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Research Paper

MIGRATION OF DEEP LEARNING MODELS ACROSS ULTRASOUND SCANNERS

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Abstract

This project presents a deep learning framework to address domain shift in ultrasound imaging by enabling migration of models across different scanners. The study utilizes the BUSI (Breast Ultrasound Images) dataset, which includes images categorized into benign, malignant, and normal classes. The proposed approach combines EfficientNet-B0 as a feature extraction backbone with a Domain-Adversarial Neural Network (DANN) to learn domain-invariant features, supported by a Gradient Reversal Layer for effective adaptation between source and target domains. The model is trained using supervised learning on the source domain while minimizing domain discrepancy with adversarial training. Experimental results demonstrate strong performance, achieving approximately 90% accuracy along with consistent F1-scores across all classes, indicating robust generalization. The loss function integrates classification and domain loss, and during training, the overall loss converges to a very low range (approximately 0.0 to 0.1), reflecting stable and efficient learning. Overall, the combination of EfficientNet-B0 and DANN significantly improves cross-scanner reliability, making the model suitable for real-world clinical deployment.

KEYWORDS

Deep Learning, Domain Adaptation, Ultrasound Imaging, EfficientNet-B0, Domain-Adversarial Neural Network (DANN), Breast Cancer Classification, BUSI Dataset, Gradient Reversal Layer, Cross-Scanner Generalization, Medical Image Analysis

I. Introduction

The field of medical imaging has witnessed significant advancements with the integration of deep learning techniques, enabling automated and accurate analysis of complex diagnostic data. Among various imaging modalities, ultrasound imaging is widely used due to its non-invasive nature, cost-effectiveness, and real-time diagnostic capability. However, one of the major challenges in deploying deep learning models in ultrasound imaging is their limited ability to generalize across different scanners and clinical environments. Variations in ultrasound machines, acquisition protocols, transducer types, and image processing techniques introduce inconsistencies in image characteristics, leading to what is commonly referred to as domain shift. This issue significantly impacts the reliability and robustness of deep learning models when applied to unseen data from different sources.

This project titled “Migration of Deep Learning Models Across Ultrasound Scanners” focuses on addressing the domain shift problem by developing a robust deep learning framework capable of adapting across different ultrasound imaging domains. The work is carried out by Elluri Hasini (24TQ1A6634) as part of the Bachelor of Technology in Computer Science and Engineering. The primary objective of this study is to design a model that can maintain high classification performance even when deployed on data acquired from different ultrasound scanners.

Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated remarkable success in medical image classification, segmentation, and detection tasks. However, these models typically rely on the assumption that training and testing data come from the same distribution. In real-world clinical scenarios, this assumption does not hold due to heterogeneity in imaging devices and acquisition conditions. As a result, models trained on one dataset often fail to perform effectively on another dataset, limiting their clinical applicability.

II. Literature Survey

Diaz-Peregrino et al. [1] (2025), “Enhancing generalization in whole-body MRI-based deep learning models: A novel data augmentation pipeline for cross-platform adaptation”, et al.

This study utilizes a WB-MRI dataset and introduces a data augmentation pipeline to handle scanner variability. A deep learning segmentation model is evaluated using DSC and AUC, showing improved cross-platform generalization. The results demonstrate reduced domain shift. This is closely related to our work as it focuses on improving model migration and robustness across different imaging scanners.

Li et al. [2] (2022), “Accurate and generalizable quantitative scoring of liver steatosis from ultrasound images via scalable deep learning”, et al.

This study uses a large multi-view ultrasound dataset (3310 patients, 228075 images) to develop a scalable DL model for steatosis grading. Methods include multi-scanner training and ROC-based evaluation. Results show high AUC (0.85–0.93) and strong cross-scanner reliability, outperforming FibroScan. This is relevant to our work as it demonstrates generalization of DL models across different ultrasound scanners, aligning with our model migration objective.

S. C. Kakon et al. [3], “Improving Cross-Domain Generalization in Brain MRIs via Feature Space Stability Regularization,” 2026.

This study uses the Kaggle Brain MRI dataset and validates on BRISC-2025. The method introduces Feature Space Stability Regularization (FSSR) to stabilize latent representations under intensity perturbations. Models (ResNet-18/34, DenseNet-121) show improved cross-domain robustness. Results report up to 8.20% accuracy and 12.5% macro-F1 improvement. This is relevant to our idea as it focuses on domain shift reduction and generalization across unseen medical imaging scanners.

