# MR image prediction at high field strength from MR images taken at low field strength using multi-to-one translation

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*Abstract—* **Patients with implants may need to undergo Magnetic Resonance Imaging (MRI) at lower field strengths to avoid negative impacts from the strong electromagnetic fields. However, the quality of low-field MRI images may be inferior, potentially leading to inaccurate clinical diagnoses. To overcome this limitation, our study proposes a convolutional neural network developed by using U-Net to generate high-field MR images from low-field ones. The proposed model employs multiple MRI contrasts at lower field strength to generate MR images in one or several contrasts at higher field strength. This method overcomes the limitations of previous research which only utilized a single contrast (one contrast-to-one contrast translation) or multiple contrasts including MR image at high (target) field strength as input. After creating a dataset for multi contrast-to-one contrast translation, the model was optimized using techniques such as data augmentation and selection of the best model with minimum validation loss. The generated MR images were evaluated using metrics such as Mean Squared Error (MSE), Pearson Correlation Coefficient (Corr), and Peak Signal-to-Noise Ratio (PSNR). The results indicate that for predicting T1- and PD-weighted MR images at high field strength, the average range of MSE and PSNR over the test dataset (1392 images) did not result in improvements compared to one-to-one translation, while Corr shows improvement in PD-weighted MR image prediction. Also, the reported results for the average range of MSE and PSNR suggest improvements in high-field T2-weighted MR image prediction using multi-to-one translation.**

*Keywords—* **magnetic resonance imaging, prediction of MRI contrasts, convolutional neural network**

## I. INTRODUCTION

Magnetic Resonance Imaging (MRI) is a widely used diagnostic tool in clinical settings, and the main magnetic field strength used can vary from 0.2 to 3 Tesla depending on the targeted area, the required precision for diagnosis, and scanner availability [1, 2, 3]. However, for patients with implanted medical devices (e.g., patients with brain implants), the use of strong electromagnetic fields like MRI can have detrimental effects, including movement of implanted medical devices, burns in the surrounding tissue, and malfunction or failure in the implanted medical device [4, 5, 6, 7, 8]. To mitigate these risks, it may be necessary to take MR images from these patients at lower field strengths, such as 0.5 Tesla. As a result, the quality of images taken at lower field strengths can be inferior, potentially leading to inaccurate clinical diagnoses and inappropriate medical treatment. Furthermore, our study is motivated by the high costs of magnetic resonance imaging (MRI), particularly for high-field MRI. Thus, low-field MRI has emerged as a more affordable and accessible alternative to patients, but its image quality may not be sufficient for certain applications [9].

To address this issue, this study proposes a technique that enhances the quality of low-field MR images by predicting MR images taken at high magnetic field strength, offering potential cost savings to patients and healthcare providers. It is worth noting that this technique can be applied beyond the specific field strengths tested in this study, such as predicting 7T MR images from 1.5T or 3T ones. In previous research, deep learning models have been used in various ways to predict the image at higher field strength in different contrasts. These include: I) predicting MR image at high field strength in specific contrast from another contrast at the same field strength (cross-modality) [10, 11]. For example, they have used T1-weighted images to predict T2-weighted images at the same field strength. II) predicting MR image at higher field strength in specific contrast (mostly T1-weighted) using the same contrast at lower field strength (i.e., one-to-one translation) [12]. III) predicting MR image at higher field strength using an MR image in another contrast at the same field strength (target field strength) in addition to the MR image at lower field strength as the second input [13]. These studies have limitations such as using only one contrast to predict the image of the same contrast at higher field strength and using inputs at high (target) field strength which is not possible to be applied for patients who are not allowed to be scanned at high field strength.

Each MRI contrast has unique features, applications, and sensitivity to different tissue properties. Also, MR images are often acquired with a weighting factor (e.g., T1-weighted), which means that other contrasts (e.g., T2 and PD) have minor contribution to the data acquisition. As a result, depending on the scanning parameters, one contrast may be a combination of other contrasts at different field strengths, and MR image in a specific contrast at high field strength may be better predicted through the combination of several contrasts at a lower field strength.

