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Transfer-Learning for Cross-Weighted MRI Liver Cirrhosis Segmentation Using CirrMRI600+

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Abstract

Accurate and fully automated liver segmentation can significantly improve disease detection and personalised treatment planning. Liver cirrhosis is the final stage of liver disease and is characterised by fibrosis and the remodeling of the liver, which increases the mortality rate. Magnetic resonance imaging (MRI), particularly T1- and T2-weighted sequences, provides a powerful non-invasive tool for assessing liver structure and pathology. However, manual delineation of cirrhotic liver regions is both time-consuming and prone to human error, with performance heavily dependent on the radiologist's expertise. Reliable segmentation is further complicated by pronounced morphological distortions and heterogeneous signal characteristics associated with cirrhosis. In this study, we address these challenges using a fully convolutional ResNet-UNet framework that employs cross-weighted transfer learning, retrained on T1-weighted MRI data to capture general anatomical representations and fine-tuned on T2-weighted images to adapt to contrast and pathological variability, using the CirrMRI600+ dataset. The proposed model achieved the highest Dice coefficient of 0.89 and mIoU scores of 0.81 on the testing set, surpassing the performance of training a single ResNet-UNet on T1 and T2 separately, without transfer learning.

This cross-weighted training paradigm demonstrates the effectiveness of contrast-domain pretraining for robust and efficient liver segmentation, paving the way for multimodal MRI integration in hepatic disease assessment and advancing progress toward automated cirrhosis staging and personalised therapeutic planning.

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1. INTRODUCTION

Cirrhosis and other chronic liver diseases significantly increase the risk of liver cancer, which is the third leading cause of cancer-related mortality worldwide [1],[2]. Liver diseases remain a major global health concern, particularly due to the silent pandemic of metabolic syndrome, a risk factor for various liver diseases. Accurate segmentation of the liver from MRI scans is essential for the quantitative diagnosis of hepatic pathologies such as cirrhosis, fibrosis, and hepatocellular carcinoma. Precise segmentation provides detailed information about the extent and location of liver damage, which can support clinical decision-making, including treatment planning, including liver transplantation, and targeted therapies.

Recent advances in deep-learning-based liver MRI segmentation have been driven by the release of the CirrMRI600+ dataset [3], which provides more than 600 T1- and T2-weighted MRI scans with high-quality annotations of cirrhotic livers. The dataset developers benchmarked 11 state-of-the-art (SOTA) segmentation networks, including nnU-Net, TransUNet3D, Swin-UNETR, Attention U-Net, and nnSynergyNet3D, reporting competitive Dice similarity coefficients across modalities. However, these baselines treat T1- and T2-weighted images as independent datasets, training separate models for each contrast. This approach neglects the shared liver anatomy across modalities and fails to exploit the potential of cross-modality knowledge transfer.

The report indicates that the baseline models yield reasonable segmentation accuracy despite their susceptibility to variations in modality and limited cross-domain generalisation between T2 and T1 modalities. An example of this is seen when only T2-weighted scans are used for training, which results in the model not becoming consistently converged to a solution or producing accurate segmentations because of a small sample size and high variability of the T2-weighted signal. T1-weighted scans generally yield more consistent anatomical information but yield poorer contrast with respect to pathology. These observations give rise to an opportunity to transfer knowledge from T1-weighted images, which provide a high level of anatomical representation, to T2-weighted images, which provide a high level of pathological discrimination, via transfer learning. The CirrMRI600+ dataset is an extremely useful benchmark for evaluating the comparative performance of baseline methods; however, the majority of previously evaluated methods in the literature focus on the architectural design of the implemented models, with very little emphasis placed on the methodology implemented to learn from data. To date, no baseline method has included any reference to transfer learning or to domain adaptation when training on MRI data utilizing either the T1 or T2-weighted MRI modalities. Therefore, the use of this dataset has not been thoroughly investigated with regards to the benefit of transferring knowledge from each modality into the other.

