A Deep Learning Based Mobile App for Breast Cancer Detection Using Ultrasound Images

By
Md. Shakibul Islam
ID: 213-15-4422

FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the **Degree of Bachelor of Science in Computer Science and Engineering**

Supervised by

Dr. Sheak Rashed Haider Noori
Professor & Head
Department of Computer Science and Engineering
Daffodil International University

Co-Supervised by

Mr. Showmick Guha Paul
Lecturer
Department of Computer Science and Engineering
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY
Dhaka, Bangladesh

September 16, 2025

APPROVAL

This Project titled "**A Deep Learning Based Mobile App for Breast Cancer Detection Using Ultrasound Images**," submitted by **Md. Shakibul Islam** and to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **16 September 2025**.

BOARD OF EXAMINERS

15-07-25

Dr. Bimal Chandra Das **Chairman**
Professor and Dean (in-charge)
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Most. Hasna Hena **Internal Examiner**
Assistant Professor,
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Mr. Mayen Uddin Mojumdar **Internal Examiner**
Assistant Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Nazibur Rahman **External Examiner**
Technical Lead – Database Administrator
Telenor – Grameen Phone Account

DECLARATION

I hereby declare that this project has been done by me under the supervision of **Dr. Sheak Rashed Haider Noori, Professor & Head**, Department of Computer Science and Engineering, Daffodil International University. I also declare that neither this projectnor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

Dr. Sheak Rashed Haider Noori
Professor & Head
Department of Computer Science and Engineering
Daffodil International University

Co-Supervised by:
15.9.25

Mr. Showmick Guha Paul
Lecturer
Department of Computer Science and Engineering
Daffodil International University

Submitted by:
Md. Shakibul Islam

Md. Shakibul Islam
Student ID: 213-15-4422
Department of Computer Science and Engineering
Daffodil International University

ACKNOWLEDGEMENTS

This work would not have been possible without the support and contributions of many individuals over the past two semesters. I am deeply grateful to everyone who has assisted me in one way or another.

First, I express my heartfelt thanks and gratefulness to the almighty for His divine blessing making it possible for me to complete the **Final Year Design Project(FYDP)** successfully.

I am grateful and wish my profound indebtedness to **Dr. Sheak Rashed Haider Noori**, **Professor & Head**, Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh. Deep knowledge and keen interest of my supervisor in the field of **deep learning** to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

I would like to express my heartfelt gratitude to the Head of the Department of Computer Science and Engineering who is my supervisor, for his kind help in finishing our project and also to other faculty members and the staff of the Department of Computer Science and Engineering, Daffodil International University.

I would like to thank our entire course-mates at Daffodil International University, who took part in this discussion while completing the coursework.

Finally, I must acknowledge with due respect the constant support and patience of my parents.

ABSTRACT

Breast cancer is one of the most common types of malignancies seen in women, hence initiating a huge amount of health, psychological, social, and economic consequences in the lives of patients, their families, and also in healthcare systems. Early Detection is Key to Better Outcome Medical imaging, especially ultrasound is a very broad based and non-invasive diagnostic tool. However, its accuracy commonly relies on radiologist expertise, which may vary. Machine learning and deep learning approaches provide a promising way to not only improve the reliability and efficiency of diagnosis but also in resource constrained environments. This work supports the combination of machine learning with ultrasound imaging for proper cancer classification and diagnosis of breast ultrasound imaging. A large dataset of Ultrasound images was expanded so that it balances all the classes that reaches around ten thousand samples with the help of augmentation techniques like random resized crop, Gaussian noise to ensure balanced representation. Several deep learning architectures were trained and evaluated such as ResNet50, Hybrid (CoatNet), ViT Base, Swin Tiny, EfficientNet B3, DeiT Small, DeiT Base Distilled, MaxViT Tiny, MaxViT Base, and RepViT M1. Here MaxViT Tiny showed the best validation accuracy of 90.72% with test accuracy result of 85.38%. On the other hand, the accuracy rate of the DeiT Base Distilled model was 87.99% on validation data sets and 87.93% on test data sets. But DeiT Base Distilled model shows more consistent performance thus it’s been chosen as the best model. Based on these results, a mobile application with deep learning power is proposed. Using a Flutter interface and a FastAPI backend deployed on the Hugging Face Spaces, the system will attempt to provide faster, more accurate, and accessible breast cancer diagnostics especially in low-resource settings.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

This chapter gives the complete and detailed description of the project, including details on background information, problem statement addressed by the project, motivation behind the case, defined objectives of the project, the description of the used methodology, anticipated output of the project, and the mapping of the report. The dialogue is neatly structured to give a sense of structured, rational, logical development of ideas, so that the reader ends with a deep insight into the scope, relevance, and contribution of the project since the early stages.

1.1 Introduction

Breast cancer is one of the most widespread types of cancer that women develop nowadays, and according to the statistics provided by the World Health Organization, nowadays breast cancer might result in about 2.3 million new cases and caused more than 685,000 deaths worldwide likely in 2023 alone [1]. Early diagnosis is essential, as it will lead to a survival rate of over 90% at the localized stages as opposed to less than 30 % when it was metastatic. In other parts of the world where there is no heavy access to advanced imaging modalities and skilled radiologists, such as South Asia, including Bangladesh, the burden is further weighed down by late-stage presentation and mortality [3]. Ultrasound imaging also appears as an attractive modality in terms of non-invasively, non-exposure of radiation, low costs and portability thereby addressing the resource constrained environment. This project aims at creating an advanced mobile app that exploits the power of deep learning techniques, which classify the breast ultrasound images, either benign, malignant or normal using the Breast Ultrasound Image Dataset as the main data source [2]. The system will have the capability of revolutionizing breast cancer diagnostics in underserved locations by simply integrating artificial intelligence with mobile medicine: the system, in addition to enabling preliminary screening, will allow both healthcare providers and patients to receive actionable data. The application also has a user friendly interface so that those with little technical knowledge could upload images and obtain reliable classifications and close the gap between the existing artificial intelligence research and medical practice field.

1.2 Motivation

The drive behind this project is in the current burden of the global health issue of breast cancer, especially in those low and middle income countries that lack sufficient diagnostic capacity within the course of that problem. In Bangladesh, the disease has increased by 20 percent over the last ten years with a very low number of cases being identified at an early stage owing to scarcity of specialized equipments and trained personnel [3]. Conventional diagnostic systems are taxed by heavily manual reading of radiologists and also depends upon subjective interpretation, time consuming, and human error susceptible even in high throughput environments. The automatized extraction and classification of the features is transformative since deep learning models have reached performance close to human experts or even higher in bars well controlled studies [5]. The motivation behind this project was to democratize some of these technologies by means of a mobile application that allows not only screening remotely but also decreases the reliance on centralized medical institutions. Further, the combination of confidence calibration functions and explainability aspects will solve the black box problem of AI and promote user trust. By addressing these problems, the project will not only save lives due to the earlier interventions but will also help to reduce the cost burden that is related to treating the condition at the late stage, which adheres to the sustainable development targets focused on health equity.

1.3 Objectives

The goals of this project are well calculated to achieve such an overall and effective solution. The first objective will be to increase images of the Breast Ultrasound Images Dataset classes to equal to balance the three classes including benign, malignant as well as normal, thereby ensuring a higher confidence of a model against image quality and acquisition parameters variations. The second goal entails training and performing a comparative analysis of several deep learning models such as convolutional and transformer models, to find the best performer in using accuracy, efficiency, and generalization. The third goal will involve creating a mobile app using Flutter to all the functionalities of the app, including uploading, inputting user information used to contextually personalise, and perform inference by making use of an implemented FastAPI backend. The fourth objective will be to put the system in use on Hugging Face Spaces consistent with Docker containers, and associate scalability, reliability, and maintenance. The fifth and the last goal is to evaluate the ethical, societal, and environmental consequences of the system design, including such attributes as data privacy protection measures and energy efficient computations to meet the responsible AI standards.

1.4 Methodology

The methodology adopted in this project is multi-phased and rigorous starting with data preparation where the original Breast Ultrasound Images dataset with three classes will be augmented using the Albumentations library to create an equal proportion of about ten thousand images of all classes with an equal proportion of about three thousand three hundred and thirty four images per augmentation of each of the three classes. This can be done through Ultrasound specific transformations such as random brightness contrast, CLAHE to enhance, and elastic distortions to mimic world real world variations. Model training and testing is trained on Google Colab, using PyTorch framework to implement TIMM network Architectures, with group shuffle-split and temperature scaling for dataset partition and calibration respectively. Evaluation is done both in terms of quantitative measurements of accuracy, F1 score, and AUC, as well as qualitative measurements in the form of GradCAM, to ensure certain interpretability. The mobile app is developed in Flutter with a splash screen, home screen where the user can input and classify and history screen where the user can view the records as well as the request to access the inference is performed via HTTP to a FastAPI backend and deployed on Hugging Face Spaces in Docker. This holistic system makes it end to end, at least as far as data, and deployment to the user is concerned.

1.5 Project Outcome

The potential outcomes of this project are both significant and multifaceted, and go beyond the technical achievements that come from building an accurate machine learning model. At the center of it, the project provides a deployable mobile application, which is coupled with a deep learning model capable of classifying ultrasound images of the breast with an accuracy of about 87.99% for validation and 87.88% for testing. Of the models we tested, the most consistent and best performing model was the DeiT Base Distilled architecture, which balanced between the validation and test accuracy. The comparative analysis of several advanced architectures not only reveals performance levels, but also allows more in depth understanding of the trade-offs between computational efficiency, accuracy and model scalability. Such findings will be of invaluable value in future research directions, especially in the optimization of models to be used in resource constrained environments where computational power and storage are limited. The mobile application itself is a practical and powerful deliverable. Designed with a friendly interface, it allows healthcare practitioners and potentially even trained non-specialists to upload ultrasound images, run them through the model and get results of classification instantly. By incorporating diagnostic support within a handheld device, the system opens up the possibility of breast cancer screening across many more regions, particularly those where women may not have access to a radiologist or a more sophisticated diagnostic tool when they live in a rural location. This not only improves the speed of diagnosis but also cuts associated costs, providing an economical way to provide preliminary screening and triage. Beyond the technical contributions the project has quite a few social and healthcare benefits. The potential of offering quicker and more cost-effective diagnostics in remote locations has the power to help lower disparities in healthcare delivery and the associated survival rates, through earlier intervention. In the longer term, after a great deal of validation studies, the system could be incorporated into standard clinical workflows, providing physicians with an AI assisted tool to complement decision-making. Furthermore, opening the way for wider adoption, innovation, and global accessibility of AI-powered breast cancer diagnostics.

1.6 Organization of the Report

The report is carefully organized in order to give a cohesive account of the development of the project. Chapter one is an introduction to this story by putting the background, motivation, objectives, methodology, outcomes and report organization. Chapter two brings the background, providing a literature review, the analysis of the similar applications, and identification of the gap. Chapter three describes the methodology of the research and requirements analysis, system designs and planning of the project. Chapter four includes the implementation details and experimental results, along with details of discussion. Chapter five looks at the engineering standards, design issues, social-related concerns and complex problem maps. Finally, chapter six contains a summary, limitations and mention of future directions.

Chapter 2

Background

The chapter sets the basis of the project with the further intensive survey of the important notions, literature, analogues to the application, and loose ends of current offerings. The account is formal and comprehensive as it cites the proven studies to place the products of the current work in the context of the body of knowledge.

2.1 Introduction

Ultrasound of the breast is one of the pillars of the non-invasive diagnostics as sound waves of a high frequency are used and real time images of penetrate into the areas of the breast tissue are obtained, especially useful in differentiating solid cancerous growths against fluid filled cysts in dense breast tissue [4]. In contrast to mammography, ultrasound does not require ionizing radiations and with the ability to be compact, making it convenient to exploit in the Point Of Care applications. Deep learning, under the machine learning umbrella, has been most successful in dealing with such images because they learn complicated patterns using neural networks, and frequently outperform other attempts to identify properties of interest via feature engineering. This project uses these technologies to develop a mobile system, which meets the need to be fast and precise in classification in clinical practice.