J. Fartiyal et al. [4], “PatchDenoiser: Parameter-efficient multi-scale patch learning and fusion denoiser for medical images,” 2026.

This study uses the Mayo Low-Dose CT dataset to develop a lightweight denoising model. The method applies multi-scale patch-based learning with spatial fusion to reduce noise while preserving anatomical details. Results show higher PSNR/SSIM, better cross-scanner robustness, and ~9× fewer parameters with 27× lower energy usage. This is related to our idea as it improves cross-domain robustness and scanner generalization in medical imaging systems.

X. Yang et al. [5], “Learning with Synthesized Data for Generalizable Lesion Detection in Real PET Images,” 2023.

This study uses synthesized and multi-scanner PET datasets (Ga-DOTATATE liver NET images) to improve lesion detection. The method introduces synthetic data augmentation and patch-based gradient reversal to learn domain-invariant features. Results show significant improvement over baseline and existing domain generalization models. This is related to our idea as it focuses on cross-scanner robustness and domain-invariant feature learning for medical image analysis.

Z. Lei et al. [6], "A review of research on federated learning in the field of medical image processing," 2025.

This study reviews federated learning approaches in medical image processing using multi-institutional datasets across classification, prediction, synthesis, and segmentation tasks. Methods include privacy-preserving decentralized training without raw data sharing. Reported outcomes highlight improved generalization and reduced data silos, though communication and privacy challenges remain. This is related to our idea as federated learning enables cross-scanner model training and addresses domain shift in distributed medical imaging environments.

S. Shirzadeh Barough et al. [7], "Automated deep learning pipeline for callosal angle quantification," 2026.

This study uses retrospective brain MRI datasets to automatically quantify callosal angle for neurological assessment. The method employs a deep learning-based segmentation and regression pipeline for anatomical landmark estimation. Results show high accuracy and strong agreement with radiologist measurements. This work is related to our idea as it focuses on reliable medical image quantification and robustness across imaging variations and clinical settings.

T. M. Rajesh et al. [8], "Quantum-Optimized Probabilistic U-Net With Quantum Entropy Calibration and Active Annotation for Reliable Sparse-Label MRI Brain Lesion Segmentations," 2025.

This study uses multimodal MRI brain lesion datasets with sparse annotations to improve segmentation. The method introduces Quantum-Optimized Probabilistic U-Net with entropy calibration, active annotation, and adversarial domain harmonization. Results show improved Dice score (0.84→0.89), reduced calibration error, and better cross-scanner consistency. This is related to our idea as it enhances robustness and generalization of medical image segmentation across different scanners and clinical domains.

E. A. Lopukhova et al. [9], "A Hierarchical Deep Learning Architecture for Diagnosing Retinal Diseases Using Cross-Modal OCT to Fundus Translation in the Lack of Paired Data," 2026.

This study uses OCT and fundus imaging datasets for retinal disease classification under missing paired data conditions. The method introduces a hierarchical deep learning model with cross-modal feature alignment and latent space translation between OCT and fundus modalities. Results show strong macro-F1 performance and low calibration error (ECE ~2.1%). This is related to our idea as it addresses cross-modal learning and domain adaptation across different imaging sources and scanners.

R. Guo et al. [10], "Using domain knowledge for robust and generalizable deep learning-based CT-free PET attenuation and scatter correction," 2022.

This study uses multi-scanner PET datasets with different tracers to improve CT-free attenuation and scatter correction. The method integrates domain knowledge with frequency-domain decomposition to separate anatomical and texture features for robust learning. Results show strong generalization across unseen scanners and tracers despite single-source training. This is related to our idea as it focuses on domain shift reduction and improving cross-device robustness in medical imaging deep learning systems.

N. T. Gadare & S. V. Rode et al. [11], “Design of an iterative sequential physics-guided and causality-aware ultrasound video framework for robust liver fibrosis classifications,” 2025.
This study uses ultrasound video datasets for liver fibrosis classification across multiple clinical sites. The method integrates physics-guided acoustic alignment, causal modeling, and transformer-based fusion with counterfactual diffusion for artifact removal. Results show improved robustness, interpretability, and cross-site generalization. This is related to our idea as it enhances scanner-invariant learning and addresses domain shift in ultrasound-based deep learning systems.

