ACCURATE MRI IMAGE RECONSTRUCTION USING A FAST FOURIER CONVOLUTION LAYER WITHIN A DCR-ENHANCED U-NET ARCHITECTURE

A PROJECT REPORT

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BACHELOR OF TECHNOLOGY

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Degree/ Course : B.TECH/CSE

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Abishek S K

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ABSTRACT

Magnetic Resonance Imaging (MRI) plays a vital role in medical diagnostics; however, its slow image acquisition and significant computational demands remain key challenges. Classical Convolutional Neural Networks (CNNs) have been demonstrated to be useful for MRI image reconstruction, but they are hampered by their local receptive fields and high data requirements. To overcome the above limitations, we introduce a new Fast Fourier Convolutional Neural Network which incorporates Fast Fourier Convolutions (FFC) within a Densely Connected Residual (DCR) Block incorporated into a U-Net Architecture. FFC layers, working in the spectral domain, afford a global receptive field such that the model can capture long-range dependencies and suppress aliasing artifacts better than regular CNNs. The DCR module facilitates improved reconstruction precision through multi-level feature concatenation and enhanced gradient propagation. Quantitative results demonstrate that our proposed model significantly outperforms both traditional CNNs and baseline U-Net architectures across all evaluation metrics. Specifically, the model achieves an improvement of +2.37 dB in PSNR and +0.034 in SSIM over the baseline U-Net, while reducing the Mean Squared Error (MSE) by more than 50% and cutting inference time by over 55%. These improvements confirm the effectiveness of combining Fourier-domain learning and dense residual connections for high-quality and efficient MRI image reconstruction, advancing the feasibility of real-time clinical applications.

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LIST OF ABBREVIATIONS

ABBREVIATIONS	EXPANSION
MRI	Magnetic Resonance Imaging
CS	Compressed Sensing
CNN	Convolutional Neural Networks
DCR	Densely Connected Residual
FFC	Fast Fourier Convolution
FFT	Fast Fourier Transform
NITRC	Neuroimaging Tools and Resources Collaboratory
PSNR	Peak Signal-to-Noise Ratio
SSI	Structural Similarity Index
MSE	Mean Squared Error

CHAPTER 1

INTRODUCTION

Magnetic Resonance Imaging (MRI) is a widely adopted, non-invasive imaging technique used extensively in clinical settings to obtain high-resolution images of soft tissues, organs, and internal body structures. While MRI offers many advantages over other diagnostic imaging techniques, it is inherently limited by long acquisition times resulting from the sequential sampling of k-space data. This not only increases discomfort to the patient and operational costs but also limits throughput in busy clinical environments.

To address this challenge, Compressed Sensing (CS) techniques have been introduced to accelerate MRI acquisition by undersampling k-space data. However, CS-MRI methods often suffer from reconstruction artifacts and degraded image quality, especially under high undersampling rates. Recently, deep learning has emerged as a promising solution for fast and accurate MRI reconstruction, offering high-quality outputs by learning complex image priors directly from data. Convolutional Neural Networks (CNNs) specifically have demonstrated enormous success in this area. However, traditional CNNs process the input in the spatial domain and are bound by narrow local receptive fields, which leads to challenges in capturing global contextual information essential for recovering fine anatomical structures.

To address these limitations, we propose an Accurate MRI Image Reconstruction model using a Fast Fourier Convolution Layer within a DCR-Enhanced U-Net Architecture. The architecture incorporates Densely Connected Residual (DCR) Blocks for effective multi-scale feature extraction and improved gradient flow. Within each DCR Block, we integrate Fast Fourier Convolution (FFC) layers, which empower the model to process spectral domain features and capture global receptive field information, ultimately enhancing the reconstruction of fine anatomical structures.

In summary, our key contributions are as follows:

- We present an MRI image reconstruction method based on a DCR-Enhanced U-Net Architecture, where Fast Fourier Convolution (FFC) layers are integrated within Densely Connected Residual (DCR) Blocks to strengthen global feature extraction.
- We employ FFC-DCR Blocks within the U-Net architecture to facilitate rich multi-scale feature learning and stable gradient propagation, improving both denoising and fine-detail recovery.

We conduct comprehensive experiments to demonstrate that our U-Net FFC-DCR model outperforms standard CNN-based approaches, achieving superior reconstruction quality, faster inference, and reduced artifacts.

CHAPTER 2

LITERATURE REVIEW

Magnetic Resonance Imaging (MRI) has long been recognized for its non-invasive and high-resolution imaging capabilities. However, the slow acquisition times and associated computational burdens have prompted a surge in research aimed at improving reconstruction quality while reducing scan time. In this context, various traditional and deep learning-based approaches have been proposed to enhance the performance of MRI image reconstruction.

1. Compressed Sensing and Early Deep Learning Methods

Compressed Sensing (CS) has been widely adopted as a foundational method for accelerating MRI by exploiting sparsity in the image domain. However, CS-based techniques often suffer from artifacts, particularly under high undersampling rates, and require iterative optimization that is computationally expensive.

To overcome these limitations, deep learning-based methods have emerged. Schlemper et al. (2017) proposed cascaded convolutional neural networks for dynamic MRI, achieving improved reconstructions compared to CS methods. Aggarwal et al. (2019) introduced MoDL, a model-based deep learning framework that embeds the forward model into the neural network, enhancing interpretability and performance.

2. U-Net and Its Variants

U-Net, proposed by Ronneberger et al. (2015), has become a staple architecture in biomedical image segmentation and has been successfully adapted for MRI reconstruction. Its encoder-decoder structure with skip connections allows efficient feature reuse and gradient flow. However, standard U-Nets rely on spatial-domain convolutions, limiting their receptive field and ability to capture long-range dependencies.