This research proposes a framework to overcome the aforementioned limitations by utilizing multiple MRI contrasts at lower field strength to predict the MR image in one or several contrasts at higher field strength (multi-to-one translation). This approach is based on the understanding that different MRI contrasts show different properties of the tissue and are applied based the clinical and research question [14]. The goal of this study is to investigate the possibility of generating 3T MR images from 0.5T ones by using convolutional neural networks (CNNs), in particular U-Net, and designing a network for multi-to-one translation. Also, please note that multi-to-multi translation is equivalent to applying the multi-to-one translation multiple times for each individual output contrast.

## II. Materials and Method

### A. Data

In this work, due to the limitation of suitable datasets including MRI scans at 0.5T and 3T in multiple contrasts and for the same subjects, MRI scans at 1.5T and 3T were utilized for training and test. Information eXtraction from Images (IXI) dataset which includes MR images in 3 contrasts (T1-, T2-, and PD-weighted) for 181 subjects at 1.5T and another set of 181 subjects at 3T was used for creating a dataset in 3 contrasts for the same pseudo-subjects at 1.5T and 3T [15].

### B. Pre-processing

To make the IXI dataset applicable for multi-to-one translation from lower field strength to higher field strength and create a dataset including MR images in multiple contrasts at both 1.5T and 3T for the same pseudo-subjects (i.e., different subjects but with non-affine registration), several preprocessing steps were performed. The MR images were reoriented to the standard orientation, cropped to 150x256, and the brain was extracted using FSL software [16]. Next, to generate MR images for the same pseudo-subjects, subjects at 1.5T and 3T were paired based on sex and age and T2- and PD-weighted MR images were registered to T1-weighted MR images at each field strength. Afterwards, 1.5T MR images were taken as reference and 3T MR images (same pseudo-subjects) were registered to respective contrast at 1.5T using Advanced Normalization Tools (ANTs) Software [17]. Finally, after transforming 3D MR images to 2D, we selected the slices occupied by the brain (i.e., 10 slices per 3D MR image) and avoided slices with no or little brain and applied data augmentation techniques such as: flipping, rotating with the angle of $\pm 5$ degrees, adding noise (e.g., Gaussian and Salt and Pepper), and scaling. As a result, data size for each contrast at each field strength was increased to 3618, 1566, and 1392 for train, validation, and test sets, respectively.

### C. Deep neural network architecture

Convolutional Neural Networks (CNNs) are common machine learning models for the generation of synthetic images [18]. U-Net is one popular type of CNNs that has shown more promising results in domain transfer, super-resolution, and other similar non-MRI applications compared to other networks [19]. In this study, our goal was to implement a UNet-based model for multi-to-one translation (e.g., T1-, T2-, and PD-weighted at 1.5T$\rightarrow$T1-weighted at 3T), so that we can investigate the effect of using multiple contrasts at lower field strength to predict the image in specific contrast at higher field strength and compared it to one-to-one translation (e.g., T1-weighted at 1.5T$\rightarrow$T1-weighted at 3T)(Fig. 1).

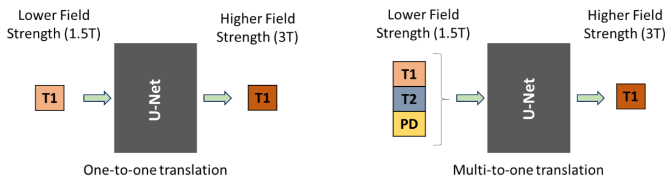


Fig. 1: One-to-one vs. Multi-to-one translation

In general, U-Net consists of encoder (down-sample) and decoder (up-sample) parts with skip connections which can be visualized in a U-shaped architecture [20]. As Fig. 2 illustrates, similar to the base architecture of U-Net, the implemented model is made of: I) 4 down-sampling blocks in the contracting path each consisting of 2 convolutional layers with a kernel size of 3x3, same padding, and stride of 2 pixels. The first convolutional layer is followed by a rectified linear unit (ReLU) activation function, while the second is followed by a ReLU activation function and a 2x2 max-pooling operation with a stride of 2 pixels. II) 4 up-sampling blocks in the expanding path including up-sampling layer (nearest-neighbor interpolation) followed by 2 convolutional layers with a kernel size of 3x3, same padding, and stride of 2 pixels (dropout with a rate of 0.2 was added to the first convolutional layer in each block). Also, features from each block in the encoder were concatenated with their corresponding block in the decoder using skip connections. Finally, a 1x1 convolutional layer with a stride of 1 and a linear activation function was used as the output layer. Moreover, the model can accept images of any size (e.g., 150x256 in this case), as the input layer resizes them to the standard size of 224x224, and then converts them to their original size in the output layer.