In the current project, we propose to use transfer-learning techniques to improve the accuracy of liver segmentation using cross-modal knowledge transfer between T1- and T2-weighted MRI data, and we will provide a summary of the key contributions of our work below.:

1. We identify and analyse the limitations of existing CirrMRI600+ benchmark models, highlighting the lack of cross-modality feature sharing between T1 and T2 MRI scans.

2. We introduce a ResNet-UNet-based transfer learning framework that leverages pretrained weights from T1-weighted data and fine-tunes on T2-weighted images for improved segmentation of cirrhotic liver regions.

2. RELATED WORK

The recent release of CirrMRI600+ dataset provided the first large, expert-annotated benchmark for cirrhotic liver segmentation and staging. The dataset developers evaluated 11 state-of-the-art 3D segmentation networks to establish baseline performance and reproducibility standards for future research [3]. In this section , we review those benchmarked methods and discuss their strengths and limitations for cirrhotic liver segmentation.

nnU-Net is an auto-configuring U-Net framework that automatically adapts preprocessing, architecture, and training to the dataset. It frequently serves as a strong, reproducible baseline in medical

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imaging. The nnU-Net often achieves competitive Dice scores on CirrMRI600+ and other medical tasks thanks to its smart configuration and robust augmentations. However, its design remains fundamentally local (convolutional) and therefore primarily captures local spatial features. As a result, it may miss long-range contextual cues when liver morphology is highly distorted by cirrhosis; moreover, its automatic tuning may not optimally exploit multimodal (T1/T2) differences without manual modification [4].

Swin-UNETR integrates a transformer-based encoder (Swin Transformer) with a UNet-style decoder to capture long-range dependencies. Transformers can capture global context and complex texture patterns, which are attractive for cirrhotic livers. In practice on CirrMRI600+, however, Swin-UNETR did not consistently and substantially outperform strong CNN baselines (e.g., nnU-Net / Synergy variants), and its higher memory and compute costs can make training and inference less practical for large 3D volumes. These findings suggest that although transformers provide global contextual modelling, they do not automatically guarantee large gains for this task without careful design and regularization [5].

Hybrid CNN-Transformer models are an integration of convolutional encoders with Transformer bottlenecks (or attention modules). These models work to learn both local spatial features and global contextual information. In experiments using CirrMRI600+, hybrid models produced respectable performance, but, like standalone Transformers, did not outperform optimised CNNs consistently. In addition, the use of Transformer modules often increased complexity and sensitivity to hyperparameters; therefore, gains were minimal in several instances [6].

Attention U-Net is based on the original U-Net model with Attention gates added to the skip connections to improve focus on salient regions. This provides better focus on relevant liver boundaries and fewer false positives in some cases. However, since the Attention gates are local in nature, they do not fully compensate for the need to consider context when the shape of the liver is very atypical, and the use of Attention alone cannot account for the domain shift between the T1 and T2 contrasts. [7].

Vnet is an early volumetric CNN architecture designed for 3D medical segmentation. VNet provides strong baselines for volumetric tasks but is relatively old and less flexible than modern residual/attention/transformer hybrids. In the CirrMRI600+ benchmark, VNet achieves acceptable segmentation but typically underperforms more modern architectures tailored to multi-scale feature fusion [8].

Ensemble or synergy – based networks combine multiple architectural principles (e.g., residual connections, attention, multi-scale fusion). In CirrMRI600+ benchmarks, synergy models were often among the top performeing approaches . Although these models achieve high Dice scores, they are often complex, computationally heavy, and harder to reproduce or deploy clinically. Complexity makes ablation and interpretability more difficult; importantly, these models were evaluated per-modality and do not leverage cross-modality transfer between T1 and T2 weighted scans [3].

Recent 3D transformer architectures designed for volumetric segmentation show promise for capturing volumetric global context. However, within the CirrMRI600+ benchmark, the improvements over tuned CNNs were often incremental. In addition, transformer models typically require careful training strategies, including stronger regularisation and larger batch sizes, to achieve optimal performance. This limits their practical advantage when per-modality data is modest [3].