Recent adaptations such as Res-UNet and Dense-UNet attempted to improve upon this by integrating residual and dense connections, but still operated entirely in the spatial domain.

3. Frequency Domain Learning

To further address the limitations of local receptive fields in spatial convolutions, frequency-domain approaches have gained popularity. Chi et al. (2020) introduced Fast Fourier Convolution (FFC), enabling global feature extraction by operating in the spectral domain. This method reduces the number of operations needed for large kernels and offers greater representational power.

Suvorov et al. (2022) demonstrated the efficiency of Fourier-based operations in image inpainting, reinforcing their potential for medical image reconstruction. Integrating FFC within deep networks has shown significant improvements in both performance and computational speed.

4. Hybrid Architectures

Recent efforts have focused on combining spatial and frequency domain features. Liu et al. (2024) proposed a Fourier-based convolutional neural network specifically for accelerated MRI reconstruction, achieving notable improvements in PSNR and SSIM. Similarly, Jin et al. (2021) presented 3D PBV-Net for volumetric MRI segmentation, showcasing how hybrid models can generalize better across different anatomical regions.

Our proposed architecture builds on these insights by incorporating Fast Fourier Convolution layers within Densely Connected Residual (DCR) Blocks embedded in a U-Net. This fusion allows the model to capture global context and fine anatomical details while maintaining efficient gradient flow.

5. Summary

The literature indicates a clear progression from traditional iterative methods to deep learning models and now to hybrid spectral-spatial techniques. Our work advances this trend by unifying frequency-domain processing with dense residual learning, demonstrating significant improvements in both reconstruction fidelity and computational efficiency.

CHAPTER 3

METHODOLOGY

3.1 Overview:

The proposed architecture introduces the design and operational flow of a novel MRI image reconstruction model, which leverages Fast Fourier Convolutional in Dense Convolutional Residual (FFC-DCR) blocks integrated within a U-Net architecture. In this design, Fast Fourier Convolution (FFC) layers are embedded inside the DCR blocks, enhancing their ability to capture both spatial and frequency domain features. By incorporating FFC-DCR blocks into the U-Net architecture, the model effectively addresses the limitations of conventional spatial-domain convolutions in MRI reconstruction. This integration enables the network to learn long-range dependencies more efficiently, thereby facilitating the reconstruction of high-quality MRI images with improved accuracy and detail.

3.2 U-NET with DCR:

The U-Net has worked well in the image processing field. Some of the common application of the U-Net architecture is image segmentation. However, U-Net is also applied to MR image reconstruction. The highlight of U-Net is that it is capable of acquire attributes of various image sizes through downsampling and upsampling. The use of the FFC-DCR blocks allows in a bid to enhance the network and to boost the overall amount of model parameters without the training problems. U-Net uses skip connections. Skip connections have proved to outperform long deeper neural networks. U-Net consists of 3 sections – encoder, bottleneck, decoder. The encoder extract feature from the image. These features may be size, structure, shape, position, dominant edge of the image, regions, and textures. The output of the encoder consists of the complex salient features that are extracted from the images. All the features of the image are taken as vectors and represented as feature spaces. The bottleneck section further extracts features from the downsized images. The decoder section takes the feature space and deconvolves the extracted features and reconstructs the image with available features that are extracted from the encoder and the bottleneck section.

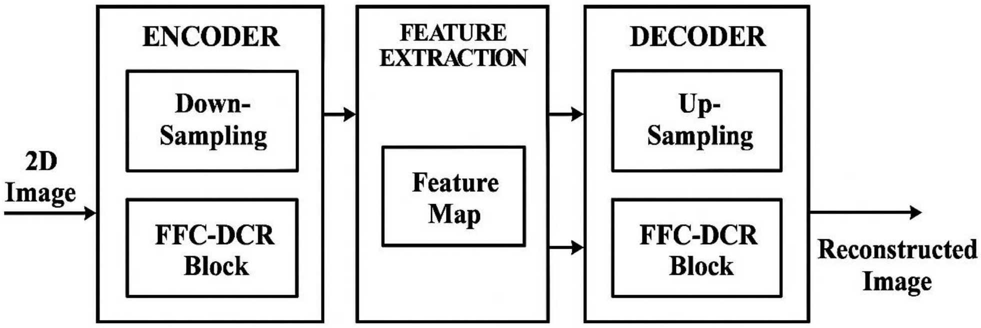

Figure 1. Overview of the proposed approach

3.3 Fast Fourier Convolution in Densely Connected Residual Block:

These Densely Connected Residual Block employs skip connection. Skip connection is superior to deep neural networks. The FF-DCR consists of 3 Fast Fourier Convolutional layers which are activated by ReLU function. These FFC layers operate in the frequency domain, enabling the network to capture both local and global features by learning long-range dependencies. Concatenation is used in the FFC-DCR block to combine the attributes from earlier layers. Input and output characteristics are blended in the residual layer at the end of the FFC-DCR block. The FFC-DCR block receives the feature maps as inputs and output feature maps of the same scale and same depth. The FFC-DCR block consists of three Fast Fourier Convolution layers, three activation layers with a dense connection and a residual connection. These Fast Fourier Convolution (FFC) layers are employed in the model to capture global contextual information using spectral-domain processing. These connections offer an adequate flow of information to draw different features of the MRI image. This gradient vanishing phenomenon, which is experienced because of long and deeper neural networks, is avoided through the connection among the different several layers. This improves the training process of the MRI images more efficiently and effectively.