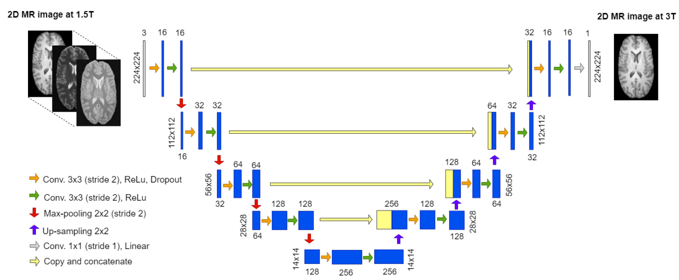


Fig. 2: Proposed U-Net architecture

### *D. Training*

The model was implemented in python using TensorFlow backend on a computer equipped with 32Gb RAM and NVidia Geforce RTX 3080 graphics card. It was trained on training set and validated using validation set using 150 epochs of training with a batch size of 32 using Adam optimizer with a learning rate of 0.001. Both Huber and Mean Squared Error (MSE) were utilized as loss functions; as MSE had the highest performance in training the network, it was used for the reported results. However, MSE and Huber loss functions may not be very sensitive to local errors and therefore, other loss functions have to be explored in future research. Also, the model with the minimum validation loss during 150 epochs of training was saved for further model evaluation using the test data with a size of 1392.

### *E. Evaluation metrics*

To evaluate the results, evaluation metrics including MSE, Pearson Correlation Coefficient (Corr), and Peak Signal to Noise Ratio (PSNR) as defined in Eq. 1, 2, and 3, respectively, were used.

$$MSE(x,y) = \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2. \quad (1)$$

$$\rho(x,y) = \frac{\sum_{i=1}^{n}(y_i-\mu_y)(x_i-\mu_x)}{\sigma_x \times \sigma_y}. \quad (2)$$

$$PSNR(x,y) = 10\log_{10}(\frac{I_{max}^2}{MSE}), I_{max} = maximum\ pixel\ value. \quad (3)$$

## III. Results and discussion

To determine the best model, parameters such as activation function, loss function, and convolutional layers were applied in various combinations. To investigate the effect of MRI contrast selection, the result of predicting each contrast by multi-to-one translation and one-to-one translation were compared as shown in Table 1. As the reported results of MSE and PSNR suggest, for predicting T1- and PD-weighted MR images at high field strength, using multiple contrasts as input did not result in improvements, while the reported Corr was higher for multi-to-one PD-weighted MR image prediction. Also, the results of T2-weighted MR image prediction had improvements using multi-to-one translation.

Moreover, Fig. 3 indicates that although the reported values of MSE, Corr, and PSNR for generated MR images using one-to-one and multi-to-one translation are within a close range, T2- and PD-weighted images generated using multi-to-one translation are sharper with more detail compared to those generated through one-to-one translation, which are smoother and less detailed. Additionally, synthetic images generated using U-Net exhibit smoothing compared to the original images, which may result in lower diagnostic accuracy.

Table 1: Quantitative results of generated MR images using U-Net for multi-to-one/one-to-one translation compared with the ground-truth images evaluated using MSE, Corr, and PSNR metrics on the test dataset (The direction of vertical arrow indicates the trend for higher image qualities. Results are reported as the mean ± standard deviation and the best results are highlighted in bold).

| Translation(1.5T→3T) | MSE↓ | Corr↑ | PSNR↑ |
|---|---|---|---|
| T1 →T1 | **0.0028±0.0016** | 0.98±0.003 | **25.83±1.71** |
| T1, T2, PD → T1 | 0.0033±0.002 | 0.98±0.003 | 25.16±1.87 |
| T2 → T2 | 0.0046±0.0022 | 0.94±0.018 | 23.78±1.95 |
| T1, T2, PD → T2 | **0.0043±0.0018** | 0.94±0.016 | **23.97±1.72** |
| PD → PD | 0.0047±0.002 | 0.98±0.006 | **23.55±1.76** |
| T1, T2, PD → PD | 0.0047±0.002 | **0.99±0.005** | 23.49±1.73 |

