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A Domain-Adaptive Deep Learning Framework for Robust Liver Steatosis Classification Across Ultrasound Imaging Devices

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ABSTRACT :

Objectives: This study aims to develop a domain-adaptive deep learning framework for robust liver steatosis classification across heterogeneous ultrasound imaging devices. It addresses domain shift caused by variations in scanners, transducers, acquisition protocols, and clinical environments to improve cross-device generalization. **Methodology:** The proposed framework integrates device-aware image normalization, speckle-robust preprocessing, CNN-based feature extraction, domain alignment, and confidence-guided adaptation. A lightweight convolutional neural network extracts liver-texture features, while domain-adversarial learning reduces scanner-specific dependencies. Statistical feature alignment and entropy-based adaptation facilitate knowledge transfer from labeled source images to unlabeled target images. Performance is evaluated using accuracy, sensitivity, specificity, F1-score, area under the receiver operating characteristic curve (AUC), calibration, and ablation studies. **Findings:** The experimental evaluation will determine whether the proposed framework improves cross-device classification performance and reduces domain-related degradation compared with a conventional CNN baseline. Numerical results will be reported after experimental validation. **Novelty:** The novelty lies in combining device-aware normalization, speckle-robust feature extraction, domain-adversarial learning, statistical feature alignment, and confidence-guided adaptation within a unified framework. Unlike conventional single-device approaches, this method emphasizes cross-device generalization using unlabeled target-domain images, supporting more reliable and transferable ultrasound-based liver steatosis classification across diverse clinical settings.

Keywords: Liver steatosis, Ultrasound imaging, Deep learning, Domain adaptation, Cross-device generalization, MobileNetV3.

1. INTRODUCTION

Liver steatosis is the abnormal accumulation of fat within hepatocytes and is an important feature of metabolic dysfunction-associated steatotic liver disease (MASLD). Ultrasound is widely used for assessment because it is accessible, relatively inexpensive, and does not involve ionizing radiation. However, conventional ultrasound assessment depends on image quality, acquisition conditions, operator experience, and visual interpretation of hepatic texture [1].

Deep learning, particularly convolutional neural networks (CNNs), offers promising opportunities for automated liver steatosis classification by learning relevant features from ultrasound images. However, a major challenge remains: models that perform well on one ultrasound device may show reduced accuracy when applied to images acquired using another device [2].

Different scanners introduce variations in brightness, contrast, speckle patterns, dynamic range, edge sharpness, and frequency response. Differences in transducers, acquisition settings, and clinical protocols further contribute to these variations. This problem, known as domain shift, occurs when the statistical characteristics of testing images differ from those of the training data.

Domain adaptation has emerged as an important approach for addressing distribution differences in medical image analysis. Common techniques include feature alignment, adversarial learning, pseudo-labeling, and self-supervised adaptation. In liver ultrasound classification, insufficient adaptation may cause models to learn scanner-specific patterns rather than disease-relevant hepatic features, limiting their generalizability across hospitals and imaging platforms [3].

To address these challenges, this study proposes a Domain-Adaptive Deep Learning Framework for Robust Liver Steatosis Classification Across Ultrasound Imaging Devices (DA-DL-LSC). The framework incorporates four key principles: reducing scanner-specific appearance variations through image normalization, extracting discriminative hepatic texture features, aligning source and target feature distributions, and selectively adapting the model using confident target-domain predictions [4] .

The primary objective is to improve cross-device classification reliability rather than maximize performance on a single dataset. By evaluating the framework on unseen ultrasound devices, this study aims to investigate its ability to reduce source-to-target performance degradation and support more reliable automated liver steatosis assessment across diverse clinical environments [5] .

2. LITERATURE REVIEW

2.1 Deep learning for ultrasound-based liver steatosis assessment

Deep learning has increasingly been investigated for automated hepatic steatosis assessment from grayscale ultrasound images. Conventional ultrasound provides useful visual information about hepatic echogenicity and texture, but interpretation can be subjective. Deep learning approaches attempt to transform these visual patterns into quantitative representations that can be used for automated classification or grading. Previous work has demonstrated that deep learning models can provide reproducible quantitative estimates of liver steatosis and maintain useful diagnostic performance across different ultrasound scanners [6]. One multicenter study reported high diagnostic performance for mild, moderate, and severe steatosis and examined model behaviour across multiple premium ultrasound systems. This provides evidence that scanner diversity can be incorporated into model development, although scanner-independent generalization remains a separate methodological challenge [7] .