A broad body of literature on liver segmentation and lesion/fibrosis detection across MR and CT provides important context. Representative, high-quality studies include both methodological advances and dataset-specific analyses. Several peer-reviewed works have reported MRI liver segmentation using modern

CNN variants and attention mechanisms such as dual-attention 3D U-Net variants, demonstrating improved boundary delineation, particularly for lesion segmentation. However, many of these studies focus on non-cirrhotic or lesion-centric datasets (e.g., CHAOS, MSD subsets), and therefore their findings may not fully translate to the diffuse cirrhotic remodelling observed in CirrMRI600+ [9].

Recent studies have also explored fibrosis staging and cirrhosis detection from MRI using two-stage or multi-task pipelines (segmentation followed by classification). For instance , Gupta et al. developed a two-stage T2-MRI pipeline for advanced fibrosis detection (Radiology AI / PubMed), and Zeng et al. proposed a multi-scale attention model for cirrhosis stage estimation using CirrMRI600+ as a benchmark. These studies demonstrate effectiveness of combining segmentation with downstream classification tasks. However, they highlight that per-contrast training (T1 or T2 alone) can limit generalisation across scanner and sequence variations [10].

From the above review, it can be onserved that cross-contrast transfer learning has not been explicitly explored. Although, cirrMRI600+ dataset includes both T1 and T2 weighted scans, the official benchmarks train and report separately for each contrast. Pretraining on T1 (which provides stable anatomical priors) and fine-tuning on T2 (which emphasises pathological contrast) is a promising strategy to combine the strengths of both contrasts. To the best of our knowledge, this transfer strategy has not been investigated in the published CirrMRI600+ baselines studies.

In this study, we employ a ResNet-UNet segmentation backbone that is pretrained on the T1 subset and subsequently fine-tuned on the T2 subset of CirrMRI600+ dataset. Pretraining on T1 enables the encoder to learn modality-invariant anatomical representations suh as liver shape, boundaries, and vascular patterns. Fine-tuning on T2-weighted images adapts the decoder/head to pathology-sensitive intensity patterns, thereby; improving segmentation performance for cirrhotic liver structures.

3. METHOD

This section describes the proposed cross-contrast transfer learning framework for liver segmentation using the CirrMRI600+ dataset. The proposed method is motivated by the observation that T1-weighted MRI provides stable anatomical structure, whereas T2-weighted MRI expresses stronger pathological cues associated with cirrhosis (fibrosis, oedema, nodularity). To leverage the complementary properties of these contrasts, we design a ResNet-UNet segmentation model that is pretrained on T1 volumes and fine-tuned on T2 volumes. The proposed framework consists of four main steps. First, a preprocessing step to normalise, resize, and augment the CirrMRI600+ dataset. Second, a ResNet-UNet backbone is trained using the T1 subset (310 3D volumes) to learn modality-invariant anatomical representations: liver boundaries, lobar structure, vasculature, surface curvature. Third, a T2 fine-tuning step to initialise the same model with T1-trained weights and adapt the decoder and late encoder layers to T2-specific pathological contrast: fibrosis bands, regenerative nodules, surface irregularities. Finally, the model performs a voxel-wise liver segmentation step to predict liver cirrhosis boundary regions from T2, improved by the anatomical priors learned from T1. The architecture and the transfer schedule are illustrated in Figure 1.