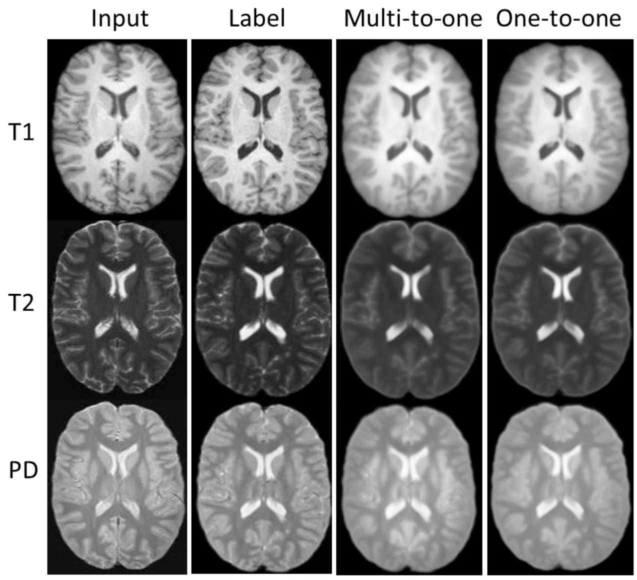


Fig. 3: The comparison of generated MR images using U-Net model for both multi-to-one and one-to-one translation for one subject on a test dataset. From left to right: input MR images; label MR images; generated MR images using multi-to-one translation; generated MR images using one-to-one translation are displayed.

Possible considerations that may lead to these results include: I) limitation in a dataset which includes MRI scans in multiple contrasts at low and high field strength for the same subjects. As the dataset used for training and testing was created using registration techniques, there may be small errors in registration that lead to differences in some parts (e.g., edges) of the input image (MR image at 1.5T) and the target image (MR image at 3T), which can negatively impact the reported evaluation values for the generated and target images. II) using common global evaluation metrics such as MSE, Corr, and PSNR that may not be capable of capturing small local errors and showing the location and the spatial scale of the error which potentially result in overlap or small difference between the range of reported values for the best and worst outputs. To address these limitations, improve the results, and test generalizability, further explorations are needed, such as: I) utilizing the network on real data, II) investigating other deep neural architectures, III) using alternative metrics, which are more sensitive to artifacts and local errors.

## IV. Conclusion

The use of MRI at high field strengths can have adverse effects on patients with implanted medical devices. To mitigate these risks, MR images of these patients are usually taken at lower field strengths, possibly resulting in lower image quality and potentially leading to inaccurate clinical diagnoses. To address this issue, this study proposed a U-Net model that enhances the quality of low-field MR images by predicting MR images taken at high magnetic field strength in one or several contrasts, utilizing multiple MRI contrasts at lower field strength. The results showed that using multi-to-one translation for T2-weighted MR image prediction had improvements compared to using a single contrast. In contrast, for T1- and PD-weighted MR images, although the multi-to-one translation resulted in more detailed and sharper outputs, the evaluation values were similar and did not demonstrate any improvements (except for Corr which demonstrated improvement in PD-weighted MR image prediction). The study has limitations, such as the use of an artificial dataset and global evaluation metrics. Further research is needed to address these limitations and improve the results by applying different techniques, such as using additional data, exploring different deep neural network architectures, and utilizing more sensitive and localized evaluation metrics.

## Conflict of Interest

The authors declare that they have no conflict of interest.