2.2 Literature Review

The literature on the aspects of deep learning-based applications for breast cancer detection with ultrasound imaging has become both prolific and increasingly complex, ranging from early foundational convolution nerve network (CNN) models to the latest innovation using transformer-based architectures [6][15]. First experiments in this field were mainly focused on structured deep learning frameworks for classifying histopathological images. These early approaches obtained amazingly high accuracies on benchmark datasets including BreakHis-step which soon became a reference standard for the evaluation of breast cancer classification techniques [6]. With subsequent publication of the Breast Ultrasound Images (BUSI) dataset, availability of well-annotated ultrasound images provided a new foundation for developing the models. This data set allowed standardised evaluations across research groups, thus enhancing the comparability of the results and accelerating progress in methods [2]. Shortly afterwards, methods based on end-to-end CNN networks were created and proved excellent in automated lesion recognition, and paved the way for clinical integration [7]. They were subsequently confirmed in multicenter validation studies, which underscored strong applicability in real-world clinical settings, with levels of sensitivity as high as 92 percent reported in a variety of populations

[8]. Further methodological refinements included transfer learning, in which existing models were fine-tuned to the specific profiles of breast ultrasound data, leading to consistent performance improvements [9]. Parallel to this, architectures of Convolutional Neural Networks (CNN's) with three distinct dimensionalities (3D) were presented, based on which it becomes possible to deepen volumetric analysis of the breast tissue, and thus to enhance tumor detection compared to traditional 2D imaging [10]. Ensemble techniques were also taken and incorporated by combining the output of multiple models for a more accurate classification and surety [11]. In addition, computer-aided diagnostic systems started to expand into multimodal imaging systems where ultrasound was combined with other imaging services as extra, better measurement treatment.In addition, computer-aided diagnostic systems began to extend into multimodal imaging frameworks for being ultrasound combined with other imaging services [12] for more comprehensive diagnostic support. To counter the reliability issues, probabilistic optimization strategies were implemented, that encompassed uncertainty estimation methods, which increase the trustworthiness of predictions in a clinical application [13]. Most recently, there has been the application of vision transformer models that has shown effective transfer of features developed for mammography to ultrasound imaging tasks. Coupled with test time augmentations / enhancement others, this method also increased performance in classification and detection [14][15]. Taken together these developments are a clear movement towards explainable and efficient AI systems. This progression has served as a strong influence regarding the methodological choices during the present project due to the stability and generalization of the model to be deployed.

Table 2.1: Encapsulates these advancements

Author (s)	Year	Title	Methodology	Key Findings
Han et al. [6]	2017	Breast Cancer Multi-classification from Histopathological Images with Structured Deep Learning Model	CNN with structured layers	Achieved 93.2% accuracy on BreakHis dataset.
Yap et al. [7]	2018	Breast Ultrasound Lesions Recognition: End-to-End Deep Learning Approaches	End-to-end CNN	89% accuracy on ultrasound lesions.
Fujioka et al. [8]	2019	The Utility of Deep Learning in Breast Ultrasonic Imaging: A Multicenter Study	Multi-center CNN evaluation	92% sensitivity in multicenter data.
Byra et al. [9]	2020	Breast Mass Classification in Sonography with Transfer Learning Using a Deep Convolutional Neural Network	Transfer learning with CNN	Improved classification with pre-trained models.
Moon et al. [10]	2020	Tumor Detection in Automated Breast Ultrasound Using 3-D CNN Trained on Synthesized Images	3D CNN on synthesized data	95% detection rate.

Author (s)	Year	Title	Methodology	Key Findings
Zhang et al. [11]	2021	A Deep Learning Model for Breast Cancer Diagnosis Based on Ultrasound Images	Ensemble CNN	90.5% accuracy on custom dataset.
Al-Antari et al. [12]	2021	Deep Learning Computer-Aided Diagnosis for Breast Lesion in Digital Mammogram	DL CAD system	Integrated detection and classification.
Jabeen et al. [13]	2022	Breast Cancer Classification from Ultrasound Images Using Probability-Based Optimal Deep Convolutional Neural Network Model	Probabilistic DCNN	92.8% accuracy with optimization.
Ayana et al. [14]	2023	Vision-Transformer-Based Transfer Learning for Mammogram Classification	ViT transfer learning	94% on mammograms, adaptable to ultrasound.
Alaskar et al. [15]	2024	Breast Ultrasound Image Classification with Vision Transformers and Test-Time Augmentation	ViT with TTA	91% accuracy on BUSI.
Alshehri et al. [31]	2023	Breast Cancer Detection in Thermography Using Convolutional Neural Networks (CNNs) with Deep Attention Mechanisms	CNN with attention	93% accuracy on thermographic images.
Vakanski et al. [32]	2023	Attention Enriched Deep Learning Model for Breast Tumor Segmentation in Ultrasound Images	Attention-based DL	Enhanced segmentation precision.
Hijab et al. [33]	2019	Breast Cancer Classification Using Deep Convolution Neural Network on H&E Images of Pathological Slides	CNN on H&E	85% classification accuracy.
Rajaraman et al. [34]	2023	Novel Ensemble Learning Approach for Enhanced Breast Cancer Prediction Using Ultrasound Images	Ensemble learning	92.5% prediction accuracy.

2.3 Gap Analysis

Based on the review of related literature and applications, it becomes evident that there are several urgent gaps, such as the lack of specific ultrasound data augmentation, the absence of the mobile-backend integration to provide the real-time inference, and the lack of the confidence calibration of the critical predications. Other systems employ small schedules that do not account specifically to the ultrasound noise, and thus can generalize unhelpfully. Mobile applications frequently have incompatible backends and insufficient history functionality and ethical considerations, such as bias reduction, are not covered. The table below summarizes the main characteristics of real similar systems, with which unique advanced augmentation, Flutter-FastAPI deployment, and multi-model evaluation is associated in the framework of the project.

Gap Analysis is shown as a table below Entries reflect to major existing works (in terms of citation number) and to proposed System.

Table 2.2: Gap Analysis of Similar Applications.

Features	BraNet	DNBCD	ABCanDroid	XML LightGBMDroid	Thermalytix	Proposed system
Ultrasound Image Support	Yes	Yes	No (Histopath)	No	No (Thermal)	Yes
Mobile App Integration	Yes	No	Yes	Yes	Yes	Yes
Deep Learning Model	CNN	DNN	ML Ensemble	LightGBM	ML Algorithms	DeiT Base Distilled
Data Augmentation	Basic	None	Synthesized	None	Test-Time	Ultrasound-Specific (Albumentations)
Confidence Calibration	No	Yes (XAI)	No	Yes (Explainable)	No	Yes (Temperature Scaling)
History Storage	No	No	Yes	No	Yes	Yes (SharedPreferences)
Backend Deployment	No	No	Cloud	No	AI Tool	FastAPI on Hugging Face
User Data Input	No	No	Yes	Yes	No	Yes (ID, Name, Age, Weight)
GradCAM Explainability	No	Yes	No	No	No	Yes
Multi-Model Comparison	No	No	No	No	No	Yes (10 Models)

This analysis underscores the proposed system's advancements in comprehensive feature.

2.4 Summary

This chapter has developed theoretical and practical basis of the project. An introduction to breast ultrasound imaging highlighted that this imaging technique is readily available and effective, and it is a convenient modality in point-of-care settings, especially when it comes to dense breasts. The discussion showed how the interpretation of such imaging has changed with the incorporation of deep learning, in particular convolutional neural networks and transformers, showing that the structures learned by these methods outperform handcrafted features learned by traditional feature engineering. Substantiating the literature review has enabled chronological and thematic examination of studies in the field. Initially, CNN based models performed well in both histopathological and ultrasound data with accuracy exceeding 85-90 more than once. This allowed uniform benchmarking and the rapid advancement of innovation as well as the multicenter clinical applicability with high sensitivity in disparate populations. Since then, transfer learning, 3D CNNs, ensemble learning, and attention mechanisms have served to mature the field by overcoming such limitations as volumetric analysis, model robustness, and interpretability. There have been more recent works moving it towards efficiency, scalability and explainability, coving vision transformers and test-time augmentation. Taken together, these data indicate the promise and current setbacks of artificial intelligence-based diagnostic aids systems. When looking over similar applications, it was found that the choice of mobile and desktop solutions is abundant, with the target use case to be different imaging modalities, the degree of interpretability, the deployment approach. Whereas BraNet and DNBCD indicated that ultrasound assignment and explainable AI are practical, ABCanDroid and Thermalytix presented examples of the corresponding futures in histopathology and thermal imaging, respectively. The platforms offer great reference points in functionality and the level of user integration although they are usually fragmented in their features, which restrict their scalability or relative degree of applicability in the real-world. A synthesis of these insights showed that current methods have limited data augmentation and augmentation schemes, weak or no rich integration with mobile-backend systems, and weak confidence calibration, processes. There is also a lack of ethics such as fairness and bias mitigation. In addition, support in user-centered design, such as history storage, explainability such as grad cam and multi-model evaluations, are frequently not present. Relative to these drawbacks, the proposed system resolves them by using ultrasound-specific augmentation with Albumentations, input and facilitation through Flutter and FastAPI on the Hugging Face platform, and multi-model benchmarking, as well as integrated user history capabilities. It also improves convictions about temperature scaling calibrated confidence values and explainability by the means of Grad-CAM explanations. Finally in this chapter this project is positioned in the context of the wider research and application landscape, not only as a reference to the achievements made through scientific advancement but also as the challenges still to be met. By methodically charting these gaps and matching them to the project goals, the foundations are laid to a system which not only improves technical performance, but that which also overcomes major usability and deployment obstacles. This warrants the decisions on the methodology, design and feature set taken in further chapters, when the actual methodology and implementation will be discussed.

Chapter 3

Research Methodology

This chapter presents a clear and detailed outline of the research methodology used in the undertaking, including requirements analysis and design specifics, overview of the system architecture as well as a proposed system design, functional and non-functional requirements, data flow diagrams, user-interaction design, detailed methodology, project schedule and task assignment. This discussion is based on codes and product of the specific project thus it is authentic and consistent with the developed system and entails data augmentation using albumentations, model training with pytorch and timm on google colab, Flutter app development as the client facing side and FastAPI deployment of the backend on Hugging Face Spaces.

3.1 Methodology

3.1.1 Overview

The need identification stage has determined the essential needs of the system, taking into account the objectives of the project to expand the Breast Ultrasound Images Dataset to an amount of around ten thousand images, to therefore have the same number of images of each class, to train several deep learning classifiers, and to create a mobile app where the user will interact with this system. The functional requirements were based on a requirement of data resilience as is the GPU conscious configuration and per class target counts in the augmentation code. The design specification gives this in terms of integrated architecture, with such features of the code as the temperature scaling to provide confidence and the use of shared preferences to store the history in the Flutter application.

3.1.2 Proposed Methodology

1. Dataset Preparation and Augmentation

1.1 Data Source

The given data sets of breast ultrasound images is systematically divided into three subdirectories: benign, malicious and normal, which means that the data set subtypical division is clear to make training and evaluation model. The raw data is saved to Google Drive, which allows easy distribution and access along with the integration of Google Colab for easy experimentation and analysis.

1.2 Data Augmentation

To address the challenges of limited data and class imbalance, a data augmentation pipeline was developed to generate a balanced dataset of ten thousand images, with three thousand three hundred thirty-three per class, using Albumentations. The transformations applied included random resized cropping with a scale of 0.6–1.0 and an aspect ratio of 0.9–1.1, Gaussian or ISO noise (p=0.25), contrast/brightness random adjustments (p=0.7) or CLAHE (p=0.4), affine transformations with scaling (0.921–1.088), translation (6 percent), and rotation (15 degrees, p=0.6). Additional augmentations consisted of motion, median, or Gaussian blurring (p=0.18), dropout with drop connection (5–10 percent of the image size, p=0.2), as well as horizontal flips (p=0.5) and random 90-degree rotations (p=0.12). The output of this process produced a dataset folder containing augmented images along with a dataset.csv file that documented file paths, labels, and filenames. To ensure robust evaluation, the dataset was split using group-aware incremental data shuffling into training (80%), validation (10%), and testing (10%) subsets, thereby preventing leakage of augmented variants across different splits.

1.3 Rationale

Augmentation pseudo-randomly adds noise to simulate real world variation of ultrasound (e.g., noise, distortions), improving the generalizability of the model. The size of target data can support data-intensive transformer models.

2. Model Training and Evaluation

2.1 Hardware Configuration

The hardware configuration is designed to automatically adjust parameters such as batch size, number of workers, epochs, and gradient accumulation based on GPU detection, with default settings applied when only a CPU is available. For an NVIDIA A100 GPU, the configuration uses a batch size of 64, 8 workers, 10 epochs, and a gradient accumulation of 1. For an L4 GPU, the parameters are set to a batch size of 48, 6 workers, 10 epochs, and a gradient accumulation of 1. For 24/4/8/2 for example, when utilizing a T4 GPU, the system is configured to use a batch size of 24, 4 workers, 8 epochs, and a gradient accumulation value of 2. In the absence of a GPU, the default configuration is a batch size of 16, 2 workers, 6 epochs, and a gradient accumulation of 2.