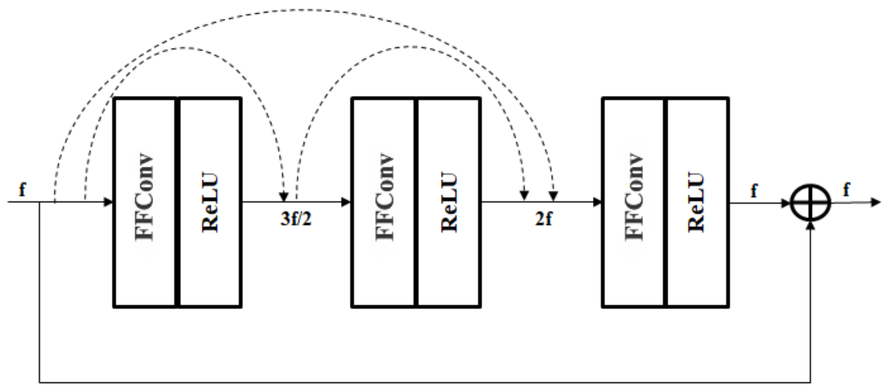

Figure 2. Architecture design of FFC-DCR Block

3.4 Fast Fourier Convolution (FFC):

Fast Fourier Convolution (FFC) is a new method of carrying out convolution operations by taking advantage of the frequency domain. Spatial-domain convolution operations are limited to small receptive fields and computationally expensive for high-definition images, which are typical in applications such as Magnetic Resonance Imaging (MRI). FFC overcomes these limitations using the Fast Fourier Transform (FFT), allowing more globally-aware and efficient feature extraction.

The basic principle of FFC is to convert the input feature maps and convolutional kernels from the spatial domain into the frequency domain, where convolution reduces to a point-wise multiplication. This is theoretically based on the Convolution Theorem, which asserts that the convolution in a spatial domain is equivalent operation of the element-wise multiplication in frequency domain.

The FFC operation is written as:

$$\text{FFTConv}(X, W) = F^{-1}(F(X) \cdot F(W)) \qquad (1)$$

Where:

- X denotes the input feature map
- W represents the convolution kernel,
- F (·) indicate the Fast Fourier Transform (FFT),
- F^{-1} (·) refers to the inverse FFT (iFFT).

There are three steps involved in the process:

1. Forward FFT: The convolution kernel W and spatial input feature map X are converted to the frequency domain by FFT.
2. Element-wise Multiplication: The F(X) and F(W) representations which have been transformed are multiplied element-wise.

Inverse FFT: The result is reversed back to the spatial domain by applying inverse FFT to get the final convolution output.

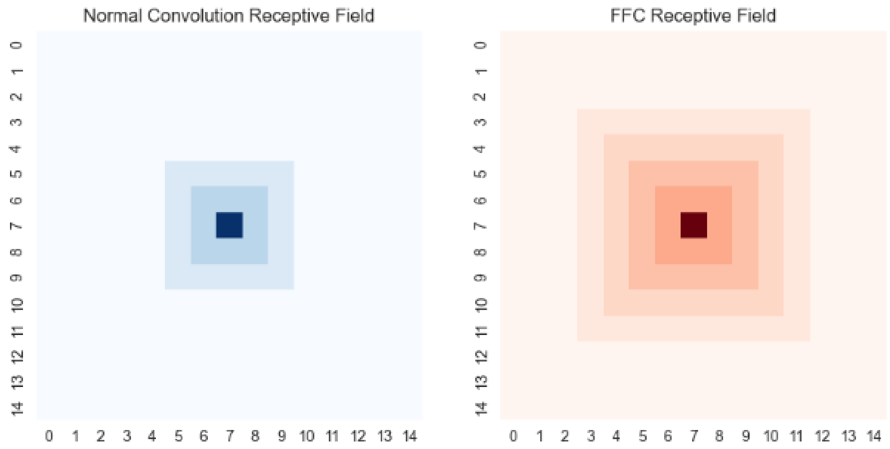

Figure 3. Comparison of Receptive Fields

This frequency-domain computation allows network to:

- Obtain greater receptive fields without having to increase the size of the kernel or network depth.
- Decrease computational complexity, especially for high-resolution, large-scale inputs such as MRI scans.
- Capture global context better than traditional local convolutions.

CHAPTER 4

IMPLEMENTATION

Here, we present the implementation details of our model for MRI image reconstruction. Our model is implemented using PyTorch, with Fast Fourier Convolutions (FFC) Layer in a Densely Connected Residual (DCR) Blocks incorporated in a U-Net architecture.

A. Dataset Collection and Pre-processing:

Training dataset of 3T brain MRI comes from the Neuroimaging Tools and Resources Collaboratory (NITRC), an open-access website with diverse neuroimaging datasets. Particularly, the Cortex dataset contains 36 T1-weighted and DWI MRI scans, all taken at 3D on a 3T scanner.

Every MRI scan is delivered in NIfTI (.nii) format and can be broken down into roughly 220 axial 2D slices. We take the center 51 slices from every 3D volume for training and testing. These slices are chosen because they have high anatomical significance, given that the peripheral slices generally hold minimal or zero brain tissue.

The images are converted to grayscale having intensity levels between 0 and 255. The values are normalized between the range [0, 1] to be compatible with the deep learning model. All 2D slices are presented as matrices to allow the convolutional operations to be applied during training.