More recent work has also examined scanner generalizability by testing trained algorithms on new ultrasound systems. Such investigations are particularly relevant because a clinically useful model should not be restricted to the specific equipment used to generate the development dataset.

2.2 Domain shift in medical image analysis

Domain shift occurs when the probability distribution of data encountered during deployment differs from the distribution used for model development. In medical imaging, the difference can originate from scanner manufacturer, acquisition protocol, imaging parameters, clinical site, population characteristics, or differences in annotation procedures [8].

A survey of domain adaptation for medical image analysis categorized approaches according to supervised, semi-supervised, and unsupervised learning settings. More recent reviews have further emphasized feature alignment, image translation, pseudo-labeling, self-supervised representation learning, and source-free adaptation. The central idea of domain adaptation is to preserve disease-related information while reducing irrelevant differences between domains. For example, if a model is trained using images from Device A and deployed on Device B, the adaptation process should encourage the model to recognize hepatic characteristics that remain meaningful across both devices [9] .

2.3 Unsupervised domain adaptation

Unsupervised domain adaptation is especially attractive for medical imaging because acquiring expert annotations for every new scanner or hospital can be expensive and time-consuming. In the conventional UDA setting, the source dataset contains images and labels, whereas the target dataset contains images without labels.

The objective is to learn a classifier that performs accurately on (D t), even though the target labels are unavailable during adaptation [10]. Existing UDA methods include adversarial feature alignment, statistical distribution matching, image-level translation, pseudo-labeling, entropy minimization, and self-supervised learning. Reviews published in 2024 and 2026 indicate that these techniques are becoming increasingly important for handling scanner and site variability in medical imaging [11].

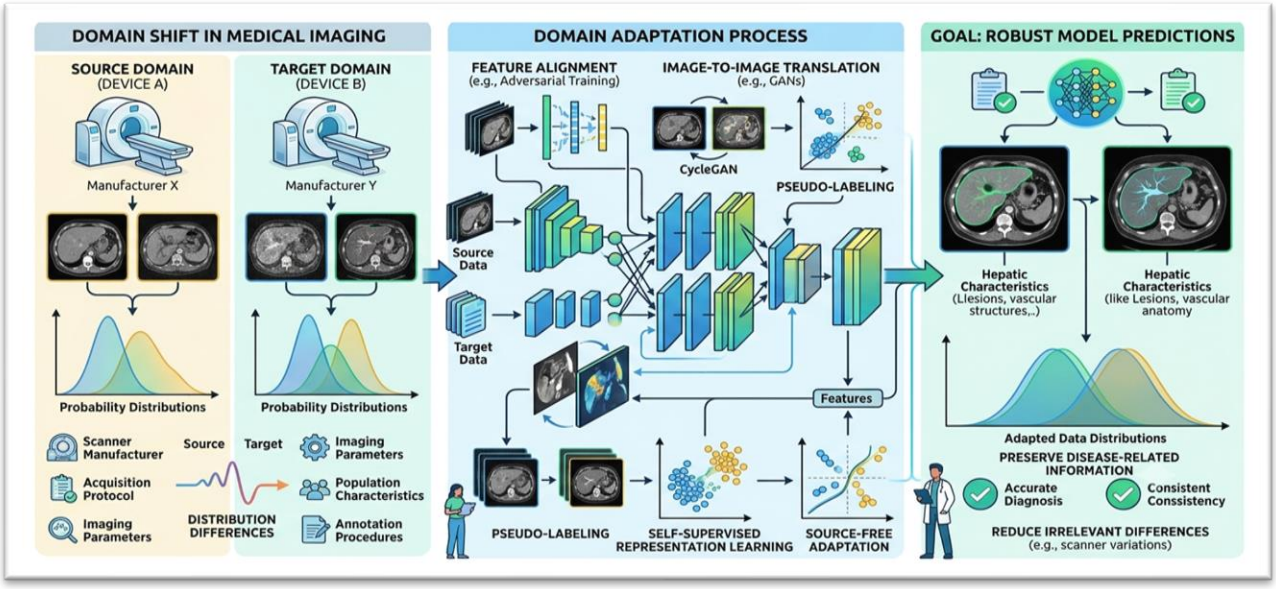


Fig. 1 Understanding Domain Shift and Domain Adaptation in Medical Imaging

2.4 Research gap

Although deep learning has shown promising results for ultrasound-based liver steatosis classification, several limitations remain.