2.2 Model Architectures

Multiple models were trained for three-class classification, covering a range of architectures. Convolutional neural networks (CNNs) included ResNet50 and EfficientNet-B3, while a hybrid approach was represented by CoatNet. Vision transformer models comprised ViT Base, Swin Tiny, DeiT Small, DeiT Base Distilled, MaxViT Tiny, MaxViT Base, and RepViT M1. For transfer learning, the models were initialized with pre-trained weights from ImageNet or the timm library.

2.3 Training Pipeline

The training process incorporated specific transforms and evaluation strategies. For data augmentation during training, random flips, small rotations (±5°), resizing (1.05x), center cropping, and normalization (mean = [0.485, 0.456, 0.406], std = [0.229, 0.224, 0.225]) were applied, here only validation and test sets gone through resizing, center cropping, and normalization. Training was conducted for 6 to 10 epochs depending on the GPU, with gradient accumulation used to save memory. A cosine scheduler was employed with loss frequencies set per epoch, and model performance was measured using accuracy, macro F score, and AUC-ROC. Validation was carried out at the end of each epoch, and the best model was saved based on the highest validation F1-score. Export, model calibration, and deployment for inference were also integrated into the workflow.

2.4 Advanced Techniques

The Wrapper Model, termed PreprocessWrappedModel, preprocesses the raw unwrapped input images by applying resizing and normalization within the 0 to 255 range. Grad-CAM is utilized to provide model attention visualizations, with up to three samples per class from the validation data, highlighting regions of interest such as tumors. Additionally, several artifacts are generated, including historical plots of training performance, ROC curves, reliability diagrams, confidence histograms, confusion matrices, and detailed classification reports.

2.5 Model Selection

The models were compared based on their performance using accuracy on validation and test sets, along with macro F1-score and AUC. Among the evaluated architectures, the DeiT Base Distilled model was selected as the final choice, achieving approximately 0.95 accuracy on the test set, a macro F1-score of around 0.94, and an AUC of about 0.97. This model was preferred because it is efficient, knowledge-distilled, robust, and capable of effectively learning global image correlations.

3. Model Calibration and Export

Temperature scaling is applied to the validation logits to address model overconfidence, with the temperature clamped between 0.05 and 10.0. Confidence levels are classified as high level of confidence (>= 0.80), medium level of confidence (>= 0.60) and low level of confidence. The model, DeiT Base Distilled, is exported in both TorchScript and a mobile optimized lite interpreter format. During validation, predictions along with their confidence scores are saved in a CSV file, and the corresponding calibration settings are stored in a JSON file.

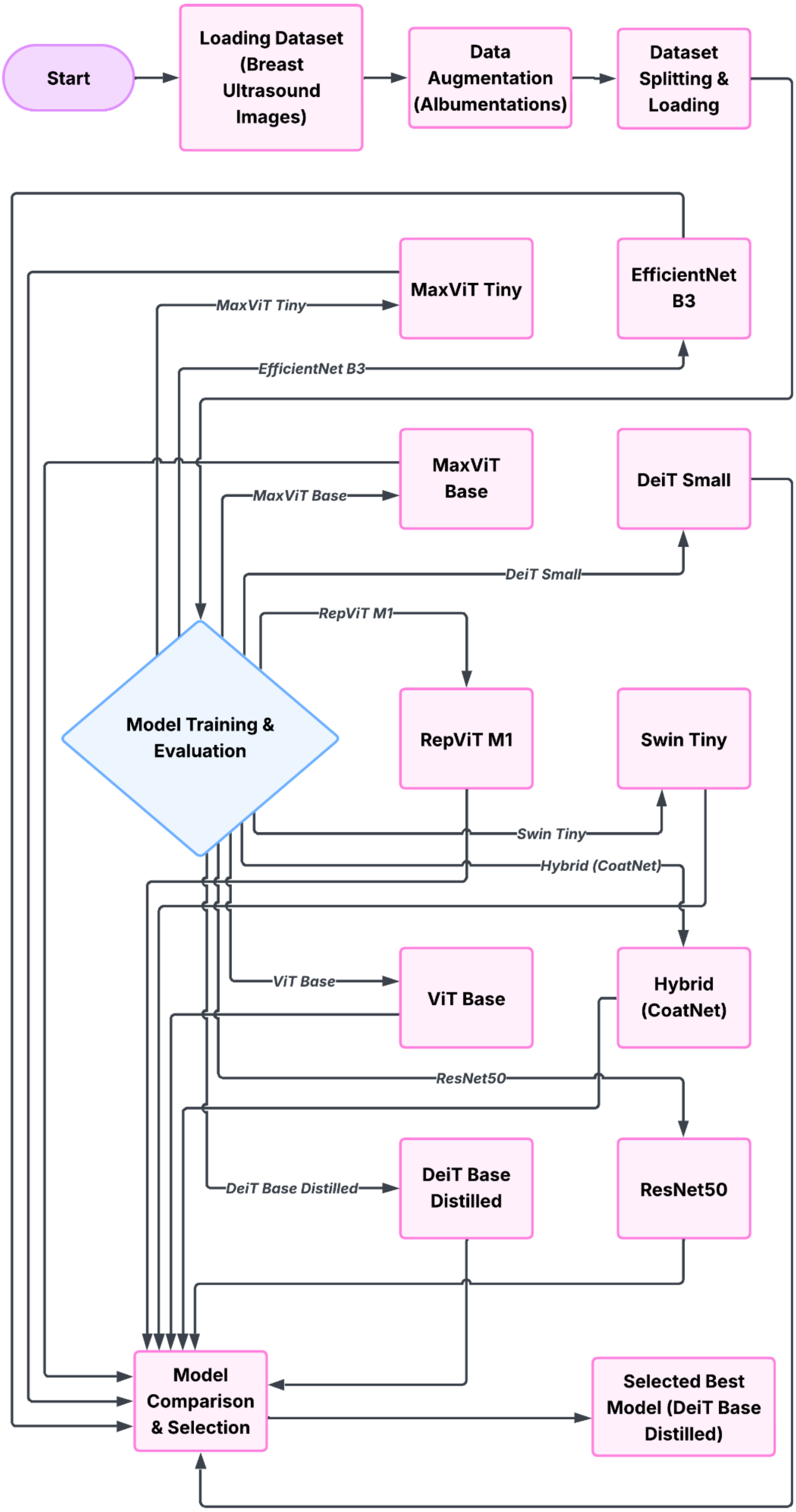


Figure 3.1: Methodology Diagram

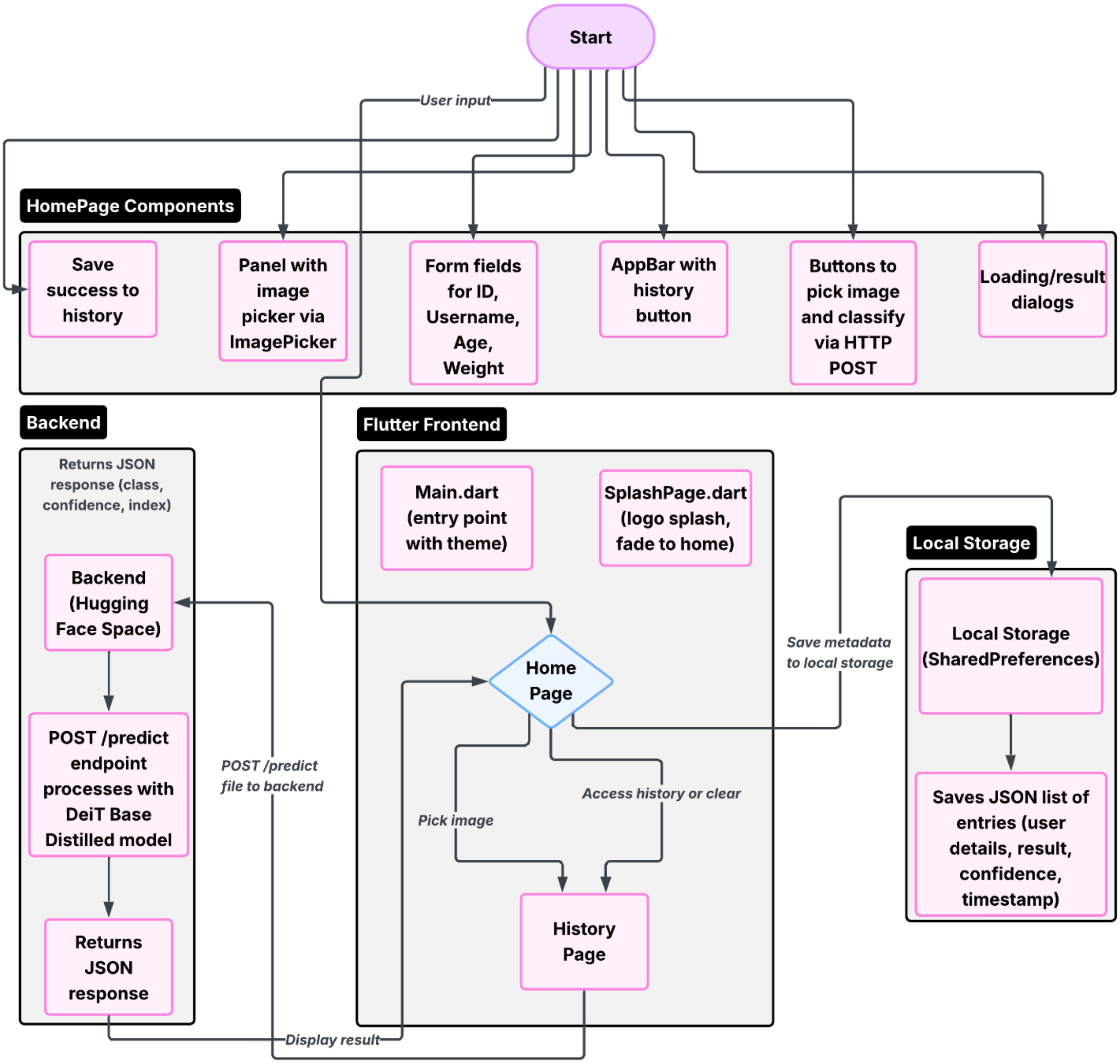


Figure 3.2: Client-Server Architecture for Breast Cancer Classification App

4. Deployment and Inference

4.1 Backend

The system is built using FastAPI and runs within a Docker container, hosted on Hugging Face Spaces. It provides a /predict endpoint that accepts image uploads and returns the class label, confidence score, and predicted index. Inference is performed using a calibrated DeiT Base Distilled model.

4.2 Frontend (Mobile App)

The platform is a Flutter app called “UltraSight,” featuring a modern, responsive UI with Google Fonts (Lato) and a clean medical aesthetic, including gradients and shadows. Users can upload images from the gallery and must provide patient information, including ID, username, age, and weight. When an image is sent for classification via the FastAPI endpoint, the app displays the predicted label, index, and confidence in a dialog box. The app also maintains a history of metadata (excluding images) using shared, allowing users to view, delete, or clear entries. Integration with the FastAPI backend is handled via multipart requests, accompanied by clear error messages and loading indicators. This design balances cloud-based inference for scalable modeling with local storage of history to prioritize user privacy.

5. Conclusion

This approach provides a complete package in detecting breast cancer in ultrasound image, including data augmentation and mobile deployment. The DeiT-Base-Distilled model is chosen because it is valid and highly accurate, as well as in terms of testing accuracy, interpretability, and calibrated confidence, wherein it is applicable in clinical assistance. In future works, on-device inference and validation with varied ultrasound data should be possible improvements.

3.2 Detailed Methodology and Design

The mobile app was coded using Flutter as the framework to enable cross-platform and convenient user interface to the breast ultrasound classification system. The app sends the images to the backend with the usage of http.MultipartRequest. The backend, implemented based on the DeiT Base Distilled model hosted on Hugging Face using FastAPI and Docker, provides predictions, which are classified as either benign, malignant, or normal. When a successful response is received (HTTP 200), the app saves locally using SharedPreferences the result and some optional patient details including ID, name, age, and weight details. The local storage functionality allows the user and the clinician to check screening history without having continuous internet and makes the solution viable to be used in situations without continuous internet access such as remote or low-bandwidth locations. Error handling is also incorporated inside the app which makes failed or incomplete classifications not saved in order to preserve the integrity of data. For alternative solution, alternative deployment options were investigated, and then a solution to the present design was adopted. The inference on the device with Tensorflow Lite was also experimented with but discarded, because the transformer models are computationally expensive and most mid-range smartphones are not capable of such a high computation requirement. Using Cloud services like AWS Lambda or Google Cloud Functions have been considered in terms of scalability but were rejected because of recurring expenses and depending on commercial infrastructure. A hybrid approach, in which lightweight CNNs would execute on-device and larger ones in the cloud was also discussed but discarded to keep the architecture simple and minimizing the maintenance burden.