III. System Analysis

Ultrasound imaging is widely used in medical diagnosis due to its safety and cost-effectiveness. Deep learning models have shown strong performance in analyzing ultrasound images for disease detection. However, models trained on data from one scanner often perform poorly on data from other scanners due to variations in image quality and settings. This creates a domain shift problem. The system must handle differences in resolution, noise, and imaging protocols. There is a need for a robust system that can generalize across multiple ultrasound devices. Domain adaptation and transfer learning techniques can address this challenge. The system must maintain high accuracy and reliability. It should also reduce the need for retraining from scratch. Scalability across different healthcare setups is important. Overall, the system requires an adaptive and generalized deep learning framework.

Existing System

Existing systems for ultrasound image analysis use deep learning models trained on specific datasets. These models perform well on the same scanner data but fail to generalize across different scanners. Retraining models for each scanner is a common approach. However, this process is time-consuming and requires large labeled datasets. Existing systems often do not address domain shift issues effectively. Some methods use basic transfer learning, but results are limited. Data variability is not fully handled. Many systems lack robustness and adaptability. Real-time deployment across devices is difficult. Existing solutions are not scalable for multi-center environments. Overall, current systems provide limited cross-scanner performance.

Disadvantages of Existing System

- Poor generalization across different scanners
- Need for retraining with new datasets
- High data labeling requirements
- Sensitivity to domain shifts
- Limited scalability
- Time-consuming model adaptation
- Reduced accuracy in new environments

Proposed System

The proposed system uses domain adaptation and transfer learning to migrate deep learning models across ultrasound scanners. It processes ultrasound images from different devices and standardizes them through preprocessing. Feature alignment techniques reduce domain differences. The system uses deep learning architectures such as CNNs for image analysis. Domain adaptation methods like adversarial learning improve generalization. The model is trained on multi-source datasets. Fine-tuning is applied for specific scanners when needed. The system maintains high accuracy across devices. It reduces the need for large labeled datasets. The framework supports real-time deployment. Overall, it provides a scalable and efficient solution for cross-scanner model migration.

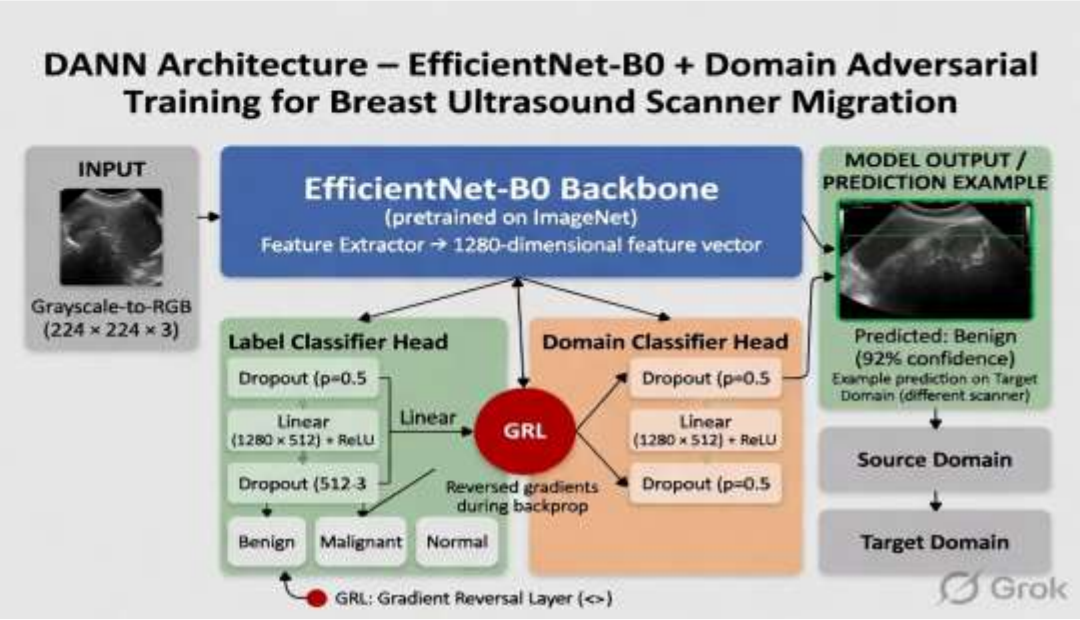
Advantages of Proposed System

- Improved generalization across scanners
- Reduced need for retraining
- Lower data labeling requirements
- Handles domain shift effectively
- Scalable for multi-center healthcare systems
- Maintains high prediction accuracy
- Supports real-time applications