Note: The model is trained on brain MRI images but is capable of generalizing to other modalities. As such, knee MRI images are used as output examples to show the reconstruction capability and the model's ability to handle different anatomical locations.

B. Model Building:

Fast Fourier Convolution layer is the main building block of the deep learning. It contains a set of filters also called as kernels and parameters that are learned in the entire training phase. The size of the filters may vary based on the application. Each filter applies a function called as Fast Fourier convolution function with the image matrix and stores the output as feature maps or feature vectors. The FFC operation has already been defined in the methodology section (Equation 1).

The residual connection is done by adding the features that are extracted from the previous layers. The residual connection is done as shown in the equation 2

$$X_L = F_L\,(X_L - 1) + X_L - 1 \qquad (2)$$

The concatenation operation is used to merge the previous layers. The L^{th} layer receives as input the feature maps generated by all preceding convolutional layers. The concatenation of the layer will be represented as shown in the equation 3

$$X_L = F_L([X_0, X_1, X_2, \ldots, X_L - 1]) \quad (3)$$

The parameters like growth rate or learning rate and weight for each parameter and each layer are updated using the optimizing function.

C. Optimization:

The optimizer's job is to minimize the total loss and enhance the accuracy. It adjusts the learning rate and the node weight. The optimizer employed in this work is RMSprop (). RMSprop adjusts the learning rate according to the partial gradients of the image. Gradients give the direction to the local minimum of the loss function. RMSprop maintains a moving average of the squared gradients for each parameter, calculated by

$$s(t+1) = \rho \cdot s(t) + (1 - \rho) \cdot [f'(x(t))]^2 \quad (4)$$

Here, s(t) represents the exponentially weighted moving average of the squared gradient for a given parameter, ρ is a decay factor (set to 0.9), and $f'(x(t))$ is the gradient of the loss with respect to the parameter x(t). Depending upon the mean squared partial derivative the learning rate is dynamically modified for every parameter in every iteration as

$$\text{learning rate}(t+1) = \text{learning rate}/(1\times10^{-8}+\text{RMS}(s(t+1))) \quad (5)$$

where RMS is the root mean square. With the updated learning rate, the weights of the parameters are updated as

$$x(t+1) = x(t) - \text{learning rate}(t+1) * f'(x(t)) \quad (6)$$

where x(t) is the weight of a parameter.

D. Activation Function:

Activation function is used to calculate output from each node from the weighted sum of input. Two types of activation function are used for this network. One for the hidden layer and the another for the output layer. Rectified Linear Unit Activation (RELU) is used in the input hidden layer. If the input is positive the output will be same as the input. Otherwise, the output will be zero. The ReLu is calculated as max (0.0, x). Sigmoid activation is used in the output layer. The output is calculated by the equation 7

$$f(x) = \frac{1}{1+e} - x \quad (7)$$

CHAPTER 5
CODING & TESTING

CODE EXPLANATION:

