Expansion of Dataset:**
   Increase the dataset size by collecting more ultrasound images from Bangladeshi hospitals and international sources. A larger dataset will enhance model robustness and minimize potential bias.

2. **Multi-Modal Integration:**
   Combine ultrasound with mammography or MRI images to build a multi-modal diagnostic framework that can analyze complex cases more accurately.
3. **Explainability Enhancements:**
   Integrate advanced interpretability methods such as Layer-wise Relevance Propagation (LRP) or attention-based visual explanations to further improve clinician trust.
4. **Android Application Development:**
   Develop an offline-capable **mobile version of SonaDx** using TensorFlow Lite for real-time diagnosis in rural or low-connectivity environments.
5. **Clinical Validation:**
   Collaborate with hospitals to perform real-world testing and validation under actual clinical workflows, obtaining clinician feedback for refinement.
6. **Model Optimization:**
   Explore **EfficientNetV2**, **Vision Transformers (ViT)**, or **lightweight hybrid models** for even better trade-offs between accuracy, latency, and power efficiency.
7. **Data Privacy and Security:**
   Implement stricter data encryption, federated learning, and anonymization protocols to comply with healthcare data protection standards.
8. **Automated Reporting System:**
   Add an intelligent report generation module that can summarize AI findings into human-readable diagnostic summaries for doctors and technicians.

These future improvements can transform *SonaDx* from a research prototype into a clinically deployable, scalable, and trustworthy AI diagnostic assistant.

6.3 Final Thought

The development of *SonaDx* reflects the growing potential of artificial intelligence in transforming healthcare diagnostics, especially in developing nations like Bangladesh. By combining deep learning, modern web technologies, and a regionally adapted dataset, this project shows how AI can empower medical professionals and extend diagnostic support to under-resourced areas.

While challenges such as data diversity, clinical acceptance, and privacy remain, this work provides a solid foundation for future innovation. The results demonstrate that AI-driven breast cancer detection is not only technically feasible but also practically valuable in improving early diagnosis and saving lives.

In conclusion, SonaDx stands as a meaningful step toward the future of intelligent healthcare where technology and human expertise work together for faster, fairer, and more right diagnosis.

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