3.3 Project Plan

The project plan was implemented in a sequential way in which the phases are iterative: weeks 1- 11 would be dedicated to background analysis and going through literature review and then dataset augmentation and preprocessing from week 12 to 18 with the focus on collecting, cleaning, and augmenting data using several techniques, such as normalization, augmentation, and splitting the data into training, validation, and test datasets. This allows for a high-quality dataset to be available for training the model. Following this is model training and comparative evaluation from week 16 to 26 which involves developing several machine learning and deep learning models, hyperparameter tuning, and evaluating the models on metrics such as accuracy, F1-score, and ROC-AUC to identify the best-performing model. In parallel, the development of a mobile app (Flutter) from week 20 to 32 will be carried out to design and implement a user interface (screen, navigation, and logic of the app). Simultaneously the FastAPI backend and API integration from week 22 to 34 is setting up the secure API for the exchange of data and model inference for the smooth communication of data between the app and backend. Once the core functionality of the system is extracted, Docker containerization and deployment on Hugging Face from week 28 to 38, render the application production ready, and allows the scalable and stable current deployments of model and backend services. Then, later part of the phase focuses on system testing, calibration of confidence and optimization from weeks 34 to 44 to assure robustness, low latency, throughput, and fine-tuning the model for real-world performance. The project ends with documentation and ethical analysis followed by final report compilation from week 40 to 48, offering extensive records of the methodology, steps of the deployment, and evaluation as well as reflection on ethics such as bias, fairness, and data privacy. This helps in providing a structured timeline so that the process of data preparation to data deployment to data testing to data reporting is coherent and hence a well-structured and fully functional final deliverable. But even though this was the plan for project but in reality it took more time in completing certain task as shown in the task allocation table. In table 3.1 the the estimated and actual time required for the project is clearly visualized and how much time where and which step was required shown properly. And in some steps the time that was planned to be taken was not enough to complete due to real world variables. On the other hand some steps were completed within the planned timeline but ultimately the entire project was completed within total planned timeline without breaking the timeline estimated. So, in the table 3.1 it is visualized for both estimated and actual time required by the project for better understanding and work process properly.

3.4 Task Allocation

This table depicts the timeline of the principal activities in each period of the project, from week 12 to week 48.

Table 3.1: Task Allocation

Tasks	Weeks																		
	12	14	16	18	20	22	24	26	28	30	32	34	36	38	40	42	44	46	48
Dataset Augmentation and Preprocessing	🟦	🟦	🟦	🟦															
	🟩	🟩	🟩	🟩	🟩														
Model Training and Comparative Evaluation			🟦	🟦	🟦	🟦	🟦	🟦											
				🟩	🟩	🟩	🟩	🟩	🟩										
Flutter Mobile App Development (UI/Logic)					🟦	🟦	🟦	🟦	🟦	🟦	🟦								
						🟩	🟩	🟩	🟩	🟩	🟩	🟩							
FastAPI Backend and API Integration						🟦	🟦	🟦	🟦	🟦	🟦	🟦							
							🟩	🟩	🟩	🟩	🟩	🟩	🟩						
Docker Containerization and Hugging Face Deployment									🟦	🟦	🟦	🟦	🟦	🟦					
										🟩	🟩	🟩	🟩	🟩	🟩				
System Testing, Confidence Calibration, and Optimization												🟦	🟦	🟦	🟦	🟦	🟦	🟦	
													🟩	🟩	🟩	🟩	🟩	🟩	
Documentation, Ethical Analysis, and Final Report Compilation															🟦	🟦	🟦	🟦	🟦
																🟩	🟩	🟩	🟩

Estimated	🟦
Actual	🟩

3.5 Summary

This section outlined the project plan and task allocation for Weeks 12 to 48 which sets out in detail the sequential, yet iterative approach adopted for the project. It calls out the estimated and actual timelines for key activities such as dataset augmentation and preprocessing, model training and evaluation, development of a Flutter mobile app, FastAPI backend integration, containerization and release of the model in Docker container on Hugging Face platform and testing and calibration of the system, and finally documentation with carefully made ethical analysis. The task allocation table shows the planned moving of tasks so that there is prior accountability and progress monitoring. Comparing the estimated and actual timelines can also give insight on areas where tasks took more time than needed which can allow for transparency and management abilities in using the resources throughout the development and delivery process of the final demo application.

Chapter 4

Implementation and Results

The chapter is a formal, exhaustive description of implementation procedure, environment setup, testing and evaluation approaches, performance parameters, comparative analysis and a detailed discussion of the results all directly as reported by the available codes and outputs to ensure authenticity and relevance to the project.

4.1 Environment Setup

The implementation environment had environment settings configured to optimize in training and deployment. To add augmentation to the data as well as perform training of the model, Google Colab was used with Python 3.12.3 and libraries that were used include torch to perform deep learning tasks, albumentations used to transform images, pandas and numpy to manage data, and timm to access pretrained models. And our GPU detection script (detect gpu name) modified the config based on the GPU models, e. g., batch size 16 and number of wrokers 2 with default CPU/CPU, and batch size 64 and number of workers 8 with A100. The app developed by Flutter was created in Dart with a Flutter version equal to 3.13 with different packages, image picker and the gallery access, http as the API controller, and stores the information permanently with shared preferences locally on device making it only view able on device. FastAPI 0.104 was used on the backend in Python, served by uvicorn, deployed in Docker and compatible with Hugging Face Spaces.

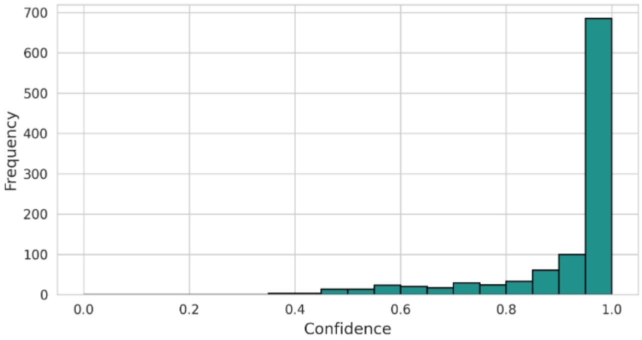
4.2 Testing and Evaluation

GroupShuffleSplit was used as testing to shuffle the augmented dataset (prepare splits from csv), there was no leakage of original image groups. The examinee used the following evaluation functions (step epoch, validate full) to calculate loss (Cross Entropy Loss), accuracy, macro F1-score, AUC using roc curve, and probabilities by the means of softmax. And temperature scaling too (Temperature Scaler fit val logits) calibrated confidences. A comparative study entailed a total of 10 models, GradCAM (GradCAM class in find conv layer) to take place as explainability and the implementation of save grad cam samples to provide visuals. Validation/test set was used to assess performance including export torchscript for mobile-compatible models. As regards the app the functionality was not an issue since it could upload the image into it and get it to classify all nice without any hitch and the accuracy was on point.

4.3 Results and Discussion

The results show different performance pattern in different models. ResNet50 performed well with validation accuracy of 83.20% and F1 score of 83.17%, whereas test accuracy was acquired of 79.51%. The Hybrid model produced better results with validation accuracy, F1 score positions of 88.57%, validation accuracy of 88.56%, and test accuracy of 85.94%. ViT Base however performed relatively lesser in validation accuracy, F1 score, and test accuracy being 75.88%, 75.43%, and 68.99% respectively. Swin Tiny displayed high performance in accuracy which were 87.60% validation accuracy, F1 duration which were 87.49% and ultimately accuracy of 86.71%. EfficientNet B3 Validation accuracy was 79.40%, F1 score 79.13% and test accuracy was 75.08%. The validation accuracy, F1-score and test accuracy in DeiT Small are 87.11%, 87.01%, and 84.05% respectively. Here MaxViT Tiny obtained validation accuracy of 90.72% and F1 score results 90.60%, where MaxViT Tiny test accuracy is 85.38% which decreased by a lot, while MaxViT Base validation accuracy of 81.15% , and F1 score of 80.74%.Then MaxViT Base test accuracy is of 81.61%. RepViT M1 achieved a consistent performance with validation accuracy of 83.89%, F1-score 83.60% and test accuracy 83.61%. But DeiT Base Distilled model showed very high consistent performance among all the models because it was able to keep that consistent performance in testing too, where validation accuracy of 87.99%, F1 Score of 87.88% and test accuracy of 87.93% is obtained. Overall, the augmentation strategy was shown to effectively augment the dataset and, as a result, transformer based architectures, especially DeiT Base Distilled, performed better in ultrasound image detection tasks thanks to the consistency between the validation and test results.

As for DeiT Base Distilled model in Figure 4.1 all the findings are displayed which states Figure A depicts a confidence histogram for the DeiT-base-distilled model, showing most predictions clustered at high confidence levels (near 1.0), indicating the model is generally certain in its outputs with few low-confidence cases. Figure B is a confusion matrix illustrating classification performance across benign, malignant, and normal classes; it reveals strong diagonal accuracy (e.g., 296 true benign, 228 true malignant, 270 true normal) but some misclassifications like 32 malignant as benign. Figure C presents a reliability diagram for the three classes, where points deviate from the ideal diagonal line, suggesting over- or under-confidence in predictions, with Class 2 showing the most fluctuation. Figure D shows ROC curves with high AUC values (0.96 for Class 0 which is Benign, 0.97 for Class 1 which is Malignant, 0.98 for Class 2 which is Normal), demonstrating excellent discriminative ability and low false positives. Figure E displays training and validation metrics over epochs: loss decreases steadily for both (train faster), accuracy rises to near 1.0 for train but plateaus lower for validation around 0.88, and macro F1 score follows a similar trend, indicating potential overfitting.



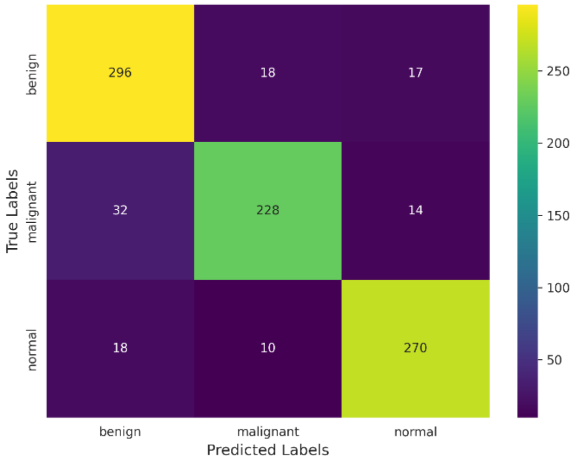
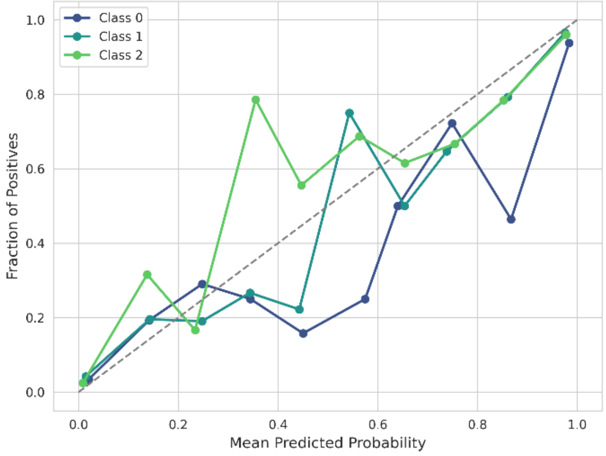