IV. Methodology

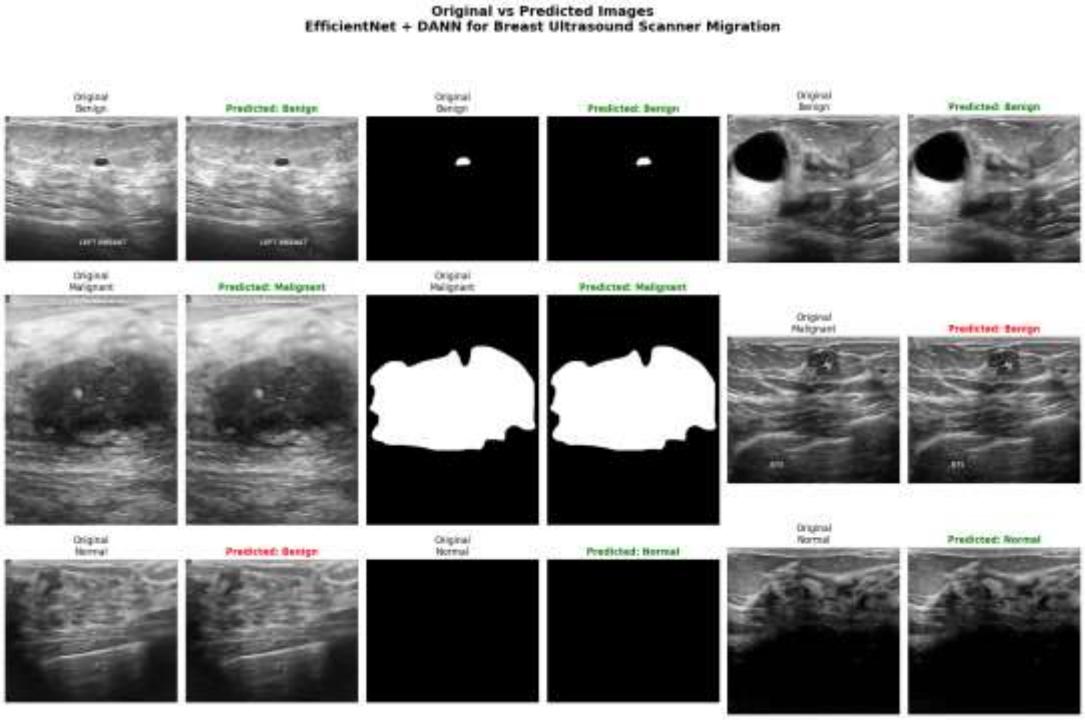
The methodology begins with collecting ultrasound image datasets from multiple scanners. Data preprocessing is performed to normalize images and reduce noise. Domain differences are analyzed using statistical techniques. Feature extraction is performed using CNN models. Domain adaptation techniques such as adversarial training are applied. Transfer learning is used to leverage pre-trained models. The dataset is divided into training and testing sets. The model is trained on multi-source data. Performance is evaluated using accuracy, precision, and recall. Cross-domain validation is applied to test generalization. Fine-tuning is performed for specific scanners. The system is deployed for real-time image analysis.