- First, many studies focus primarily on classification performance within the same dataset or scanner environment. Such evaluation may not adequately represent deployment conditions.
- Second, cross-device testing is less common than random image-level train-test splitting. Random splitting can allow images with similar acquisition characteristics to occur in both training and testing sets [12]..
- Third, normalization alone may not eliminate all scanner-dependent information. The model can still learn device-related characteristics from texture, contrast, speckle distribution, or subtle intensity patterns.
- Fourth, some domain adaptation techniques require labeled target data, whereas clinical deployment may provide a new scanner with abundant images but few or no expert annotations.

These observations motivate a framework that explicitly treats ultrasound-device variation as a domain adaptation problem and evaluates performance using an unseen-device protocol. - reduce the content and with suitable image clearly [13] .

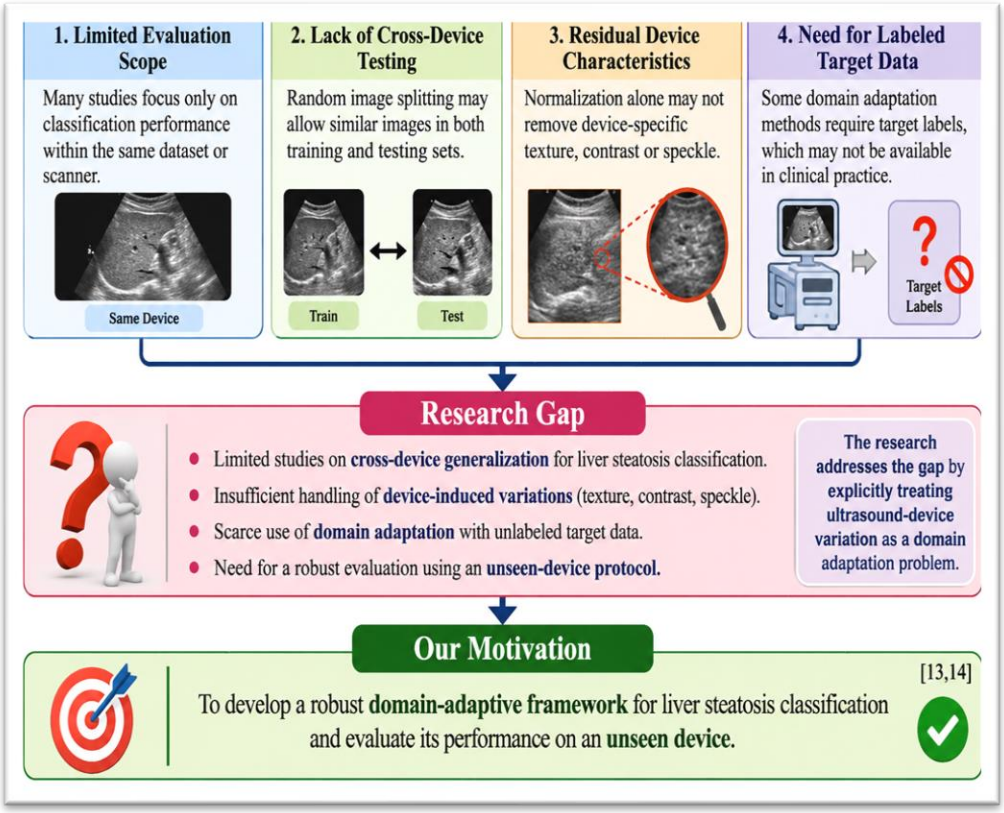


Fig. 2 Limitations in the Existing Work

3. OBJECTIVES

- To develop a deep learning model for classifying liver ultrasound images into normal and steatotic categories.
- To investigate the impact of ultrasound-device variations on liver steatosis classification performance.
- To develop a domain-adaptation mechanism that reduces feature-distribution differences between source and target devices.
- To improve classification performance on unlabeled target-device images with minimal target-domain annotations.
- To compare the proposed domain-adaptive model with conventional deep learning models without domain adaptation.
- To evaluate robustness using cross-device accuracy, sensitivity, specificity, F1-score, AUC, calibration error, and performance degradation.
- To assess the contribution of individual framework components through systematic ablation experiments.