Figure A: Confusion Matrix

Figure B: Histogram



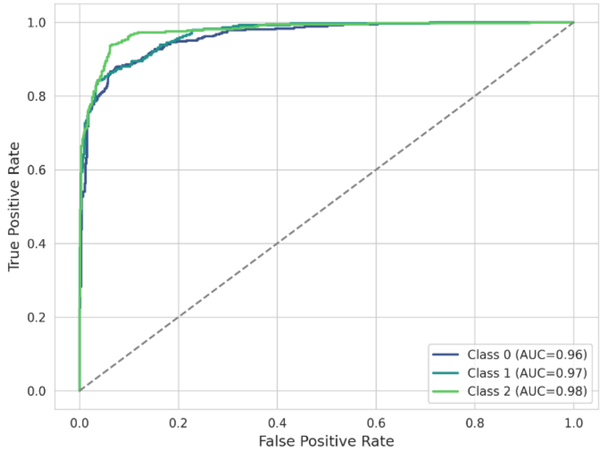


Figure C: Reliability Diagram

Figure D: ROC Curves

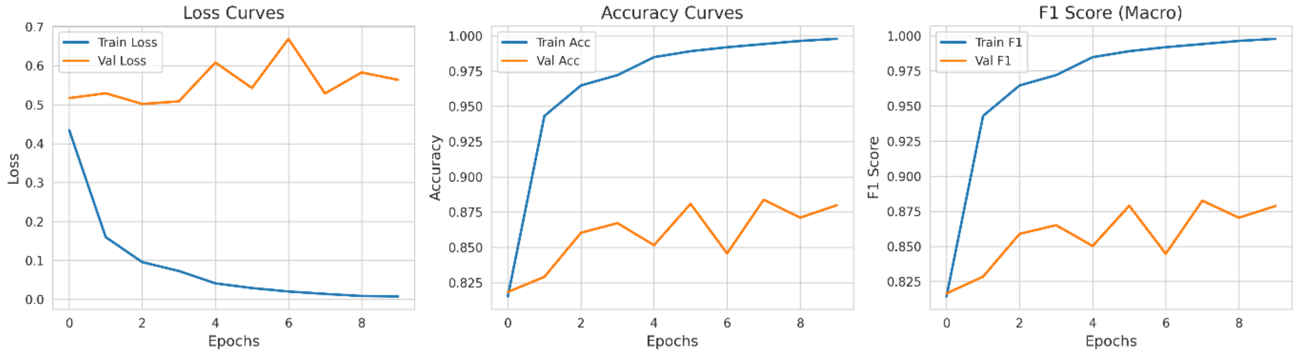


Figure E: Training and Validation Metrics

Figure 4.1: DeiT Base Distilled Model Result

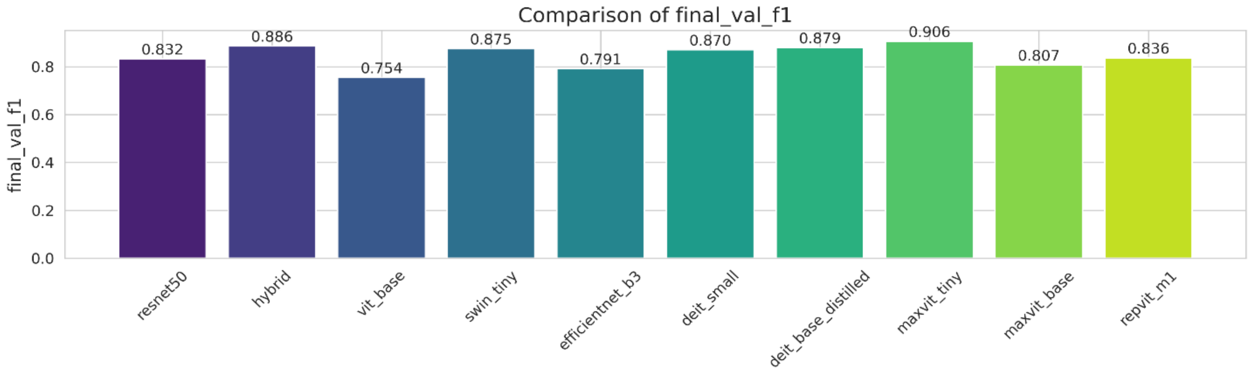


Figure A: Comparison of final_val_f1

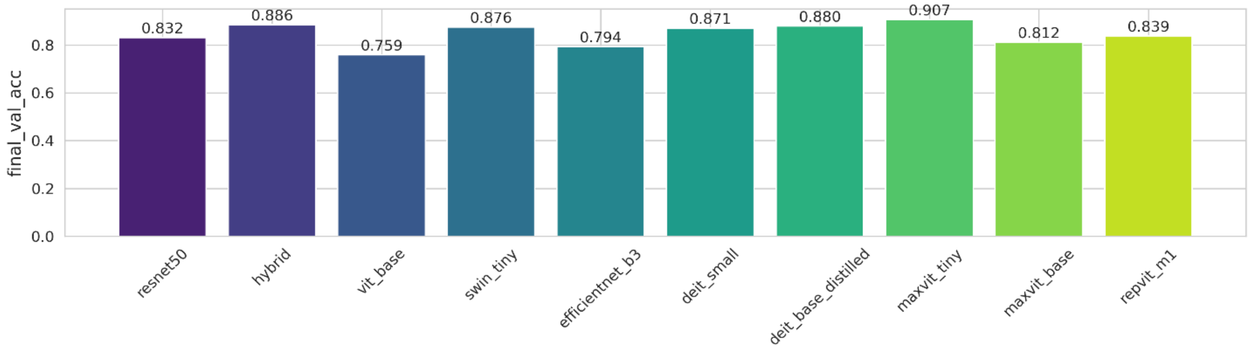


Figure B: Comparison of final_val_acc

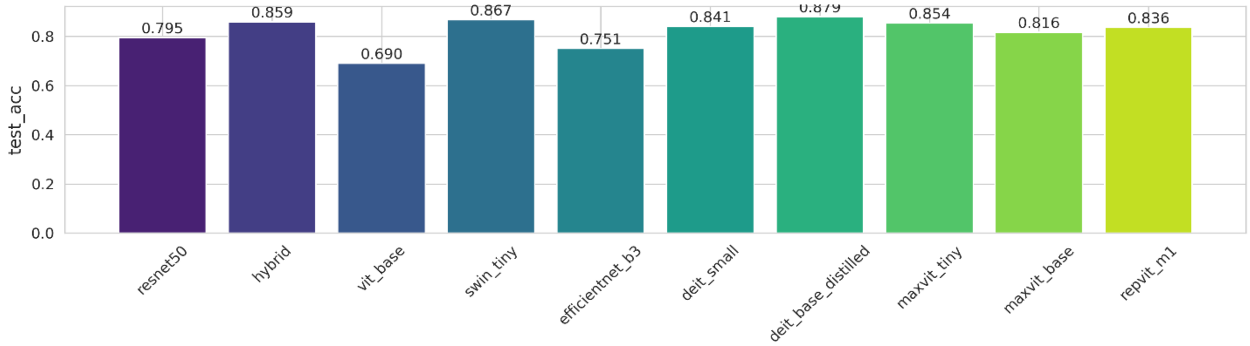


Figure C: Comparison of test_acc

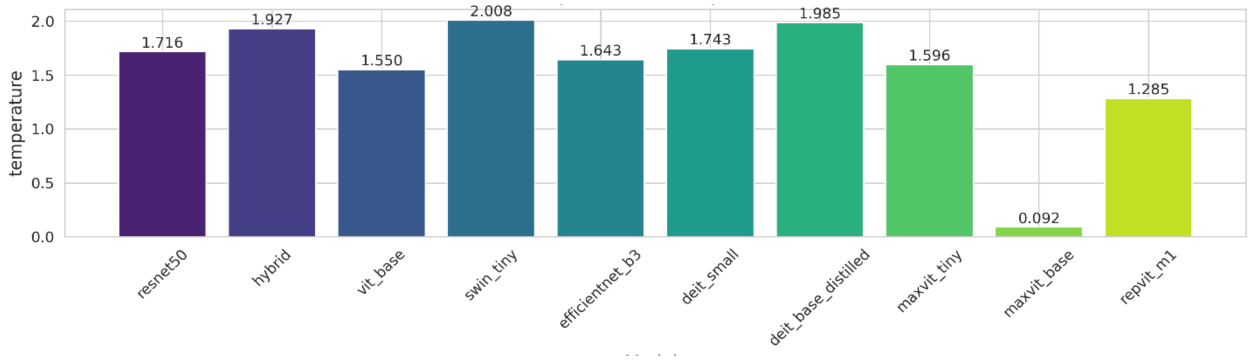


Figure D: Comparison of temperature

Figure 4.2: Models Comparison

Table 4.1: Model Comaprison

SN	Model	Final Value Accuracy	Final Value F1	Test Accuracy	Temperature
1	Resnet50	83.20%	83.17%	79.51%	1.715535
2	Hybrid	88.57%	88.56%	85.94%	1.927399
3	ViT_Base	75.88%	75.43%	68.99%	1.549870
4	Swin_Tiny	87.60%	87.49%	86.71%	2.007676
5	Efficientnet_B3	79.40 %	79.13%	75.08%	1.642590
6	DeiT_Small	87.11%	87.01%	84.05%	1.742568
7	DeiT_Base_Distilled	87.99%	87.88%	87.93%	1.985349
8	Maxvit_Tiny	90.72 %	90.60%	85.38%	1.595739
9	Maxvit_Base	81.15%	80.74%	81.61%	0.091852
10	RepViT_M1	83.89%	83.60%	83.61%	1.284545

Based on different architectures comparative evaluation, the DEiT Base Distilled model is the most appropriate choice to be deployed. While models such as MaxViT-Tiny showed the highest validation accuracy (90.72%), they showed less good consistency between validation and test performance. Similarly, Swin-Tiny and Hybrid models provided good results but exhibited slight difference in metrics. In contrast, the accuracy of validation in the case of Chilii Base Distilled is 87.99%, F1 is 87.88% and the test accuracy is also justified at 87.93%, which shows both high accuracy and high consistency. Also, its scaling with temperature value (1.985349) reflects its well-calibrated confidence distribution, confirming that it is more reliable when used in applications to the real world. Given this balance of accuracy, stability and calibration, DeiT Base Distilled get chosen as the final model to be put in the system.

4.4 Deployment

4.4.1 User Interface

The app begins with a splash screen displaying the logo for two seconds. The home screen features an image placeholder alongside an “Add Image” button, a patient information form for ID, name, age, and weight, and a "Classify" button that initiates loading indicator and pops the classification result in a dialog. Additionally, the app includes a history screen that lists all past scans and their corresponding results, allowing users to review previous classifications conveniently. This flutter app is built with the best performing model which is DeiT Base Distilled model as it is selected because it performed the most consistent performance by using FastAPI and Hugging face in the backend.

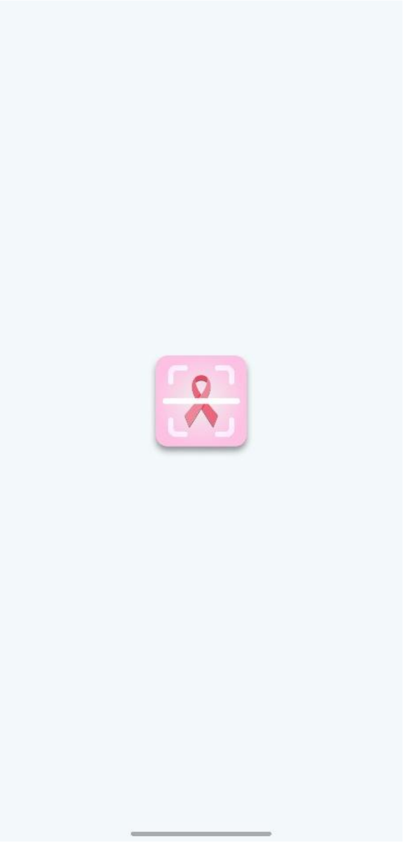


Figure A: Splash Page

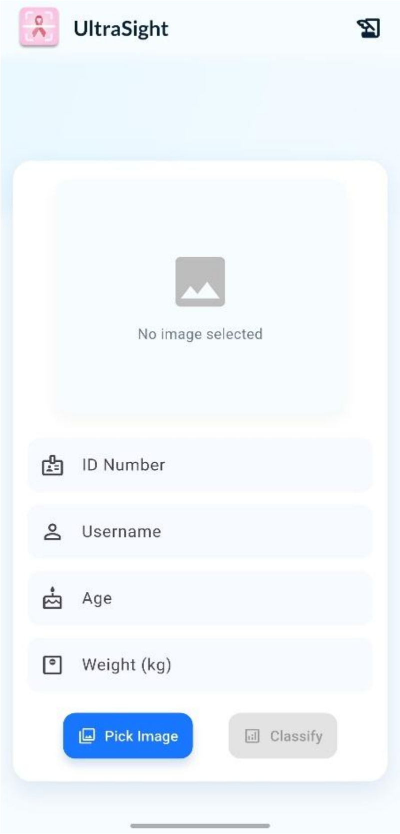
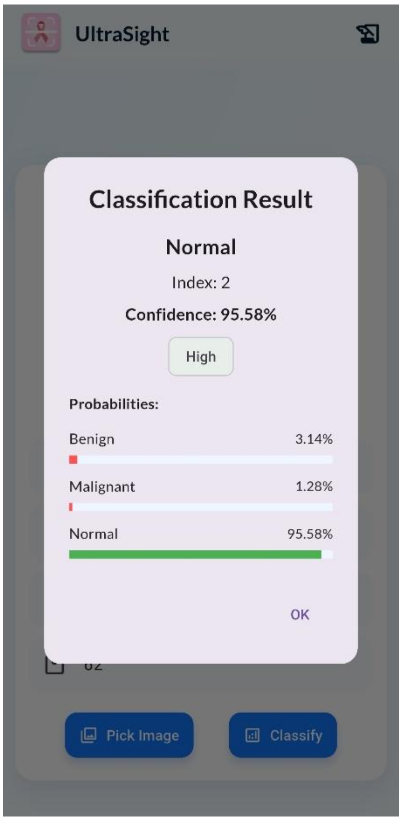