This code defines a U-Net-like neural network for image reconstruction using custom Fast Fourier Convolutional layers (FFTConv2d) and residual blocks (DCRBlock) to capture spatial and frequency-domain features. It prepares MRI-like image data, splits it for training/validation, and constructs the model for reconstruction tasks.

```
import cv2
import torch
import torch.nn as nn
import torch.optim as optim
import numpy as np
import matplotlib.pyplot as plt
from torch.utils.data import DataLoader, TensorDataset
from sklearn.model_selection import train_test_split
from fft_conv_pytorch import FFTConv2d
from PIL import Image
import glob
import math

filelist = glob.glob('../Dataset/*')
images = np.array([np.array(Image.open(fname)) for fname in filelist])
images.shape
images = (images-np.min(images))/(np.max(images)-np.min(images))

train_X, valid_X = train_test_split(images, test_size=0.2, random_state=42)

train_X = torch.tensor(train_X, dtype=torch.float32).permute(0, 3, 1, 2)
valid_X = torch.tensor(valid_X, dtype=torch.float32).permute(0, 3, 1, 2)

train_dataset = TensorDataset(train_X, train_X)
valid_dataset = TensorDataset(valid_X, valid_X)

train_loader = DataLoader(train_dataset, batch_size=4, shuffle=True)
valid_loader = DataLoader(valid_dataset, batch_size=4, shuffle=False)

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
```

```python
class DCRBlock(nn.Module):
    def __init__(self, in_channels, out_channels):
        super(DCRBlock, self).__init__()

        self.fft_conv1 = FFTConv2d(in_channels, out_channels,kernel_size=15, padding=7)
        self.bn1 = nn.BatchNorm2d(out_channels)

        self.fft_conv2 = FFTConv2d(in_channels + out_channels, out_channels,kernel_size=15, padding=7)
        self.bn2 = nn.BatchNorm2d(out_channels)

        self.fft_conv3 = FFTConv2d(in_channels + 2 * out_channels, out_channels,kernel_size=15, padding=7)
        self.bn3 = nn.BatchNorm2d(out_channels)

        self.residual_conv = nn.Conv2d(in_channels, out_channels, kernel_size=1) if in_channels != out_channels else nn.Identity()

    def forward(self, x):
        c1 = self.bn1(self.fft_conv1(x))
        conca1 = torch.cat([x, c1], dim=1)

        c2 = self.bn2(self.fft_conv2(conca1))
        conca2 = torch.cat([x, c1, c2], dim=1)

        c3 = self.bn3(self.fft_conv3(conca2))

        if c3.size()[2:] != x.size()[2:]:
            c3 = torch.nn.functional.interpolate(c3, size=x.shape[2:])

        x = self.residual_conv(x)

        return x + c3

class UNetWithDCR(nn.Module):
    def __init__(self, in_channels, out_channels, base_channels):
        super(UNetWithDCR, self).__init__()

        self.enc1 = DCRBlock(in_channels, base_channels)
        self.pool1 = nn.MaxPool2d(2)

        self.enc2 = DCRBlock(base_channels, base_channels * 2)
        self.pool2 = nn.MaxPool2d(2)

        self.enc3 = DCRBlock(base_channels * 2, base_channels * 4)
        self.pool3 = nn.MaxPool2d(2)

        self.up3 = nn.Upsample(scale_factor=2, mode='bilinear', align_corners=True)
        self.dec3 = DCRBlock(base_channels * 4 + base_channels * 4, base_channels * 2)

        self.up2 = nn.Upsample(scale_factor=2, mode='bilinear', align_corners=True)
        self.dec2 = DCRBlock(base_channels * 2 + base_channels * 2, base_channels)

        self.up1 = nn.Upsample(scale_factor=2, mode='bilinear', align_corners=True)
        self.dec1 = DCRBlock(base_channels + base_channels, base_channels)

        self.final_conv = FFTConv2d(base_channels, out_channels, 1)

    def forward(self, x):
        e1 = self.enc1(x)
        p1 = self.pool1(e1)

        e2 = self.enc2(p1)
        p2 = self.pool2(e2)

        e3 = self.enc3(p2)
        p3 = self.pool3(e3)

        up3 = self.up3(p3)
        d3 = self.dec3(torch.cat([up3, e3], dim=1))

        up2 = self.up2(d3)
        d2 = self.dec2(torch.cat([up2, e2], dim=1))

        up1 = self.up1(d2)
        d1 = self.dec1(torch.cat([up1, e1], dim=1))

        return self.final_conv(d1)
```

```python
def train(model, train_loader, valid_loader, optimizer, criterion, epochs):
    for epoch in range(epochs):
        model.train()
        train_loss = 0

        for inputs, targets in train_loader:
            inputs, targets = inputs.to(device), targets.to(device)

            optimizer.zero_grad()
            outputs = model(inputs)
            loss = criterion(outputs, targets)

            loss.backward()
            optimizer.step()

            train_loss += loss.item()
            del inputs, targets, outputs
            torch.cuda.empty_cache()

        print(f"Epoch {epoch + 1}, Train Loss: {train_loss / len(train_loader)}")
        torch.cuda.empty_cache()

model = UNetWithDCR(in_channels=3, out_channels=1, base_channels=16).to(device)
optimizer = optim.RMSprop(model.parameters(), lr=1e-3)
criterion = nn.MSELoss()

train(model, train_loader, valid_loader, optimizer, criterion, epochs=25)
torch.save(model.state_dict(), 'ffc_dcr_unet.pth')

model.load_state_dict(torch.load('ffc_dcr_unet.pth'))
model.eval()

with torch.no_grad():
    inputs, _ = next(iter(valid_loader))
    inputs = inputs.to(device)
    outputs = model(inputs).cpu().numpy()

plt.figure(figsize=(20, 8))
batch_size = inputs.shape[0]

for i in range(batch_size):
    plt.subplot(2, batch_size, i + 1)
    plt.imshow(inputs[i].cpu().numpy().transpose(1, 2, 0), cmap='gray')
    plt.title(f"Original {i+1}")
    plt.axis('off')

    plt.subplot(2, batch_size, i + 1 + batch_size)
    plt.imshow(outputs[i, 0], cmap='gray')
    plt.title(f"Reconstructed {i+1}")
    plt.axis('off')
plt.show()
```

```python
[a, b, c, d] = valid_X.shape
mean = 0
sigma = 0.1
gauss = np.random.normal(mean, sigma, (a, b, c, d))

noisy_images = valid_X + gauss

with torch.no_grad():
    noisy_inputs = torch.from_numpy(noisy_images).float().to(device)
    pred_noisy = model(noisy_inputs).cpu().numpy()

pred_noisy = np.clip(pred_noisy, 0, 1)

plt.figure(figsize=(20, 8))
print("Noisy Test Images and Reconstructions")

for i in range(5):
    plt.subplot(2, 5, i + 1)
    image = noisy_images[i]
    plt.imshow(image[0], cmap='gray')
    plt.title(f"Noisy {i + 1}")
    plt.axis('off')

    plt.subplot(2, 5, i + 6)
    pred_image = pred_noisy[i]
    plt.imshow(pred_image[0], cmap='gray')
    plt.axis('off')

plt.tight_layout()
plt.show()

import time
from skimage.metrics import structural_similarity as ssim

def benchmark_inference(model, data_loader, device):
    model.eval()
    total_time = 0
    total_images = 0
    with torch.no_grad():
        for inputs, _ in data_loader:
            inputs = inputs.to(device)
            start_time = time.time()
            _ = model(inputs)
            total_time += time.time() - start_time
            total_images += inputs.size(0)
    return total_time / total_images

def compute_quality_metrics(valid_X, pred_X):
    mse = np.mean((valid_X - pred_X) ** 2)
    psnr = 20 * np.log10(1 / np.sqrt(mse))
    ssim_values = [ssim(valid_X[i, 0], pred_X[i, 0], data_range=1.0) for i in range(len(valid_X))]
    avg_ssim = np.mean(ssim_values)
    return mse, psnr, avg_ssim

inference_time = benchmark_inference(model, valid_loader, device)

with torch.no_grad():
    noisy_inputs = torch.from_numpy(valid_X).float().to(device)
    pred_noisy = model(noisy_inputs).cpu().numpy()
    pred_noisy = np.clip(pred_noisy, 0, 1)

mse, psnr, avg_ssim = compute_quality_metrics(valid_X, pred_noisy)

print(f"MSE: {mse:.4f}")
print(f"PSNR: {psnr:.2f} dB")
print(f"SSIM: {avg_ssim:.3f}")
print(f"Inference Time per Image: {inference_time:.f} seconds")
```