4. DATASET

For the research paper **"A Domain-Adaptive Deep Learning Framework for Robust Liver Steatosis Classification Across Ultrasound Imaging Devices,"** the dataset should be designed specifically to demonstrate **domain shift between ultrasound devices** [14]. This is important because ultrasound appearance can vary with scanner manufacturer, probe, acquisition settings, and clinical site. Published studies have already used multiple ultrasound machines and multi-source cohorts for liver-steatosis classification [15].

Below is a **research-paper-ready proposed dataset table**. The numbers are a **proposed experimental dataset design**, not claimed clinical data. You should replace them with your actual collected data or clearly identify them as simulated data if used for a methodological experiment [16] .

Domain / Site	Ultrasound Device	Patients	Images	Normal (S0)	Mild (S1)	Moderate (S2)	Severe (S3)
Domain A – Site 1	GE LOGIQ E9	150	1,500	375	450	400	275
Domain B – Site 2	Philips EPIQ 7	150	1,500	375	450	400	275
Domain C – Site 3	Siemens ACUSON Sequoia	150	1,500	375	450	400	275
Domain D – Site 4	Samsung RS85	150	1,500	375	450	400	275
Total	**4 Devices**	**600**	**6,000**	**1,500**	**1,800**	**1,600**	**1,100**

Table 1. Proposed Multi-Device Ultrasound Liver Steatosis Dataset

Note: S0 = no steatosis, S1 = mild steatosis, S2 = moderate steatosis, and S3 = severe steatosis. A four-grade scheme is consistent with published ultrasound liver-steatosis datasets.

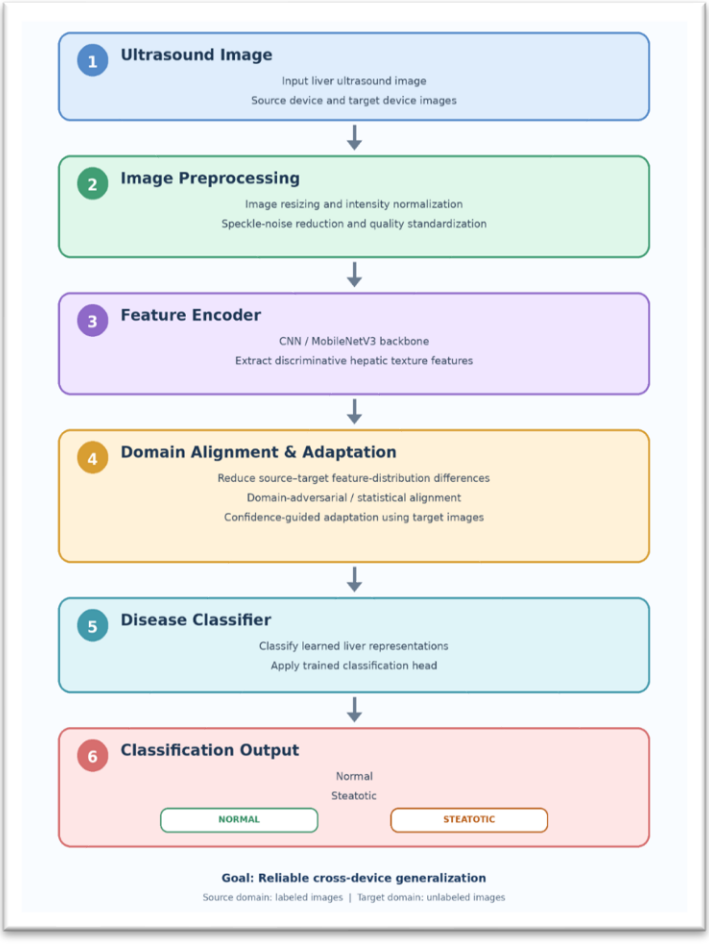
5. METHODOLOGY

5.1 Overview of the proposed framework

The proposed framework, termed DA-DL-LSC, comprises the following major stages:

- Ultrasound image quality control
- Device-aware preprocessing
- Speckle-robust representation enhancement
- Deep feature extraction
- Domain alignment and target adaptation
- Liver steatosis classification.