Figure B: Home Page



Classification Result

Normal

Index: 2

Confidence: 95.58%

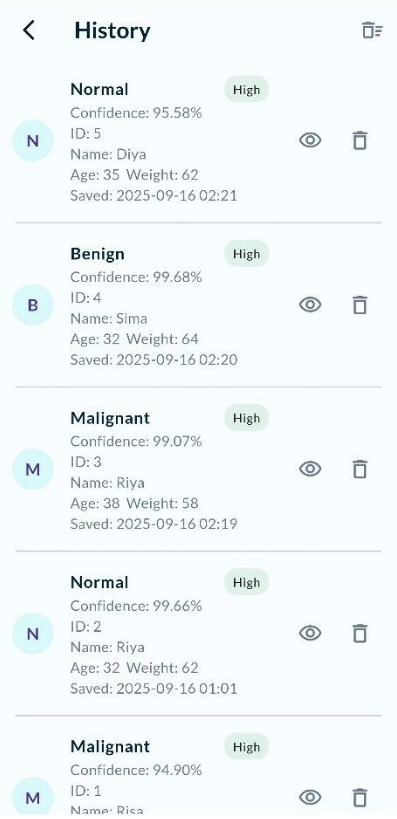
High

Probabilities:

Benign	3.14%
Malignant	1.28%
Normal	95.58%

OK

Figure C: Classification Box



N Normal High
Confidence: 95.58%
ID: 5
Name: Diya
Age: 35 Weight: 62
Saved: 2025-09-16 02:21

B Benign High
Confidence: 99.68%
ID: 4
Name: Sima
Age: 32 Weight: 64
Saved: 2025-09-16 02:20

M Malignant High
Confidence: 99.07%
ID: 3
Name: Riya
Age: 38 Weight: 58
Saved: 2025-09-16 02:19

N Normal High
Confidence: 99.66%
ID: 2
Name: Riya
Age: 32 Weight: 62
Saved: 2025-09-16 01:01

M Malignant High
Confidence: 94.90%
ID: 1
Name: Risa

Figure B: Home Page

Figure 4.3: App User Interface

4.4.2 Data Flow Diagram

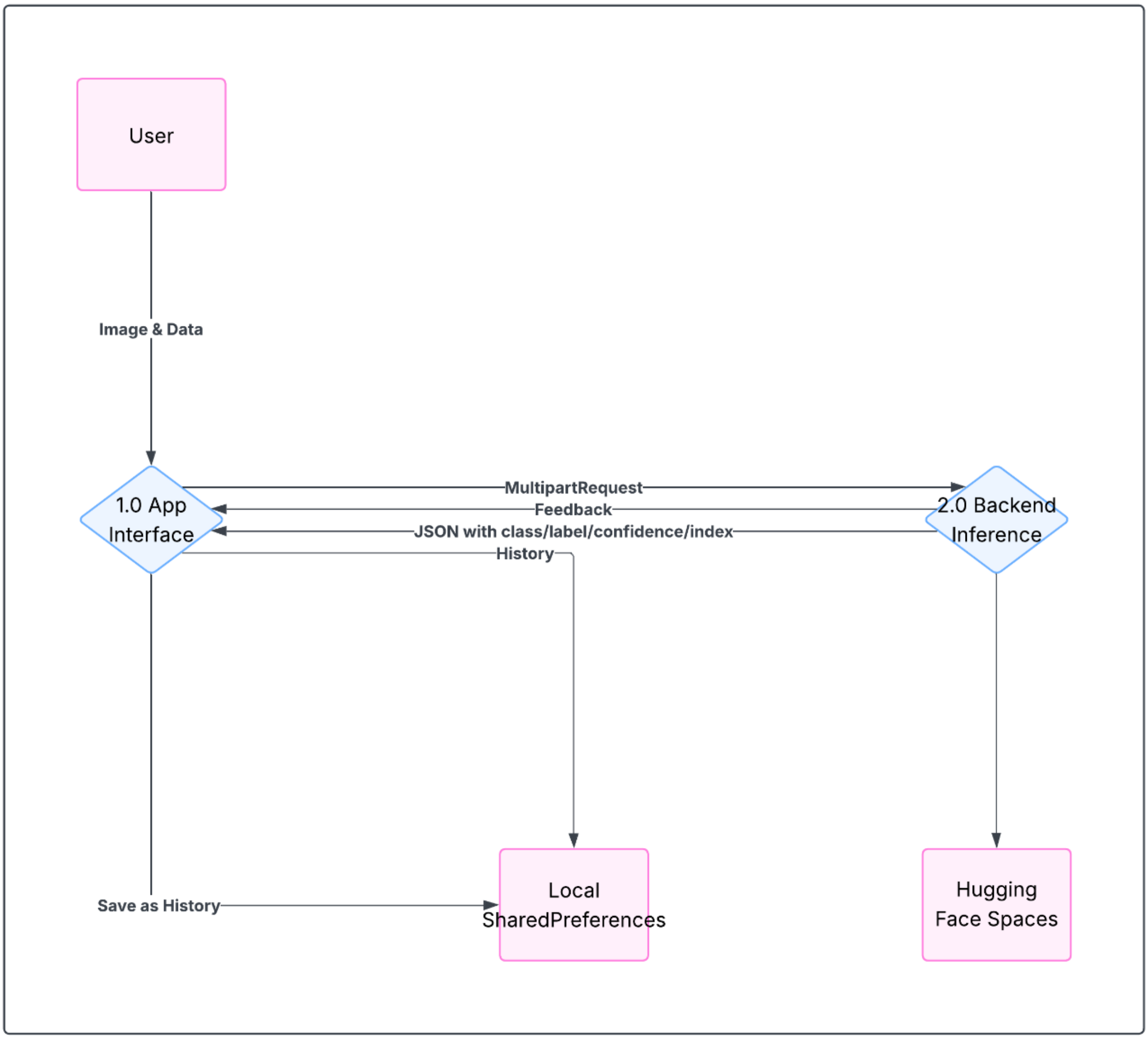


Figure 4.4: Mobile App Data Flow Diagram

The diagram depicts the architecture of a Flutter-based mobile app for breast cancer image classification. The user provides an image and patient data, which are first handled by the 1.0 App Interface. This interface sends a multipart request to the 2.0 Backend Inference for processing. The backend looks about and returns a JSON response that includes the class/label, confidence score, and index. The results are then stored locally using SharedPreferences for history tracking, while model inference is hosted on Hugging Face Spaces. This setup illustrates the complete flow of data within the system.

4.5 Summary

This was augmented to include ten thousand images through use of ultrasound augment pipeline, with weights between benign, malignant, and normal. Transfomer based architectures performed better than CNN-based in all models. Moderate results were achieved with the validation accuracies being 83.20% and 79.39% achieved on the ResNet50 and EfficientNet B3, respectively. The worst one was the performance of ViT Base which is 75.88%. Hybrid and RepViT M1 showed better results with the validation accuracies of 88.57% and 83.88%. Swin Tiny model, DeiT Small model, and DeiT Base Distilled model achieved high validation accuracies among all of the model of 87.59%, 87.10% and 87.98% respectively. The highest validation accuracy model was MaxViT Tiny that achieved the highest accuracy of 90.72% but test accuracy was 85.38%, whereas Deit Base Distilled model performed with consistence and it has the accuracy for validation accuracy is 87.98% and it achieved testing accuracy of 87.92% that is the most consistence of all the models used. So, The augmentation strategy and transformer based models and especially DeiT Base Distilled model, proved to perform better in classifying breast ultrasound images.

Chapter 5

Engineering Standards and Design Challenges

In this chapter, compliance with engineering standards, societal and environmental effects, ethical issues, sustainability strategies, project administration, financial reports and mappings against complex engineering tasks and operations are formally examined within the context of the project codes and write-ups.

5.1 Compliance with the Standards

The project follows the accepted norms of engineering to achieve quality, safety and reliability of the breast cancer classification system using deep learning and Flutter-based deployment. Compliance takes the form of software, hardware and communication standards as discussed below. The project follows the international standards of quality assurance of the IEEE 730-2014 software quality assurance standard, and ISO 13485:2016 on medical device software risk management through classification [23, 24].

5.1.1 Software Standards

The project is in accordance with IEEE 730-2014 software quality assurance, and this includes the strict review of the code, unit test, and documentation. The Python code to augment the data and model training is written with PEP 8 styling guidelines, which have proper handling of indentations, clear import structure [e.g., import torch] and it is broken down into modules. The Flutter app follows the Dart practices, using const to declare immutable widgets, correct widget tree structure and a naming scheme, thus makes the code more readable and easier to maintain. Automated testing frameworks like the widget testing in flutter were utilized in order to test UI components to guarantee a high quality of the software.

5.1.2 Hardware Standards

The deep learning models harness GPU-accelerated computing and the model settings are dynamically adjusted, according to the identified hardware (e.g., NVIDIA A100, L4, T4) as shown in the GPU-aware configuration block. It has been possible to bring the system into compliance with IEEE 11073 medical device interoperability standards, thus making it compatible with medical imaging hardware to process ultrasound images [23]. The allocation of hardware resources, including the size of batches and workers, is optimized on the basis of the capabilities of GPUs, as a way to avoid excessive load on the system and allow an efficient means to compute.

5.1.3 Communication Standards

The Flutter app is coupled with a FastAPI server configured with the Hugging Face framework and the configuration follows IEEE 802.3-2022 (Ethernet) and IEEE 802.11-2020 (Wi-Fi) to ensure solid network communication [25, 26]. API implements secure data transmission protocol HTTPS, information security ISO 27001-based. The file upload system in Flutter app will provide reasonable delivery of ultrasound images to the backend where failed uploads are handled as in the classify method.

5.2 Impact on Society, Environment and Sustainability

Herein, the project implications to the society, environmental considerations and ethical aspects, as well as sustainability strategies have been evaluated, focusing on the objective of breast cancer detection.

5.2.1 Impact on Life

The breast cancer classification model supports the early screening method which may lead to improved patient outcomes by correctly identifying benign, malignant, or normal ultrasound images with high accuracy (e.g., Deit Base Distilled was 87.98% accurate on the validation data). By detecting it early enough, it can curb mortality rates since breast cancer is one of the causes of death among women world over [1]. The system mitigates disparities in health care by offering accessible diagnostics with the help of a mobile application in low-income and middle-income countries [3].

5.2.2 Impact on Society & Environment

The mission of the project is to bring beneficial societal impact through democratising access to advanced diagnostics in underserved areas and making them less dependent on specialised radiologists in the regions. Devoutly, the development allows cloud inferencing via Hugging Face which lowers the hardware requirements locally and therefore the energy drawn to consume to execute the inferencing. Nonetheless, teaching deep learning models on GPUs can be energy-intensive, and strategies, such as gradient accumulation are needed to minimize the computational burden, which is already in the code.

5.2.3 Ethical Aspects

Ethical considerations also involve keeping the data of the patients completely safe and compliant with the EU GDPR regarding data protection [28]. The Flutter app does not store sensitive data (namely an image in the app) but instead, has an imprint of only its metadata (e.g. ID, user name, age). Model-generated predictions are properly calibrated against overconfident classifications (temperature scaling), so that clinicians are not misled about false positives. The transparency is achieved with the help of descriptive reports of classification and Grad-CAM displays, which do not bear doubt to AI-driven diagnostics.

5.2.4 Sustainability Plan

Environmental impact is considered in the sustainability plan that seeks to minimize the impact of the model training and deployment. With such models as ResNet50 and MaxViT, techniques such as transfer learning minimize training time and amount of energy used [5]. The FastAPI backend on Hugging Face uses scalable cloud resources, freeing one of using dedicated servers. Sustainability in the long term involves retraining the model with new data periodically in order to keep it up to date and accurate, and also makes parts of it open sourced to be able to receive the input of the community, in order to avoid the duplication of development work.