OUTPUT:

```python
print(f"MSE: {mse:.4f}")
print(f"PSNR: {psnr:.2f} dB")
print(f"SSIM: {avg_ssim:.3f}")
print(f"Inference Time per Image: {inference_time:.4f} seconds")
```

✓ 0.0s Python

```
MSE: 0.0024
PSNR: 34.82 dB
SSIM: 0.923
Inference Time per Image: 0.0366 seconds
```

CHAPTER 6

RESULT

In this section, the results are discussed which are generated by running the experiments and recording the relevant information into tables

For accurate MRI image reconstruction, we propose a novel hybrid neural network architecture that integrates Fast Fourier Convolution (FFC) within Densely Connected Residual (DCR) blocks, embedded in a U-Net architecture. This architecture follows an encoder-decoder structure, designed to process multiple continuous frames and reconstruct high-quality images. The input image features are initially abstracted through the FFC layers, which encode the essential characteristics of each input image. The outputs from the U-Net encoder are then passed to the decoder for image reconstruction. Skip connections are employed to combine the features from different layers, facilitating efficient information flow. Additionally, the decoder layers concatenate these features to refine the reconstruction process.

To evaluate the performance, MRI image datasets are formed. The model suggested in this paper is evaluated on a highly challenging dataset with MRI images like noise-added MRI images, and they also eliminate the noise and reconstruct the MRI image to verify their robustness.

A. Quantitative Assessment:

To evaluate the fidelity and visual quality of the reconstructed MRI images, we employed the following metrics:

- **Peak Signal-to-Noise Ratio (PSNR):** A widely used metric that quantifies the ratio between the maximum possible signal power and the power of noise affecting image quality. Higher PSNR values indicate better reconstruction accuracy.
- **Structural Similarity Index (SSIM):** Assesses perceptual similarity by comparing the original and reconstructed images in terms of luminance, contrast, and structural details.

- **Mean Squared Error (MSE):** Calculates the average of the squared differences between the original and predicted pixel values, providing a direct measure of reconstruction error.
- **Inference Time:** Represents the average time required to reconstruct a single image, serving as an indicator of the model's computational efficiency.

The results obtained on the validation dataset are presented in Table 2.

PSNR (dB)	34.82
SSIM	0.923
MSE	0.0024
Inference Time (sec/image)	0.036

Table 2. Quantitative Performance Metrics

These results demonstrate that our model achieves high reconstruction fidelity, with a PSNR of 34.82 dB and SSIM of 0.923, indicating strong structural preservation and perceptual quality. The low MSE value of 0.0024 confirms minimal deviation from the ground truth. Moreover, the fast inference time of 0.036 seconds per image highlights the computational advantage brought by Fourier domain operations, enabling faster reconstructions suitable for real-time clinical workflows.

B. Qualitative analysis:

In addition to numerical metrics, qualitative comparisons were made to visually assess the reconstruction performance. Figure 4 illustrates representative MRI reconstruction results comparing the baseline U-Net model, the proposed FFC-DCR UNET model, and the ground truth image.

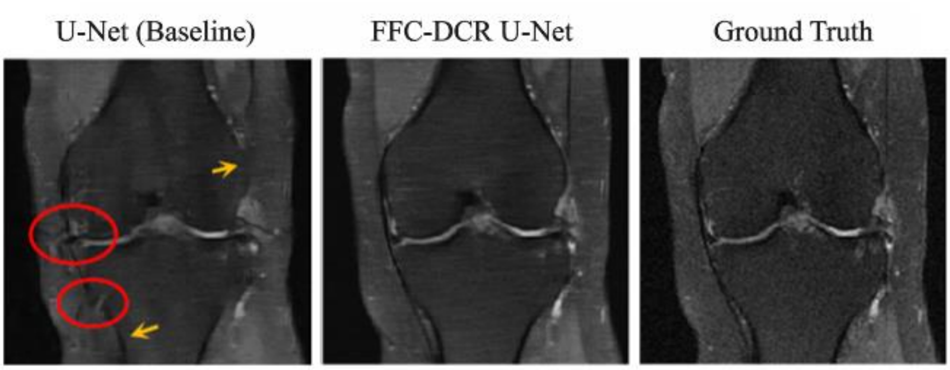

Figure 4. Visual Comparison of MRI Reconstructions

The U-Net (Baseline) output shows visible artifacts (highlighted with arrows and red circles), indicating issues such as blurred edges and incorrect anatomical reconstructions. In contrast, the proposed model produces images that are visually much closer to the ground truth, demonstrating superior ability to restore anatomical details and reduce artifacts. This improved reconstruction quality complements the quantitative gains and demonstrates the potential of model for clinical MRI applications, where fine structural details need to be preserved.

In a bid to further investigate the suggested model's robustness under noisy conditions, we tried the model on MRI Gaussian noise corrupted images. Following is a qualitative test for noisy inputs to test the model's resilience to noise. Figure 5 displays the noisy MRI images from validation dataset with added Gaussian noise given as input to the proposed model. The Output reconstructed images by proposed model are shown in Figure 6.