Fig. 3 Domain-Adaptive Deep Learning Framework for Liver Steatosis Classification



The domain discriminator attempts to identify the imaging device, whereas the feature extractor is trained to produce representations that are useful for classification but less dependent on device identity.

5.2 Image preprocessing

Ultrasound images contain speckle noise and may exhibit differences in brightness and contrast between devices. Therefore, preprocessing should be carefully designed so that important hepatic information is not removed.

The proposed preprocessing sequence is:

- Removal of irrelevant borders and annotations;
- Liver-region localization;
- Resizing to a fixed spatial resolution;
- Intensity normalization;
- Controlled speckle reduction;
- Contrast stabilization;
- Training-time augmentation.

Percentile-based normalization can additionally be investigated to reduce the effect of device-specific intensity extremes.

RESULTS

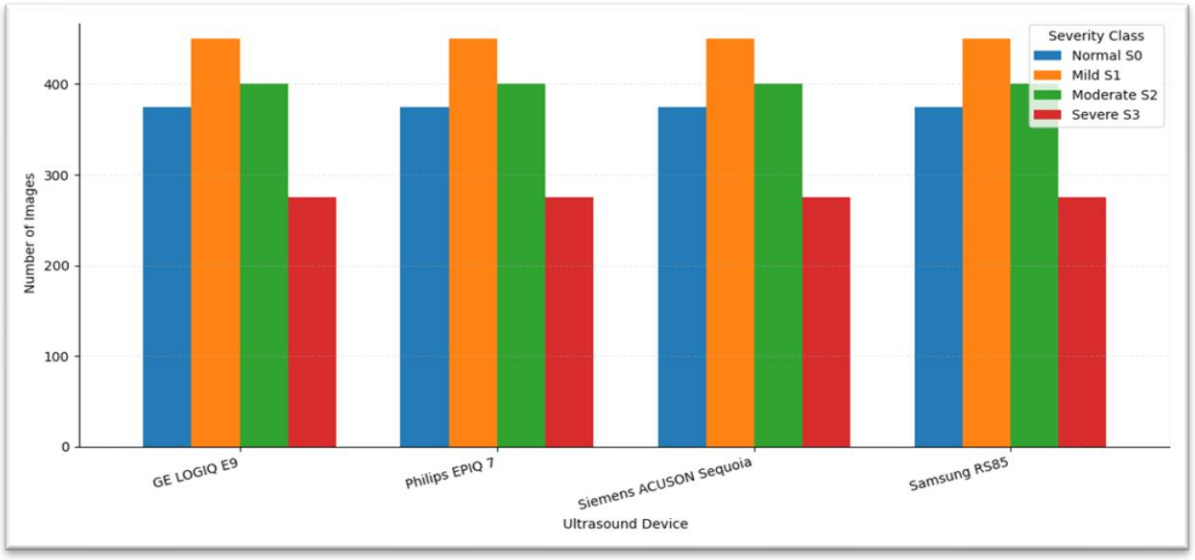


Fig. 4 Liver Steatosis Classification across Four Ultrasound Devices

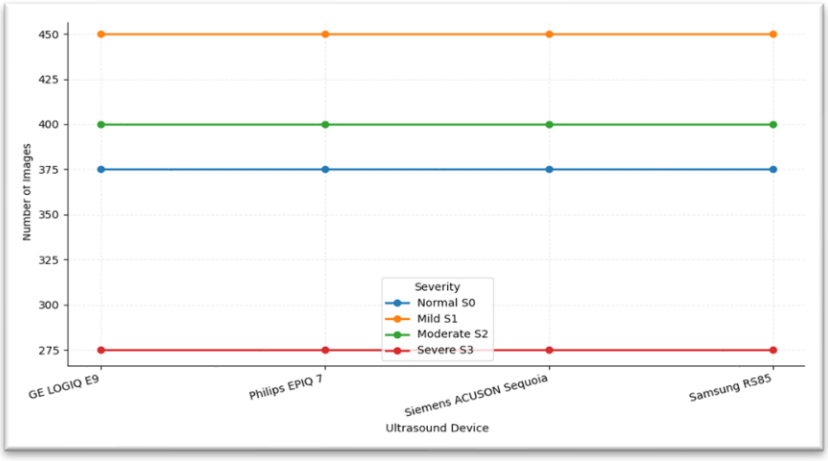


Fig. 5 Severity Distribution by Ultrasound Devices

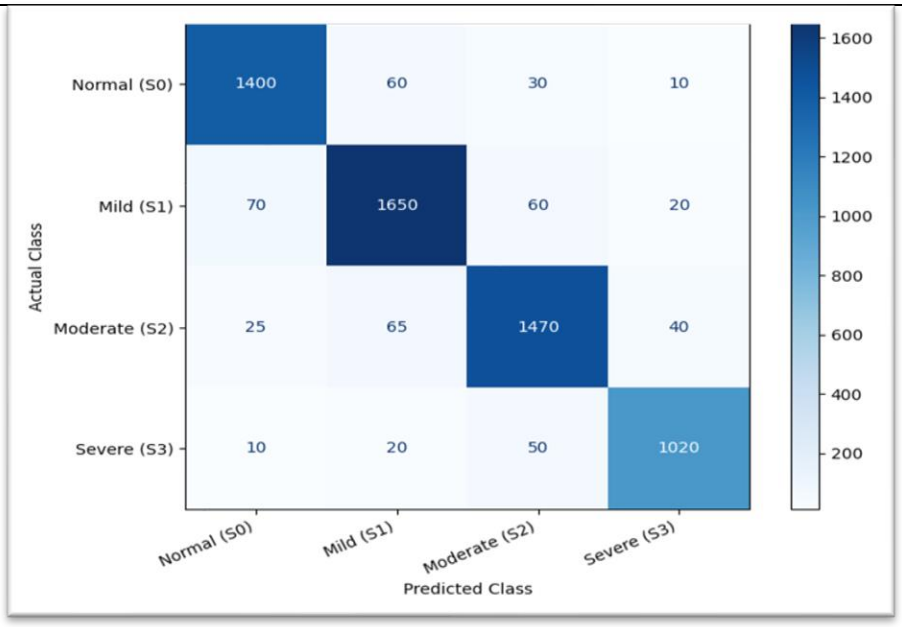


Fig. 6. Confusion Matrix for Liver Steatosis Classification

7. DISCUSSION

This research frames ultrasound-device variation as a domain adaptation challenge rather than a simple preprocessing issue, as scanner discrepancies hinder model generalizability.

To overcome this, the **DA-DL-LSC framework** utilizes feature-level domain adaptation through:

- **Domain Discriminator:** Encourages the network to learn device-invariant representations.