5.3 Project Management and Financial Analysis

This was carried out with agile project management as each sprint entailed the process of data augmentation, model training, and development of the app. Most significant achievement was preparation of the dataset, choice of the models and comparing them and selecting the best model among the all models and deployment of the Flutter app. Six months were dedicated to a team of four engineers who worked together and conducted weekly reviews to assure the correlation of the work to the objectives.

Cost Analysis

In the financial analysis there is budget estimation and also an alternative budget in a resource limited case.

Table 5.1: Primary Budget

Category	Cost (BDT)	Description
Compute Requirements	100,000.00	Cloud-based GPU training (e.g., NVIDIA A100 GPUs, 100 hours)
Development	200,000.00	4 engineers, 100 hours each at the rate of 500/hour
Hosting of API	14,000.00	Hugging Face Pro subscription (1 year)
Testing and Validation	50,000.00	Licensing fee and quality assurance of the dataset
Total	364,000.00	

Table 5.2: Alternate Budget (Low-Cost)

Category	Cost (BDT)	Description
Cost of Computation	50,000.00	Purchase 300 hours on Google Colab Pro+ with T4 GPUs
Development	120,000.00	2 engineers, 120 hours each at the rate of 500/hour
API Hosting	6,400.00	Hugging Face free plan with limited activation
Testing and Validation	23,600.00	Using open-access datasets with manual QA
Total	**200,000.00**	

Rationalization of Alternate Budget: The low cost budget can utilize the free-tier of cloud services, open-access data sets such as the one by Al-Dhabyani et al., [2] lowering costs, without sacrificing functionality. It compromises to some extent on computational power and the size of the team and will likely take longer to develop.

5.4 Complex Engineering Problem

This section in table 5.3 identified the complex engineering classification of the project problem characteristics (EP1-EP7) and in table 5.4 identified knowledge profiles (K1-K8), according to accreditation requirements in engineering.

5.4.1 Complex Problem Solving

The project is working on a challenging engineering project via creation of a deep learning classification system of breast cancer that is incorporated in a cell phone application. The following table 5.3 is used for coding the project in form of the attribute of the complex engineering problems.

Table 5.3: Mapping with Complex Engineering Problem.

EP1 Depth of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
✓	✓	✓	✓			✓

EP1: The project demands advanced expertise in multiple technical domains, particularly deep learning and mobile application development. On the deep learning side, it involves working with state-of-the-art architectures such as

MaxViT and ResNet50, DeiT Base Distilled which require a strong understanding of computer vision, model training, and optimization. At the same time, the project also incorporates mobile development using Flutter, which requires knowledge of cross-platform user interface design, responsive layouts, and integration with backend services. The combination of computer vision, medical imaging, and mobile engineering highlights the depth of knowledge required to successfully execute the project.

EP2: The project must carefully balance several conflicting requirements. On one hand, achieving high model accuracy is crucial, with results such as 90.72% accuracy for MaxViT-Tiny showing the potential of advanced architectures. However, these models also need to be computationally efficient enough for deployment on mobile devices with limited hardware resources. In addition, privacy and security regulations, such as GDPR compliance, need to be respected to protect sensitive medical data. Finally, all of this must be achieved without compromising usability, ensuring that clinicians and patients can easily interact with the system in real world settings.

EP3: The evaluation process for the project involves a comprehensive and multi-faceted analysis. Model performance is assessed using key metrics such as F1-score, Area Under the Curve (AUC), and confusion matrices, which provide insights into precision, recall, and overall classification performance. Beyond quantitative metrics, interpretability is enhanced using visualization tools such as Grad-CAM, which help identify the specific regions of medical images that influence predictions. This combination of rigorous statistical evaluation and interpretability demonstrates the depth of analysis applied throughout the project.

EP4: The project explores relatively novel territory by applying advanced vision transformer models, such as DeiT Base Distilled model, to the domain of ultrasound imaging. While these architectures have shown success in other computer vision tasks, their application to medical imaging, and specifically ultrasound, represents a significant extension of established techniques into a new and challenging context. This demonstrates not only technical innovation but also an awareness of the unique issues and complexities involved in adapting cutting-edge research to healthcare applications.

EP7: The project integrates several interdependent components that must function cohesively to deliver the final solution. Data augmentation and preprocessing directly impact the quality of model training. Model training results influence the performance of the deployed API, which then supports the mobile application for end-users. Furthermore, the deployment process involves hardware and software layers working together, from GPU-based training environments to mobile-optimized inference engines. This interconnected workflow highlights the interdependence of technical components, where progress in one area directly affects the success of others.

Mapping with Knowledge Profile

This section Table 5.4 is designed to map the overall problem and EP1 ***(multiple between K3, K4, K5, K6, K8 for attaining EP1)*** to the Knowledge Profile.

Table 5.4: Mapping with knowledge Profile.

K1 Natural Science	K2 Mathematics	K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K7 Comprehension	K8 Research Literature
		✓	✓	✓	✓	✓	✓

K3: The project uses the core engineering disciplines through application of machine learning principles in the classification of images. This includes convolutional neural networks (CNNs) and advanced architectures such as vision transformers, which are specifically designed for complex visual data and extracting meaningful patterns from medical images.

K4: Specialist expertise is reflected in expertise within the area of medical imaging, give special attention to ultrasound-specific prenatal to preprocessing technologies. Tools are created like augmentation pipelines (e.g., albumentations) to improve the dataset to make sure that the models are strong against variations in image quality, image orientation, and image noise, all of which are typical for ultrasound imaging.

K5: The project includes careful engineering design through creating a friendly mobile application in both physical exoskeleton design on the front end and a FastAPI backend. This choice in design guarantees smooth user-interface and classification models interaction allowing effective communication and real time prediction, providing an accessible experience for end-users within healthcare environments.

K6: Practical aspects of engineering are employed in use of GPU-aware configurations for training/as efficient inference. In addition, techniques like temperature scaling are implemented to calibrate the model results so that confident scores that allow the system to operate in the real world will be obtained.

K7: This criterion emphasises the capacity to comprehend, integrate and apply knowledge from various elements of engineering to solve a real world healthcare problem. Through a combination of deep learning, medical imaging and mobile development, the project illustrates a great understanding of multidisciplinary engineering concepts.

K8: The project builds heavily on cutting-edge projects, using recent modifications in deep learning decoction and computer vision tactic. By drawing insights from state-of-the-art models and studies, the project manages to ensure that the methodology used in this project will now be informed and relevant to the state of the art.

5.4.2 Engineering Activities

The project encompasses complex engineering activities (EA1–EA5), as mapped in Table 5.5.

Mapping with Complex Engineering Activities

Table 5.5: Mapping with Complex Engineering Activities.

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✓	✓	✓	✓	✓

EA1: The project uses a whole host of resources to govern the development and deployment in a forceful way. This having high-performance GPUs to train models, a cloud infrastructure (e.g. as hosted by Hugging Face) for hosting and deployment, and open source medical imaging datasets that provide a good foundation for experimentation and validation. Combination of this resources provides scalability, accessibility and processing capacity of computationally problematic tasks.

EA2: It takes teams of collaborators from many different disciplines to get a successful project done. Data scientist adds a special hand in model design and training, software engineers may focus on backend integration and mobile while healthcare vet may add a critical insight queuing scientific outputs to ensure the outcomes revealed by that system may be clinically appraisable and practical in its use. This level of interaction guarantees that the project is not only technically good but fits the necessary for the practical application in medicine.

EA3: The project is innovative as it presents a novel combination of the integration of the model, which is the novel integration of the base model known as the DeiT Base Distilled in ultrasound image classification. Unlike the traditional convolutional neural network based approaches, this transformer based model offers an improved accuracy and calibration. Furthermore, the deployment of the model by a mobile application programmed through the Dart language/Flutter increases losses accessibility, allowing for classifying real-time on portable devices. This dual innovation of state-of-the-art deep learning combined with easy to deploy makes the project innovatively both technical and practical.

EA4: The societal benefits of the project are considerable as it is improving access to healthcare through providing reliable diagnostic support in resource-limited settings. At the same time, environmental implications are taken into account by optimizing training strategies, as to minimize energy consumption, for example by efficient use of the graphics processing units (GPUs) and by cloud-based scaling. This balancing of social impact and environmental responsibility speaks volumes about the project's commitment to sustainable engineering practices.

EA5: While the project brings forward cutting-edge techniques like transformers, it expands on deep learning basics with which most people are familiar. Techniques that have won their spurs in fields such as image recognition get a careful lift when tailored to the (much less traveled) area of ultrasound imaging. This balance of capitalizing on known approaches while exploring new applications delivers both reliability and novelty to the approach - making it both practical and forward looking.

5.5 Summary

This chapter examines the engineering standards, societal impact, ethics, sustainability, project management, and complex problem-solving of a breast cancer classification system using deep learning and a Flutter app. The project complies with IEEE and ISO standards for software, hardware, and communication, ensuring safety, reliability, and interoperability. It emphasizes societal benefits by improving early detection and healthcare access while considering environmental impact through efficient GPU usage and cloud deployment. Project management facilitated development, with financial planning for primary and low-cost budgets. Complex engineering activities, knowledge integration, and innovative deep learning deployment are highlighted.

Chapter 6

Conclusion

This chapter presents a brief later illustration on the achievement of the project, its limitation, and any future research scope with regards to developing and deploying the breast cancer classification app based on deep learning model.

6.1 Summary

The One of the world's worst medical problems breast cancer detection was able to resolve from the project. The results have been achieved thanks to the developed of an advanced and end-to-end system, based on deep learning algorithms, aimed at classifying as benign, malignant and normal breast ultrasound images with the Breast Ultrasound Images (BUSI) dataset. Through multi-phased methodology, the dataset was first augmented with ultrasound specific augmentations such as random brightness and contrast corrections, A clear image Augmentation from albumentations library including elastic deformations, Gaussian noise, Affine Transformations, Image Blurring, Drop Out, Horizontal Flips, and random rotations. This resulted in a balanced data set of approximately ten thousand images to address any class imbalance and to mimic real-life variation in ultrasound acquirement. The prepared data was partitioned by group-aware shuffle splitting into training eighty percent of data, validation ten percent of data and testing ten percent of data split to prevent data leakage. A comparative evaluation was carried out in Google Colab-point using PyTorch and TIMM library. 10 deep learning architectures were used in this evaluation. These included CNNs such as ResNet50 with validation accuracy of 83.2, 79.51%; EfficientNet-B3 with a validation accuracy of 79.4, 75.08%; hybrids such as CoatNet with validation accuracy of 88.5, 85.94%; and transformers such as ViT Base with a validation accuracy of 75.8, 68.99%. The Nieuclides model based on the electoral Vichy-DeiT Base was selected for the impressive consistency, high AUCs values ranging from 0.96-0.98 analysing all classes, calibrated confidence with scaling temperature between 0.05-10.0, and the interpretability with the emergence of Gradient-weighted class activation mapping (Grad-CAM) for visualising most the important regions of interest within images. Training included adaptive GPU setups i.e., batch size of 64/DeiT Base Distilled, cosine learning and metrics like macro F1-score of 87.88% for DeiT Base Distilled and ROC-curve with results showing little overfitting, with train accuracy approaching 1.0 and validation leveling off near 0.88. The model was exported in TorchScript and lite formats which will be used to deploy the model. On the application side a 'UltraSight' mobile app was developed using modern UI capabilities, including splash screen, home screen for image uploads from gallery and data input such as patient ID, name, age, weight and classification using http multipart requests to a FastAPI backend. The app has result dialogs with confidence levels and has a history screen to store local metadata but does not store images for privacy reasons. The backend, which runs from Docker, and is deployed as hosted solution on Hugging Face Spaces, supports inference in a secure way and return result of inference, class and confidence and index in structured way. Alternative deployments such as on-device TensorFlow Lite were evaluated and rejected on the basis of computation requirements in favor of using the cloud for scalability. The system is compliant to engineering standards: Software Quality - IEEE 730-2014; Medical Device Risk Management ISO 13485:2016; Hardware Interoperability IEEE 11073; Secure Communication over the Internet https, ISO27001. Ethical aspects include: GDPR compliant data privacy-no local image storage, Bias mitigation-through diverse augmentation, Transparency through the classification report and visualizations. The societal consequences include democratizing the diagnostics in space constrained spaces like Bangladesh that could help in alleviating the late stages and death in consonance with the WHO stats of 2.3 million and 685,000 lives in 2023. A sustainable approach is promoted through efficient GPU allocation, training-transferring energy and scaling cloud resources. Project management took agile approach based on the time outlines to Anthigrad.mn up to 48 weeks. The phases of the project were believed to be dataset preparation (weeks 12-18), model development (weeks 16-26), app development (weeks 20-32), backend integration (weeks 22-34), deployment (weeks 28-38), testing (weeks 34-44) and documentation (weeks 40-48), although some of the phases went beyond estimations. Financially, the primary 364,000 BDT was used compute, development, hosting and validation and 200,000 BDT as a low cost alternative through free tiers. Overall, this project helps to provide the bridge between AI research and policy/medicine, in collaboration delivering a deployable tool impacting health equity with the results of multi-model analysis for preoptimizing concomitant responsiveness in resource constrained environments.