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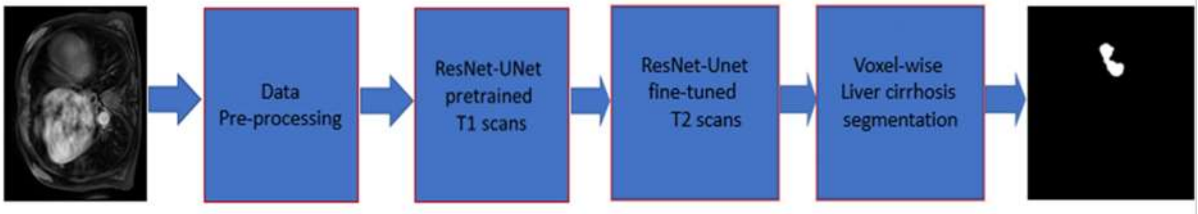

Figure 1: Proposed Model pipeline

3.1. Dataset Description

This study utilises the recently introduced CirrMRI600+ dataset, a large-scale collection of 628 high-resolution 3D abdominal MRI volumes designed specifically for cirrhotic liver research [3]. The dataset was collected from clinical MRI examinations and was anonymised before processing, comprising 310 T1-weighted and 318 T2-weighted scans (1.5T and 3T field strengths), each with expert-generated liver segmentation masks produced by experienced abdominal radiologists. CirrMRI600+ provides standardised training (70%), validation (10%), and testing (20%) splits, which we adopt to ensure reproducibility and comparability with the baseline benchmarks reported in the original study. The segmentation task is formulated as a binary semantic segmentation problem (0 = normal, 1 = cirrhotic), with the goal of learning a voxel-wise mapping. The diversity of imaging contrast and the scale of CirrMRI600+ dataset make it particularly well suited for investigating cross-modality learning strategies, including the T1-to-T2 transfer learning approach proposed in this work.

3.2 Pre-processing Pipeline

All MRI volumes in the CirrMRI600+ dataset were processed using a minimal yet effective preprocessing pipeline to ensure consistency across subjects and modalities. First, intensity inhomogeneity was corrected using the N4ITK bias-field correction algorithm, widely used for MRI non-uniformity correction because of its robustness and stability in clinical imaging workflows [11].

Following bias correction, all scans were intensity-normalised using z-score normalisation within the foreground body region, a standard technique shown to stabilise MRI intensity distributions across patients and acquisition protocols [12]. Each volume was then resized to match the required input dimensions of our ResNet-UNet architecture, following conventional practices in deep CNN-based medical segmentation to ensure a uniform input shape and efficient memory utilisation [13]. To improve model generalisation and mitigate overfitting, we applied a set of 3D data augmentation operations during training, including horizontal and vertical flipping and rotation by 90, 180, and 270 degrees, which have been demonstrated to significantly enhance robustness in volumetric segmentation tasks [14, 15]. The optimised pre-processing pipeline offers an 'ideal' or a 'standard' way of obtaining input representations that are invariant of modality and enable reliable transfer learning for T1 and T2 MRI scans. Pre-Training ResNet-Unet requires 256x256 pixel size for all images to ensure consistency across all images during the training process.

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3.3 Model Architecture: ResNet-UNet

Our proposed segmentation framework uses a hybrid architecture, consisting of the ResNet framework for deep residual learning and the UNet framework for multi-scale encoder–decoder design and is a commonly utilized backbone for segmentation of biomedical, specifically MRI (Magnetic Resonance Imaging) images. The encoder is based on a modified ResNet-50 implementation that further integrates residual connections to improve the stability of gradient flow, reduce issues related to the vanishing gradient problem (the important gradient cannot be tracked beyond a certain number of convolutional layers), and allow for deeper feature extraction using a deep learning model; this is especially useful for complex MRI textural characteristics and modality specific signal variations. The decoder maintains the classical UNet architecture, working by progressively operating on down-sampled, spatially compressed feature maps and combining them (via long skip connections ultimately from the encoder) with the activations of the original input image from the encoder, which leads to excellent retention of fine anatomical details and subsequently (+) greater accuracy in segmentation tasks in the field of medicine. [15]. To better capture multi-scale liver boundaries and tissue heterogeneity, we fuse ResNet hierarchical residual feature maps with the UNet up-sampling pathway, enabling both high-level semantic representation and precise localisation. Such encoder–decoder hybrids have demonstrated superior performance in MRI segmentation tasks,

particularly when applied to heterogeneous datasets involving T1/T2 variations [17];[18]. This architecture provides a strong, stable baseline for our proposed transfer-learning approach, where the model is pretrained on T1-weighted MRI and fine-tuned on T2-weighted MRI. Figure 2 shows the architecture of the Resnet-Unet.