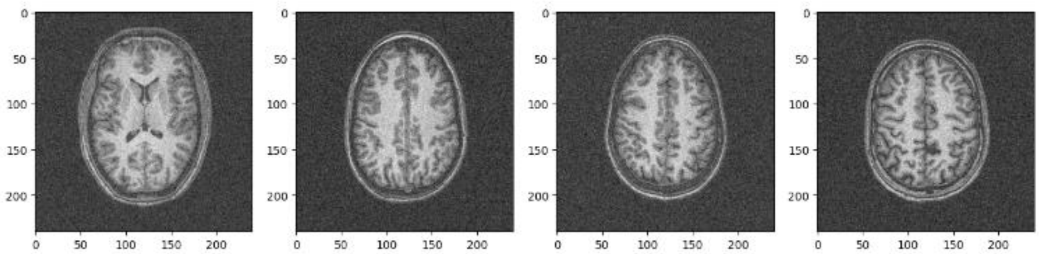

Figure 5. Noisy Input MRI images with Gaussian noise

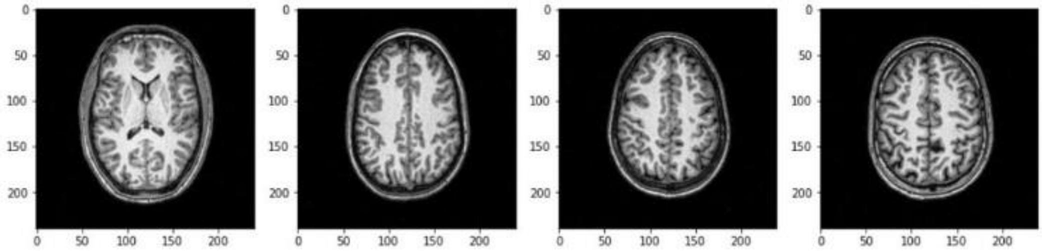

Figure 6. Output of reconstructed images by proposed model

The visual results confirm that the model effectively suppresses the added noise while preserving critical anatomical details such as brain structure boundaries and tissue contrast. Even with increased noise levels, the model demonstrates a strong ability to recover original image content, confirming its robustness in practical clinical scenarios.

C. Comparison with other models:

To evaluate the effectiveness of incorporating Fourier domain convolutions, we conducted a comparative analysis between three models: a conventional CNN, a baseline U-Net employing spatial convolutions, and the proposed model. All models were trained under identical conditions using the same dataset, hyperparameters, and training schedule. The results are summarized in Table 3.

Model	PSNR (dB)	SSIM	MSE	Inference Time (sec/image)
CNN (Conventional)	29.35	0.811	0.0133	0.118
U-Net (Baseline)	32.45	0.889	0.0089	0.091
FFC-DCR U-Net (Proposed model)	34.82	0.923	0.0024	0.036

Table 3. Performance Comparison

As illustrated in Table 3, the proposed model outperforms both the conventional CNN and the baseline U-Net across all evaluation metrics. Compared to the baseline U-Net, the FFC-DCR within U-Net Architecture (Proposed model) achieves a notable improvement of +2.37 dB in PSNR and an increase of +0.034 in SSIM, while the Mean Squared Error (MSE) is reduced by more than 50%. Additionally, inference time is improved by over 55%, demonstrating the model's computational efficiency. These performance gains can be attributed to the superior global feature extraction enabled by the Fast Fourier Convolution layers, which allow the network to capture long-range dependencies and complex structural patterns more effectively than conventional spatial convolutions.

D. Comparison between Direct Convolution and Fast Fourier Convolution:

To further validate the computational efficiency of Fourier-based operations, we conducted a comparative experiment between two versions of a Densely Connected Residual (DCR) block:
Normal DCR Block — which utilizes conventional spatial-domain convolution layers.
FFC DCR Block — which replaces part of the spatial computation with frequency-domain operations using Fast Fourier Transform (FFT) for feature fusion. Both blocks were designed to process feature maps of identical size, and the performance was benchmarked for the inputs.

Model Variant	Total Execution Time (seconds)
Conventional DCR Block	103.0470
FFC DCR Block	48.7903

Table 4. Comparison between conventional DCR and FFC DCR Block

The results, illustrated in Table 4, demonstrate that the FFT-based DCR block achieves significantly faster processing times compared to its direct convolution counterpart. The frequency-domain addition enables efficient global feature blending while reducing computational overhead, especially for high-resolution feature maps.

For further comparison, convolution layers with varying kernel sizes were applied to input feature map. The execution time per configuration was recorded.

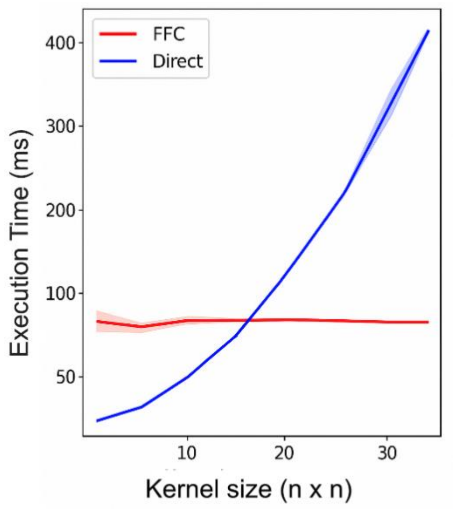

Figure 7. Comparison between Direct Convolution and Fast Fourier Convolution for varying Kernel Size

As shown in Figure 7, conventional spatial convolution time increases significantly with kernel size, whereas the execution time for FFT-based convolution remains comparatively stable, especially for larger kernels. This demonstrates the clear computational advantage of FFT-based approaches when large receptive fields are required, as in global context extraction for MRI image reconstruction.