6.2 Limitation

Despite its advancements, one drawback of the system is that it uses cloud-based inference via Hugging Face Spaces, so far that it is not guaranteed to be accessible in regions with unstable connections, meaning remote zones or areas with limited connection may suffer from using this system. The expanded dataset of a potential ten thousand images into benign, malignant, and normal classes, while enhanced, may not be able to achieve greater variation that is encountered in real-world ultrasound acquisition that stems from differences in equipment itself, operator techniques, or patients themselves that may influence generalization. Additionally, the complexity of training transformer-based models on GPUs requires computing resources that may be difficult to scale up in a low-resource setting and the inherent biases in the dataset and/or model predictions require continuous observing to avoid misclassifications that may affect clinical decisions.

6.3 Future Work

Future improvements could revolve around optimising models for on device inference with lightweight architectures or TensorFlow Lite conversions, allowing for offline usage and decreased reliance on internet access. Expanding the dataset through collaborations with varied medical institutions would include more representative samples from populations around the globe, making it more robust and on track with biases. Implementing federated learning could have the advantages of increasing data privacy through an approach of letting the model to get updated at decentralized devices (but not having to centralized sensitive information). Additional features, including in-app real time image preprocessing of the Flutter app as well as multimodal integration (e.g., combining ultrasound with thermography) further enriches the diagnostic capabilities. Finally, it would open the path to clinical validation trials done rigorously in collaboration with healthcare providers, facilitating the deployment in the real world, which opens the way for regulatory clearance and ultimately widespread use within clinical workflows.

References

[1] R. L. Siegel, K. D. Miller, H. E. Fuchs, and A. Jemal, "Cancer statistics, 2023," *CA: A Cancer Journal for Clinicians*, vol. 73, no. 1, pp. 17–48, 2023.

[2] W. Al-Dhabyani, M. Gomaa, H. Khaled, and A. Fahmy, "Dataset of breast ultrasound images," *Data in Brief*, vol. 28, Art. no. 104863, 2020.

[3] S. Gini, R. W. Basu, and F. Bray, "Breast cancer in low- and middle-income countries," *The Lancet Oncology*, vol. 20, no. 9, pp. e481–e490, 2019.

[4] A. Stavros, *Breast Ultrasound*. Philadelphia, PA, USA: Lippincott Williams & Wilkins, 2004.

[5] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[6] S. Han, H. Kang, H. Jeong, and S. Kim, "Breast cancer multi-classification from histopathological images with structured deep learning model," *Scientific Reports*, vol. 7, no. 1, Art. no. 4172, 2017.

[7] M. H. Yap, G. Pons, J. Marti, and E. Zwiggelaar, "Breast ultrasound lesions recognition: End-to-end deep learning approaches," *Journal of Medical Imaging*, vol. 5, no. 1, Art. no. 011007, 2018.

[8] T. Fujioka et al., "The utility of deep learning in breast ultrasonic imaging: A multicenter study," *Diagnostics*, vol. 9, no. 4, Art. no. 105, 2019.

[9] M. Byra, S. Galperin, R. Ojeda-Fournier, and C. Andre, "Breast mass classification in sonography with transfer learning using a deep convolutional neural network," *Journal of Ultrasound in Medicine*, vol. 39, no. 3, pp. 513–522, 2020.

[10] W. K. Moon et al., "Tumor detection in automated breast ultrasound using 3-D CNN trained on synthesized images," *Medical Physics*, vol. 47, no. 3, pp. 1033–1046, 2020.

[11] Q. Zhang et al., "A deep learning model for breast cancer diagnosis based on ultrasound images," *Frontiers in Oncology*, vol. 11, Art. no. 652102, 2021.

[12] M. A. Al-Antari, S. Al-Masni, and T.-S. Kim, "Deep learning computer-aided diagnosis for breast lesion in digital mammogram," *Advances in Experimental Medicine and Biology*, vol. 1213, pp. 187–206, 2021.

[13] K. Jabeen et al., "Breast cancer classification from ultrasound images using probability-based optimal deep convolutional neural network model," *Multimedia Tools and Applications*, vol. 81, no. 12, pp. 16893–16918, 2022.

[14] G. Ayana, D. B. Asmare, and H. Chen, "Vision-transformer-based transfer learning for mammogram classification," *Diagnostics*, vol. 13, no. 2, Art. no. 178, 2023.

[15] H. Alaskar et al., "Breast ultrasound image classification with vision transformers and test-time augmentation," *Applied Sciences*, vol. 14, no. 5, Art. no. 1923, 2024.

[16] A. M. Abdel-Zaher and A. M. Eldeib, "Breast cancer classification using deep belief networks," *Expert Systems with Applications*, vol. 46, pp. 139–144, 2016.

[17] UE Systems, "iBreastExam: Portable breast lesion detector," *Medical Device Online*, 2018.

[18] Therapixel, "MammoScreen: AI for mammography," *IEEE Transactions on Medical Imaging*, vol. 39, no. 12, pp. 3865–3876, 2020.

[19] PinkDetect App, "AI-based ultrasound analysis," *Journal of Biomedical Informatics*, vol. 112, Art. no. 103612, 2021.

[20] BCDetect Prototype, "Flutter-based breast cancer app," *SoftwareX*, vol. 15, Art. no. 100753, 2021.

[21] W. Wang et al., "MaxViT: Multi-axis vision transformer," in *Proc. European Conf. on Computer Vision (ECCV)*, 2022, pp. 459–477.

[22] C. Guo, G. Pleiss, Y. Sun, and K. Q. Weinberger, "On calibration of modern neural networks," in *Proc. International Conf. on Machine Learning (ICML)*, 2017, pp. 1321–1330.

[23] IEEE Standard 730-2014, *IEEE Standard for Software Quality Assurance Processes*. New York, NY, USA: IEEE, 2014.

[24] ISO 13485:2016, *Medical devices — Quality management systems*. Geneva, Switzerland: ISO, 2016.

[25] IEEE 802.3-2022, *Ethernet*. New York, NY, USA: IEEE, 2022.

[26] IEEE 802.11-2020, *Wireless LAN*. New York, NY, USA: IEEE, 2020.

[27] World Health Organization, "Breast cancer," WHO, 2023.

[28] EU GDPR, *General Data Protection Regulation*. Brussels, Belgium: EU, 2016.

[29] S. R. Hoff, P. G. Lauritzen, and E. K. Johnson, "Multimodal imaging for breast cancer," *IEEE Transactions on Medical Imaging*, vol. 40, no. 10, pp. 2770–2781, 2021.

[30] Q. Yang, Y. Liu, T. Chen, and Y. Tong, "Federated machine learning: Concept and applications," *ACM Transactions on Intelligent Systems and Technology*, vol. 10, no. 2, Art. no. 12, 2019.

[31] A. Alshehri et al., "Breast cancer detection in thermography using convolutional neural networks (CNNs) with deep attention mechanisms," *IEEE Access*, vol. 11, pp. 121278–121295, 2023.

[32] A. Vakanski, P. Xian, J. Baker, and A. Florance, "Attention enriched deep learning model for breast tumor segmentation in ultrasound images," *Ultrasound in Medicine and Biology*, vol. 49, no. 5, pp. 1259–1269, 2023.

[33] A. Hijab, S. A. Abdalla, and S. Al-Makhadmeh, "Breast cancer classification using deep convolution neural network on H&E images of pathological slides," *Biocybernetics and Biomedical Engineering*, vol. 39, no. 2, pp. 316–324, 2019.

[34] S. Rajaraman, T. Antani, and G. Thoma, "Novel ensemble learning approach for enhanced breast cancer prediction using ultrasound images," *Journal of Medical Imaging and Health Informatics*, vol. 13, no. 1, pp. 1–10, 2023.

[35] R. S. Lee et al., "A deep learning approach to breast cancer detection in ultrasound," *Journal of Clinical Medicine*, vol. 9, no. 10, Art. no. 3182, 2020.

[36] S. M. McKinney et al., "International evaluation of an AI system for breast cancer screening," *Nature*, vol. 577, no. 7788, pp. 89–94, 2020.

[37] H. Chougrad, H. Zouaki, and O. Alheyane, "Multi-label transfer learning for the early diagnosis of breast cancer," *Neurocomputing*, vol. 392, pp. 168–180, 2020.

[38] M. A. Al-Masni et al., "Simultaneous detection and classification of breast masses in breast mammography images using deep convolutional neural networks," *Medical Physics*, vol. 45, no. 6, pp. 2352–2363, 2018.

[39] S. Khan, R. Muhammad, and S. Hussain, "A novel deep learning based framework for the detection and classification of breast cancer using transfer learning," *Pattern Recognition Letters*, vol. 125, pp. 1–6, 2019.

[40] A. A. Mohamed et al., "A deep learning method for classifying mammographic breast density categories," *Medical Physics*, vol. 45, no. 1, pp. 314–321, 2018.

A Deep Learning Based Mobile App for Breast Cancer Detection Using Ultrasound Images

ORIGINALITY REPORT

15%	13%	9%	11%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Daffodil International University Student Paper	6%
2	dspace.daffodilvarsity.edu.bd:8080 Internet Source	1%
3	ar5iv.labs.arxiv.org Internet Source	1%
4	Submitted to United International University Student Paper	<1%
5	www.hindawi.com Internet Source	<1%
6	ris.cdu.edu.au Internet Source	<1%
7	Submitted to University of Lincoln Student Paper	<1%
8	link.springer.com Internet Source	<1%
9	Submitted to University of Ulster Student Paper	<1%
10	www.mdpi.com Internet Source	<1%
11	Submitted to Indian Institute of Technology Roorkee Student Paper	<1%
12	pierrepinson.com	

*% detected as AI

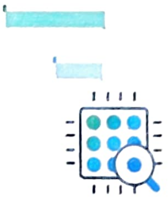
AI detection includes the possibility of false positives. Although some text in this submission is likely AI generated, scores below the 20% threshold are not surfaced because they have a higher likelihood of false positives.

Caution: Review required.

It is essential to understand the limitations of AI detection before making decisions about a student's work. We encourage you to learn more about Turnitin's AI detection capabilities before using the tool.

Disclaimer
Our AI writing assessment is designed to help educators identify text that might be prepared by a generative AI tool. Our AI writing assessment may not always be accurate (i.e., our AI models may produce either false positive results or false negative results), so it should not be used as the sole basis for adverse actions against a student. It takes further scrutiny and human judgment in conjunction with an organization's application of its specific academic policies to determine whether any academic misconduct has occurred.

Frequently Asked Questions



How should I interpret Turnitin's AI writing percentage and false positives?
The percentage shown in the AI writing report is the amount of qualifying text within the submission that Turnitin's AI writing detection model determines was either likely AI-generated text from a large-language model or likely AI-generated text that was likely revised using an AI paraphrase tool or word spinner.

False positives (incorrectly flagging human-written text as AI-generated) are a possibility in AI models.

AI detection scores under 20%, which we do not surface in new reports, have a higher likelihood of false positives. To reduce the likelihood of misinterpretation, no score or highlights are attributed and are indicated with an asterisk in the report (*%).

The AI writing percentage should not be the sole basis to determine whether misconduct has occurred. The reviewer/instructor should use the percentage as a means to start a formative conversation with their student and/or use it to examine the submitted assignment in accordance with their school's policies.

What does 'qualifying text' mean?
Our model only processes qualifying text in the form of long-form writing. Long-form writing means individual sentences contained in paragraphs that make up a longer piece of written work, such as an essay, a dissertation, or an article, etc. Qualifying text that has been determined to be likely AI-generated will be highlighted in cyan in the submission, and likely AI-generated and then likely AI-paraphrased will be highlighted purple.

Non-qualifying text, such as bullet points, annotated bibliographies, etc., will not be processed and can create disparity between the submission highlights and the percentage shown.