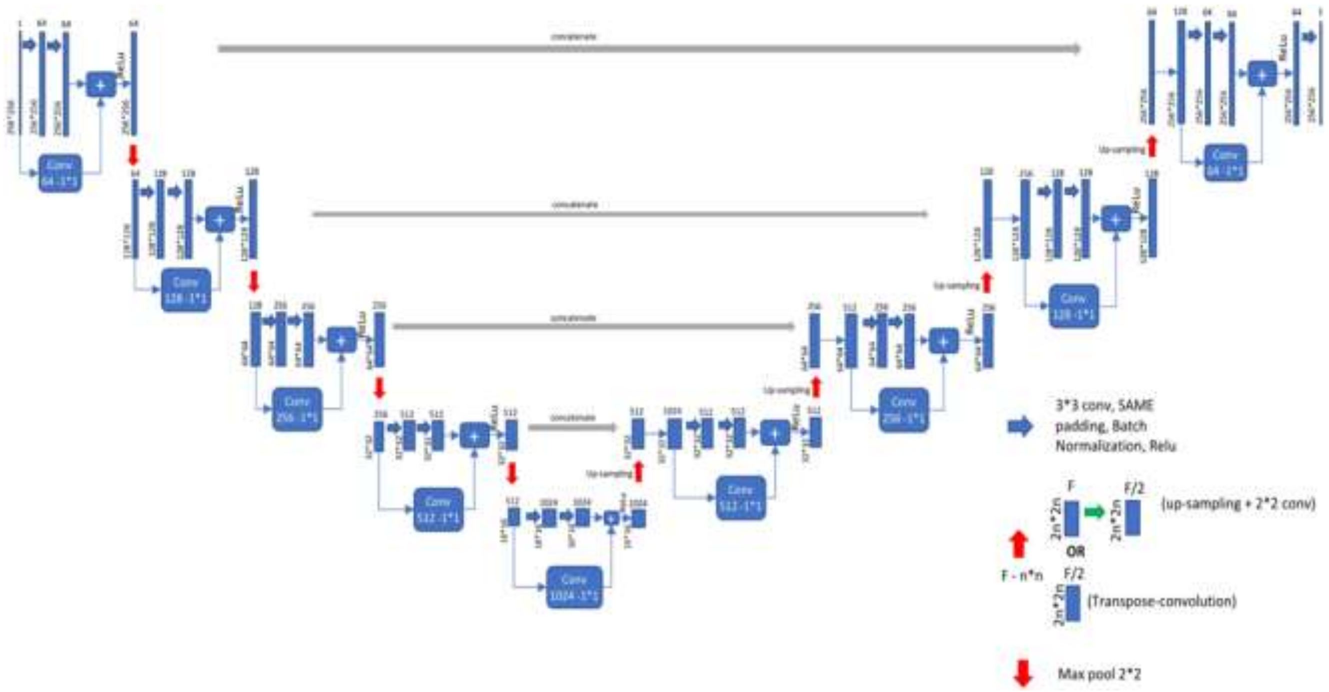

Figure 2: Architecture of ResNet-UNet

The ResNet-UNet architecture is particularly well suited to cross-modality transfer learning between T1- and T2-weighted MRI because it combines deep residual feature extraction with multi-scale spatial reconstruction, both of which help address structural and contrast differences between the two modalities.