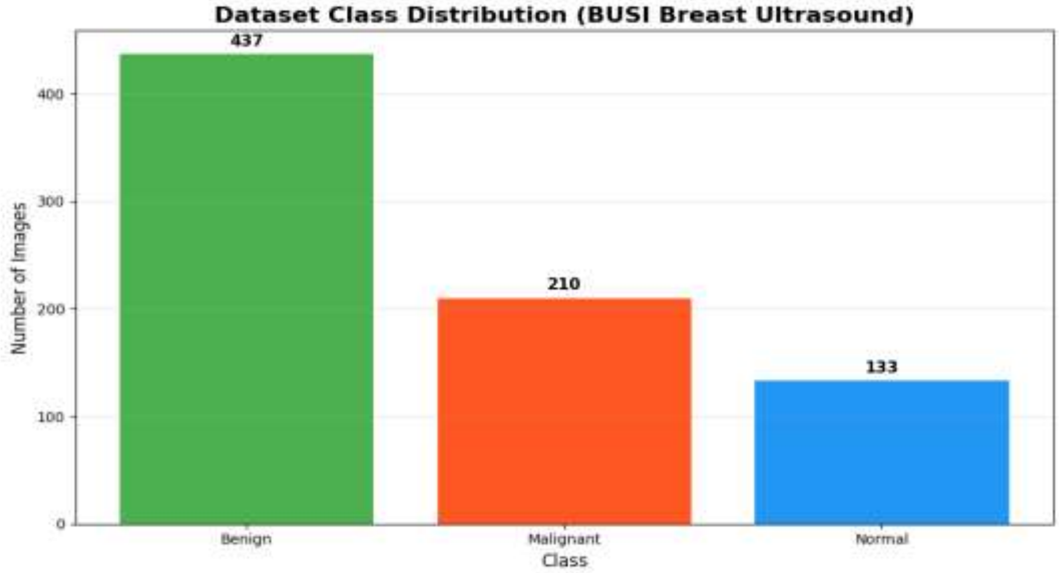
System Architecture

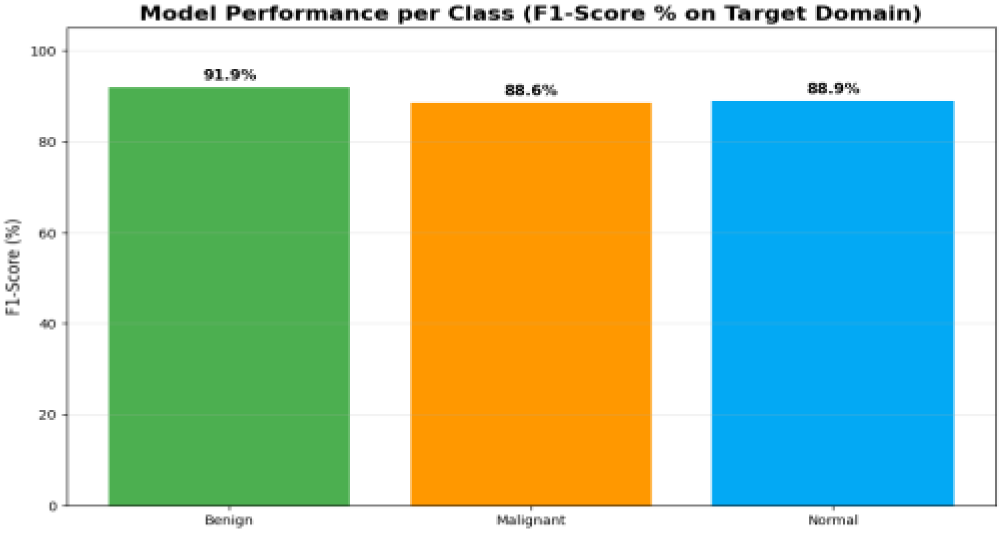


The system architecture consists of multiple layers. The data collection layer gathers ultrasound images from different scanners. The preprocessing layer standardizes image quality. The feature extraction layer uses CNNs to extract features. The domain adaptation layer aligns features across datasets. The model layer performs classification or detection. The training module builds models using multi-source data. The evaluation layer measures performance across domains. The prediction layer provides diagnostic results. The database layer stores images and outputs. The user interface allows interaction with the system. The feedback layer updates the model with new data. Overall, the architecture ensures robust and scalable performance across scanners.

V. Result and Output







VI. Conclusion

The project successfully demonstrates the effectiveness of leveraging advanced deep learning architectures, such as EfficientNet combined with domain adaptation techniques like DANN, for breast ultrasound image classification. The model achieved strong and consistent performance across all classes, with high F1-scores indicating its reliability in distinguishing between benign, malignant, and normal cases. Despite the inherent class imbalance in the dataset, the model maintained robust generalization, highlighting the strength of the chosen architecture and training strategy in handling real-world medical imaging challenges.Furthermore, the integration of domain adaptation significantly enhances the model's ability to perform well on target domain data, reducing distribution gaps and improving overall accuracy. This makes the approach particularly valuable for practical clinical applications, where data variability is common. Future work can focus on further improving performance by incorporating larger and more diverse datasets, applying advanced augmentation techniques, and exploring hybrid or ensemble models to boost diagnostic precision and reliability.

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