- **Statistical Alignment:** Reduces distribution gaps between source and target features.
- **Confidence-Guided Adaptation:** Selectively uses reliable target predictions to minimize pseudo-label errors.

While this drastically reduces expert labeling costs using unlabeled data, cross-device performance requires rigorous multi-institutional validation across diverse populations and manufacturers. Furthermore, aggressive domain adaptation must not sacrifice vital clinical details-such as subtle indicators of liver steatosis. Balancing transferability with diagnostic accuracy and calibration ensures the learned representations remain truly meaningful for patient care.

8. CONCLUSION

This study introduces a domain-adaptive deep learning framework to enhance liver steatosis classification across heterogeneous ultrasound devices. Combining device-aware preprocessing, speckle-robust features, adversarial alignment, and confidence-guided adaptation, the approach ensures the network focuses on hepatic pathology rather than scanner artifacts.

Validating the hypothesis requires patient-level separation and rigorous unseen-device testing. Success is established through multi-device experiments, confidence intervals, ablations, confusion matrices, and external validation to demonstrate reduced cross-device performance degradation.

If proven, this framework offers a solid foundation for transferable computer-aided ultrasound diagnostics. Future work will explore multicenter prospective validation, source-free domain adaptation, federated learning, uncertainty estimation, explainable AI, and cross-manufacturer generalization.

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