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Although T1 and T2 MRI exhibit markedly different intensity profiles, they preserve consistent anatomical structures, especially the liver boundary, vascular topology, and organ shape. The residual encoder (ResNet-50) is known to learn robust mid- and high-level semantic representations that are less sensitive to contrast variations and more aligned with underlying anatomy, making these features transferable across MRI modalities [16];[19]. Moreover, residual connections reduce the risk of overfitting when fine-tuning on a new domain and accelerate convergence by enabling the network to adapt features to the target modality without destabilising previously learned weights.

The decoder component of the UNet further facilitates modality transfer by leveraging skip connections that preserve spatial localization, allowing the model to adapt reconstruction pathways to T2 contrast while still benefiting from anatomical priors learned on T1 segmentation [15]. Previous studies in medical imaging show that transfer learning between MRI contrasts improves segmentation performance, especially when the target modality has fewer training samples or exhibits higher variability [20]; [21].

The ResNet-UNet is an excellent choice for transferring between T1 and T2 images because it provides a combination of generalizable semantic encoding, fine localizations, and stable optimization dynamics, thus allowing the model to keep anatomy-aware features from T1 and efficiently change to the T2 intensity distribution during fine-tuning.

3.4 Training Strategy and Optimization

The framework for our training process consists of a twin-stage learning path: pre-training with T1-weighted MRI data followed by fine-tuning using T2-weighted MRI data. This staged method takes advantage of the physiological similarities between the two imaging techniques so that our network can learn how to use the contrast information found in each modality differently. In the following two sections, we describe the entire process in detail.

A- Pretraining on T1 MRI

The model is initially trained on all available 310 T1-weighted volumes using the radiologist-provided liver masks as ground truth. During this stage, the ResNet encoder learns modality-invariant anatomical features, such as organ boundaries, vascular structures, and liver morphology. These mid-level semantic features have been shown to transfer reliably across MRI modalities because they are contrast-independent [19]; [22].

B- Fine-Tuning on T2 MRI

After convergence on T1 data, the pretrained model is fine-tuned using the 318 T2-weighted volumes. At the start of fine-tuning, only the decoder and the last two residual blocks are unfrozen at the start of fine-tuning, enabling the model to adapt to the higher T2 signal intensity of fluids and to different liver–vessel contrast patterns. Fine-tuning uses a lower learning rate to avoid catastrophic forgetting and to encourage smooth adaptation. This controlled optimisation helps the model retain anatomical priors from T1 while recalibrating intensity-sensitive filters for T2.

Fine-tuning is performed using a lower learning rate (1/10 of the pretraining rate) to avoid catastrophic forgetting and to encourage smooth adaptation. This controlled optimisation helps the model retain anatomical priors from T1 while recalibrating intensity-sensitive filters to T2 [21]; [23].

4. RESULTS AND DISCUSSION

4.1. RESULTS

This research was carried out using the CirrMRI600+ dataset (officially separated into trains, validation and tests) so that experiments could be compared fairly with full reproducibility. The proposed ResNet-UNet was trained separately on the T1 and T2 weightings and used cross-modality transfer learning: ResNet-UNet pretrained from T1 was then fine-tuned for T2. All models were trained for 10 epochs using Adam optimiser (starting learning rate 1e-4). Early stopping based on the validation Dice loss was used.

A three-metric evaluation of model performance was performed (intersection-over-union, specificity and F-measure). For all experimental settings, the proposed approach had strong performance; the average model Dice score was 0.87 for T1 and 0.84 for T2 when trained with the same modality as the dataset.

Using transfer learning led to even greater accuracy in the T2 data subset with a Dice Coefficient reaching 0.89 by using T1 pre-trained weights to fine-tune where applicable. Segregation of the liver's borders in the segmentation mask represents accurate rendering despite the presence of intensity inhomogeneities or motion artifacts, thus validating that transferring cross-modal to improve generalizability and decrease data requirements provides a true value to the ResNet U-Net pipeline's ability to correct automated liver segmentation results in variable/multiple MRI acquisition techniques. Figure 1 summarizes all the experimental conditions, and the results indicate that ResNet U-Net performed significantly better than the standard U-Net on Dice and mean IOU score calculations; therefore, using a residual encoder provides significant improvement in feature extraction when compared with U-Net and improved segmentation results. Future investigations will determine how ResNet U-Net compares to additional more sophisticated architectures such as DeepLabv3+ and nnU-Net. Figure 2 illustrates the segmentation results.