## References

1. S. Ghodbane, A. Lahbib, M. Sakly, and H. Abdelmelek, "Bioeffects of static magnetic fields: oxidative stress, genotoxic effects, and cancer studies," *BioMed research international*, vol. 2013, 2013.
2. V. Hartwig, G. Giovannetti, N. Vanello, M. Lombardi, L. Landini, and S. Simi, "Biological effects and safety in magnetic resonance imaging: a review," *International journal of environmental research and public health*, vol. 6, no. 6, pp. 1778–1798, 2009.
3. P. M. Glover, I. Cavin, W. Qian, R. Bowtell, and P. A. Gowland, "Magnetic-field-induced vertigo: A theoretical and experimental investigation," *Bioelectromagnetics: Journal of the Bioelectromagnetics Society, The Society for Physical Regulation in Biology and Medicine, The European Bioelectromagnetics Association*, vol. 28, no. 5, pp. 349–361, 2007.
4. C. G. Miller, J. Krasnow, L. H. Schwartz *et al.*, "Medical imaging in clinical trials," Springer, Tech. Rep., 2014.
5. J. B. Erhardt, E. Fuhrer, O. G. Gruschke, J. Leupold, M. C. Wapler, J. Hennig, T. Stieglitz, and J. G. Korvink, "Should patients with brain implants undergo mri?" *Journal of neural engineering*, vol. 15, no. 4, p. 041002, 2018.
6. L. Winter, F. Seifert, L. Zilberti, M. Murbach, and B. Ittermann, "Mri-related heating of implants and devices: a review," *Journal of Magnetic Resonance Imaging*, vol. 53, no. 6, pp. 1646–1665, 2021.
7. E. T. Martin, "Can cardiac pacemakers and magnetic resonance imaging systems co-exist?" pp. 325–327, 2005.
8. R. Luechinger, F. Duru, V. A. Zeijlemaker, M. B. Scheidegger, P. Boesiger, and R. Candinas, "Pacemaker reed switch behavior in 0.5, 1.5, and 3.0 tesla magnetic resonance imaging units: are reed switches always closed in strong magnetic fields?" *Pacing and clinical electrophysiology*, vol. 25, no. 10, pp. 1419–1423, 2002.
9. M. Hori, A. Hagiwara, M. Goto, A. Wada, and S. Aoki, "Low-field magnetic resonance imaging: its history and renaissance," *Investigative Radiology*, vol. 56, no. 11, p. 669, 2021.
10. A. F. Osman and N. M. Tamam, "Deep learning-based convolutional neural network for intramodality brain mri synthesis," *Journal of Applied Clinical Medical Physics*, vol. 23, no. 4, p. e13530, 2022.
11. Q. Yang, N. Li, Z. Zhao, X. Fan, E. I. Chang, Y. Xu *et al.*, "Mri cross-modality image-to-image translation," *Scientific reports*, vol. 10, no. 1, pp. 1–18, 2020.
12. X. Zhou, S. Qiu, P. S. Joshi, C. Xue, R. J. Killiany, A. Mian, S. P. Chin, R. Au, V. B. Kolachalama, and A. D. N. Initiative, "Enhancing mr imaging driven alzheimer's disease classification performance using generative adversarial learning," *medRxiv*, pp. 2020–07, 2020.
13. Q. Lyu, H. Shan, C. Steber, C. Helis, C. Whitlow, M. Chan, and G. Wang, "Multi-contrast super-resolution mri through a progressive network," *IEEE transactions on medical imaging*, vol. 39, no. 9, pp. 2738–2749, 2020.
14. M. Symms, H. Jäger, K. Schmierer, and T. Yousry, "A review of structural magnetic resonance neuroimaging," *Journal of Neurology, Neurosurgery & Psychiatry*, vol. 75, no. 9, pp. 1235–1244, 2004.
15. I. C. L. Biomedical Image Analysis Group, "IXI Dataset," https://brain-development.org/ixi-dataset, [Online; accessed 28-December-2021].
16. C. Jack, V. Lowe, M. Senjem, S. Weigand, B. Kemp, M. Shiung, and R. Petersen, "Pre-dementia memory impairment is associated with white matter tract affection," *The American Journal of Geriatric Psychiatry*, vol. 17, pp. 368–375, 2009.
17. B. B. Avants, N. Tustison, G. Song *et al.*, "Advanced normalization tools (ants)," *Insight j*, vol. 2, no. 365, pp. 1–35, 2009.
18. Y. Pang, J. Lin, T. Qin, and Z. Chen, "Image-to-image translation: Methods and applications," *IEEE Transactions on Multimedia*, vol. 24, pp. 3859–3881, 2021.
19. X. Hu, M. A. Naiel, A. Wong, M. Lamm, and P. Fieguth, "Runet: A robust unet architecture for image super-resolution," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, 2019, pp. 0–0.
20. T. Olaf Ronneberger, P. Fischer, and Computer, "U-net: Convolutional networks for biomedical image segmentation."