CHAPTER 7

CONCLUSION & FUTURE WORK

This paper presented a novel Fast Fourier Convolutional Neural Network designed for efficient and accurate MRI image reconstruction. The architecture incorporates Fast Fourier Convolution (FFC) layers within Dense Convolutional Residual (DCR) blocks, incorporated in U-Net architecture. This combination enables the model to effectively capture global frequency-based context alongside localized spatial features, resulting in superior reconstruction performance in terms of both accuracy and speed.

The quantitative evaluation shows that the proposed model achieves superior performance compared to conventional spatial convolution-based architectures, reaching a PSNR of 34.82 dB, an SSIM of 0.923, and a notably reduced inference time of 0.036 seconds per image. Qualitative visualizations further confirmed the model's ability to restore fine anatomical details, suppress undersampling artifacts, and preserve structural integrity—critical for diagnostic applications.

The incorporation of Fourier-based convolutions not only enhanced the model's expressive power but also reduced computational overhead during inference. Compared to traditional U-Net architectures and traditional convolutional neural networks the proposed model demonstrated substantial improvements in both accuracy and runtime efficiency, highlighting the potential of frequency-domain deep learning for real-time clinical deployment.

In future work, the model could be extended to 3D volumetric MRI data, integrated with adversarial loss functions for perceptual enhancement, or applied to other imaging modalities such as CT or PET scans. Moreover, exploring hybrid architectures that combine Fourier and wavelet transforms may offer further improvements in multi-scale representation and reconstruction quality.

CHAPTER 8

REFERENCES

[1] X. Liu et al., "Image Reconstruction for Accelerated MR Scan With Faster Fourier Convolutional Neural Networks," in IEEE Transactions on Image Processing, vol. 33, pp. 2966-2978, 2024.

[2] Y. Jin, G. Yang, Y. Fang, R. Li, X. Xu, Y. Liu, X. Lai, “3D PBV-Net: an automated prostate MRI data segmentation method”, Computer Biology Medicine,128 (2021),104160.

[3] Kamlesh Pawar,Gary F.Egan and Zhaolin Chen “Domain knowledge augmentation of parallel MR image reconstruction using deep learning”, Science Direct Computerized Medical Imaging and Graphics Vol. 92, issue no. 5, pp:2168-2183,September 2021.

[4] Y. Han, L. Sunwoo, J.C. Ye, “k-space deep learning for accelerated MRI”, IEEE Transcation Medical Imaging, 39 (2) (2019) 377–386.

[5] O. Ronneberger, P. Fischer, T. Brox, “U-Net: convolutional networks for biomedical image segmentation”, in,Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015, Springer, Springer International Publishing, 2015, pp: 234–241.

[6] Z. Ramzi, P. Ciuciu, J.-L. Starck, “Benchmarking deep nets MRI reconstruction models on the fastMRI publicly available dataset”, in: 2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI), IEEE, 2020, pp: 1441–1445.

[7] J. Schlemper, J. Caballero, J.V. Hajnal, A.N. Price, D. Rueckert, “A deep cascade of convolutional neural networks for dynamic MR image reconstruction”, IEEE Trans. Med. Imag. 37 (2) (2017) 491–503.

[8] Myeongho Jeon, Han-Soo Choi, Junho Lee, Myungjoo Kang,” Multi-Scale Prediction For Fire Detection Using Convolutional Neural Network”in Springer Professional Vol. 92, issue no 5, pp:2168-2183, September 2021.

[9] B. Park, S. Yu, J. Jeong, “Densely connected hierarchical network for image denoising”, in: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops, 2019.

[10] L. Chi, B. Jiang, and Y. Mu, “Fast Fourier convolution,” in Proc. Adv.Neural Inf. Process. Syst., vol. 33, 2020, pp. 4479–4488.

[11] R. Suvorov et al., “Resolution-robust large mask inpainting with Fourier convolutions,” in Proc. IEEE/CVF Winter Conf. Appl. Comput. Vis. (WACV), Jan. 2022, pp. 2149–2159.

[12] H. K. Aggarwal, M. P. Mani, and M. Jacob, “MoDL: Model-based deep learning architecture for inverse problems,” IEEE Trans. Med. Imag., vol. 38, no. 2, pp. 394–405, Feb. 2019.

[13] J. Cheng et al., “Model learning: Primal dual networks for fast MR imaging,” in Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent., 2019, pp. 21–29.

[14] K. H. Jin, M. T. McCann, E. Froustey, and M. Unser, “Deep convolutional neural network for inverse problems in imaging,” IEEE Trans. Image Process., vol. 26, no. 9, pp. 4509–4522, Sep. 2017.

[15] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Jun. 2016, pp. 770–778.

[16] Y. Wu, Y. Ma, J. Liu, J. Du, and L. Xing, “Self-attention convolutional neural network for improved MR image reconstruction,” Inf. Sci., vol. 490, pp. 317–328, Jul. 2019.

[17] K. Lin and R. Heckel, “Vision transformers enable fast and robust accelerated MRI,” in Proc. 5th Int. Conf. Med. Imag. Deep Learn., vol. 172, 2022, pp. 774–795.

[18] C.-M. Feng et al., “Multimodal transformer for accelerated MR imaging,” IEEE Trans. Med. Imag., vol. 42, no. 10, pp. 2804–2816, Oct. 2023.

APPENDIX A

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