Table 1. Liver Segmentation Performance comparison of ResNet-UNet models trained on T1, T2, and transfer learning (T1toT2) for liver Cirrhosis Segmentation.

Models	MRI Modality	Dice Coefficient	mIoU	Precision	Recall
UNet_T1 (Baseline)	T1-weighted only	0.83	0.72	0.84	0.84
ResNet-UNet_T1	T1-weighted only	**0.87**	**0.78**	**0.88**	**0.86**
ResNet-UNet _T2	T2-weighted only	**0.84**	**0.74**	**0.85**	**0.83**
Proposed model: ResNet-UNet: Transfer learning_T1_ T2	Pretrained on T1, fine-tuned on T2	**0.89**	**0.81**	**0.90**	**0.88**

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4.2. DISCUSSION

Accurate liver segmentation in cirrhotic patients remains challenging due to anatomical deformation, heterogeneous tissue appearance, and reduced contrast between the liver and surrounding organs, particularly in T2-weighted MRI. In this study, these challenges were addressed using a transfer-learning-driven ResNet-UNet framework that exploits shared anatomical representations across MRI modalities. Pretraining the segmentation network on T1-weighted MRI enables the model to learn modality-independent anatomical features such as liver shape, spatial context, and organ boundaries. Fine-tuning on T2-weighted images allows the network to adapt these representations to modality-specific intensity characteristics while preserving the learned structural information.
The observed performance improvements indicate that liver features learned from T1-weighted data generalises well to T2-weighted imaging. These findings support the hypothesis that cross-weighted transfer learning is effective for abdominal MRI segmentation. From a clinical perspective, reliable liver segmentation is a critical prerequisite for quantitative assessment of liver volume, disease progression, and treatment planning in patients with cirrhosis. The proposed framework provides a fully automated, non-invasive solution that reduces inter-observer variability and minimises manual annotation effort. Unlike conventional segmentation methods or single-modality deep learning models, the proposed approach explicitly leverages cross-modality information through transfer learning. This strategy is particularly beneficial in clinical settings where annotated T2 datasets are limited, as is common in clinical practice.
Compared with training ResNet-UNet solely on T2 images, the transfer-learning-based ResNet-UNet achieves faster convergence, improved generalisation, and greater segmentation robustness. Despite its promising performance, this study has several limitations. First, the experiments were conducted on a single dataset, and future work should validate the model's generalisability across multi-centre datasets. Second, the current framework processes 2D slices independently, which may limit spatial consistency along the axial direction. Future research will focus on extending the model to 3D architectures, incorporating advanced loss functions, such as Dice–Tversky loss, and exploring domain-adaptation techniques to further enhance cross-modality performance.

4. CONCLUSIONS

In this study, we presented a transfer-learning-driven ResNet-UNet framework for liver cirrhosis segmentation using the CirrMRI600+ dataset. By pretraining the network on T1-weighted MRI and fine-tuning it on T2-weighted images, the proposed approach effectively exploits shared anatomical features across MRI modalities

The experimental results demonstrate that cross-weighted transfer learning significantly improves segmentation accuracy, boundary precision, and robustness compared with training on T2 data alone. The proposed method offers a reliable and efficient solution for automated liver segmentation in patients with cirrhosis and shows strong potential for clinical adoption.

Overall, this study highlights the importance of cross-modality transfer learning in medical image analysis and provides a solid foundation for future research into multi-modal liver disease assessment and automated clinical decision-support system.

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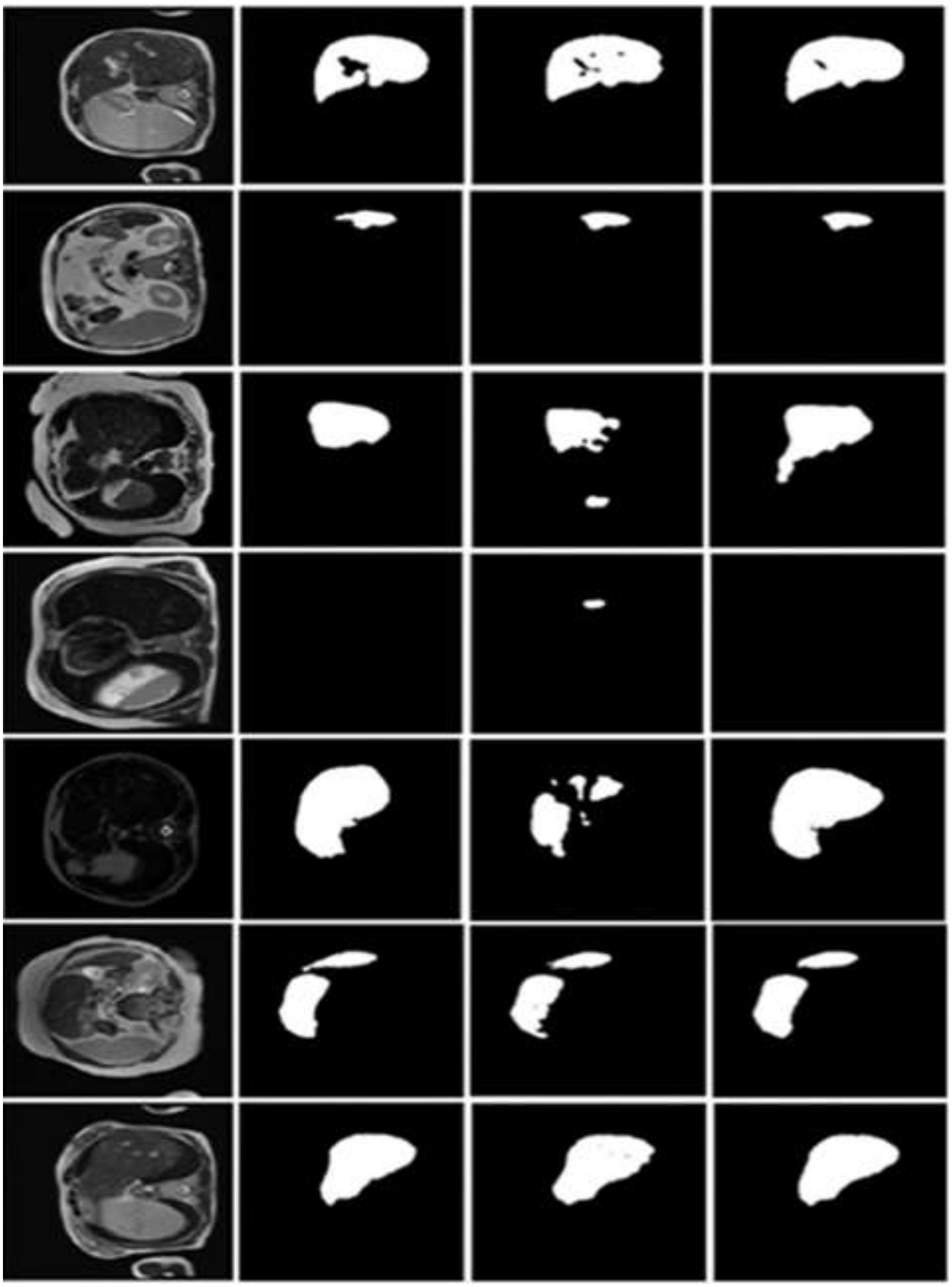

Figure 2: Prediction results for liver cirrhosis segmentation using transfer learning from T1 to T2: (Left to right) T2 testing images, Ground truth images, ResNet-UNet _T2 results, Proposed model results .

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