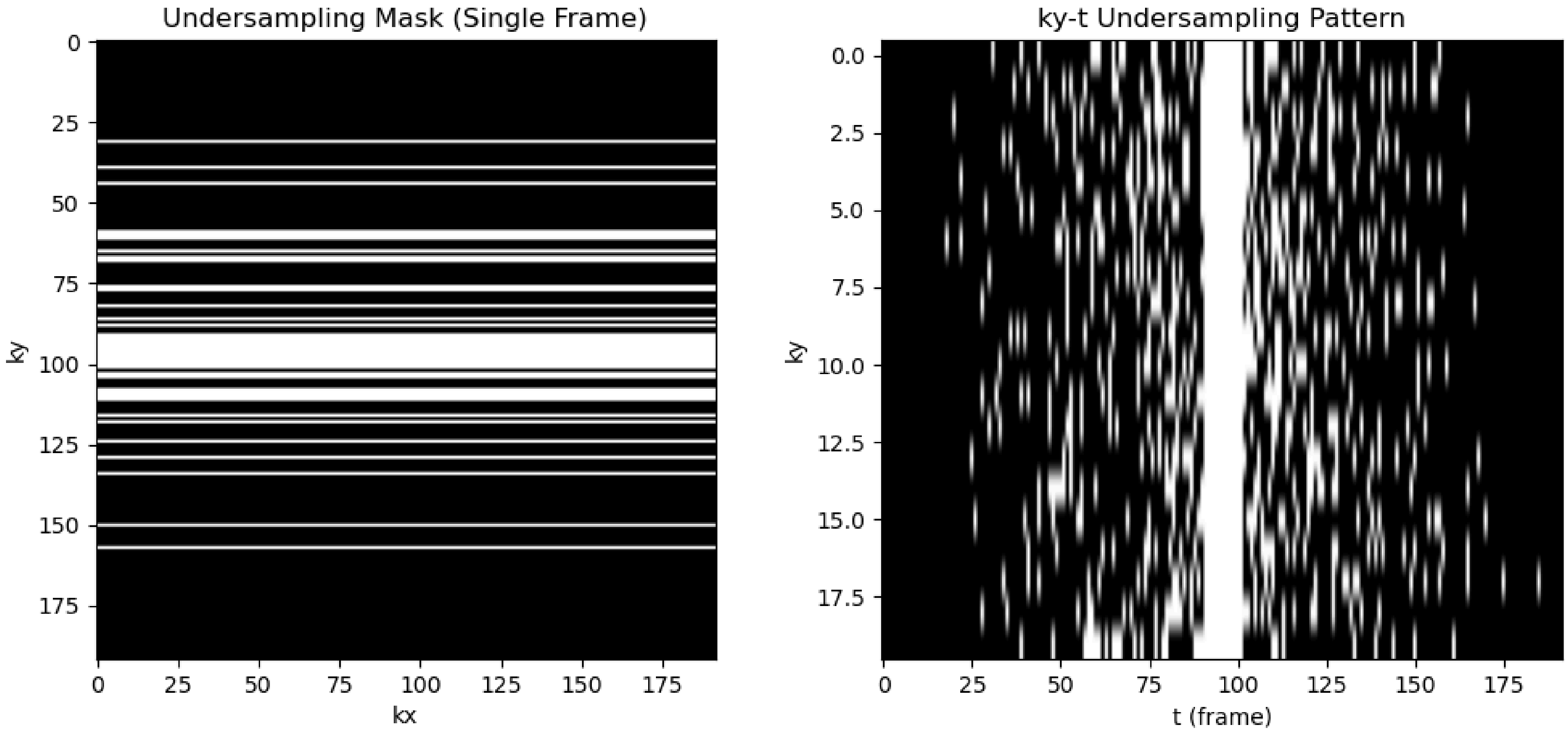
MRI Reconstruction with Deep Learning

BME1312 Project 1

Data Processing

1. **Load Data:** Load the `cine.npz` dataset containing fully sampled MRI frames.
2. **Generate Mask:** Create an undersampling mask.
    - Variable density pattern.
    - Preserves central k-space lines.
    - Random sampling in outer regions.
3. **Apply Mask:** Multiply the k-space representation of the fully sampled data by the mask.
4. **Convert to Image Space:** Apply iFFT to get the undersampled, aliased images.
5. **Format Data:** Convert complex images to pseudo-real format for model input.


Undersampling Mask (Single Frame)
ky
kx
0
25
50
75
100
125
150
175
ky-t Undersampling Pattern
ky
t (frame)
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

Model Architecture 1: UNet

- Encoder-Decoder structure with skip connections.
- Captures multi-scale features.
- **Modifications:**
  - LeakyReLU activation.
  - Dropout for regularization.
  - Batch Normalization.
  - Attention mechanism in the bottleneck.

UNet: Attention Mechanism

- Combines Channel Attention and Spatial Attention.
- **Channel Attention:** Focuses on 'what' features are important. Uses AvgPool and MaxPool along channels.
- **Spatial Attention:** Focuses on 'where' features are important. Uses AvgPool and MaxPool along spatial dimensions.
- Helps the model focus on relevant parts of the input.

```
    def _attention_block(self, features):
        # ... Channel and Spatial Attention implementation ...
```

Model Architecture 2: 3D ResNet

- Processes the temporal dimension along with spatial dimensions.
- Uses 3D convolutions and residual blocks.
- Designed to capture spatio-temporal correlations.
- `BasicBlock`: Standard residual block with 3x3x3 convolutions.

```
class ResNet(nn.Module):
    def __init__(self, block, layers, block_inplanes, ...):
        # ... 3D Conv layers, Residual blocks ...
    def forward(self, x):
        # ... Forward pass through ResNet layers ...

def resnet18(**kwargs):
    model = ResNet(BasicBlock, [1, 1, 1, 1], ...) # Example configuration
    return model
```

Combined Model Approach

1. **Input:** Pseudo-real undersampled images (real and imaginary parts as separate channels).
2. **UNet 1 (`model`):** Processes the 'real' part channels.
3. **UNet 2 (`model2`):** Processes the 'imaginary' part channels.
4. **Stack Outputs:** Combine the outputs of the two UNets.
5. **ResNet (`model3`):** Takes the combined UNet outputs (now treated as spatio-temporal data) and performs final reconstruction.

```
# Forward pass logic in train/evaluate/test
outputs1 = model(x[:, :, 0]) # Process real part
outputs2 = model2(x[:, :, 1]) # Process imaginary part
tmp = torch.stack((outputs1, outputs2), dim=2) # Combine
outputs = model3(lab.pseudo2real(tmp).unsqueeze(2)).squeeze(2) # ResNet processing
```

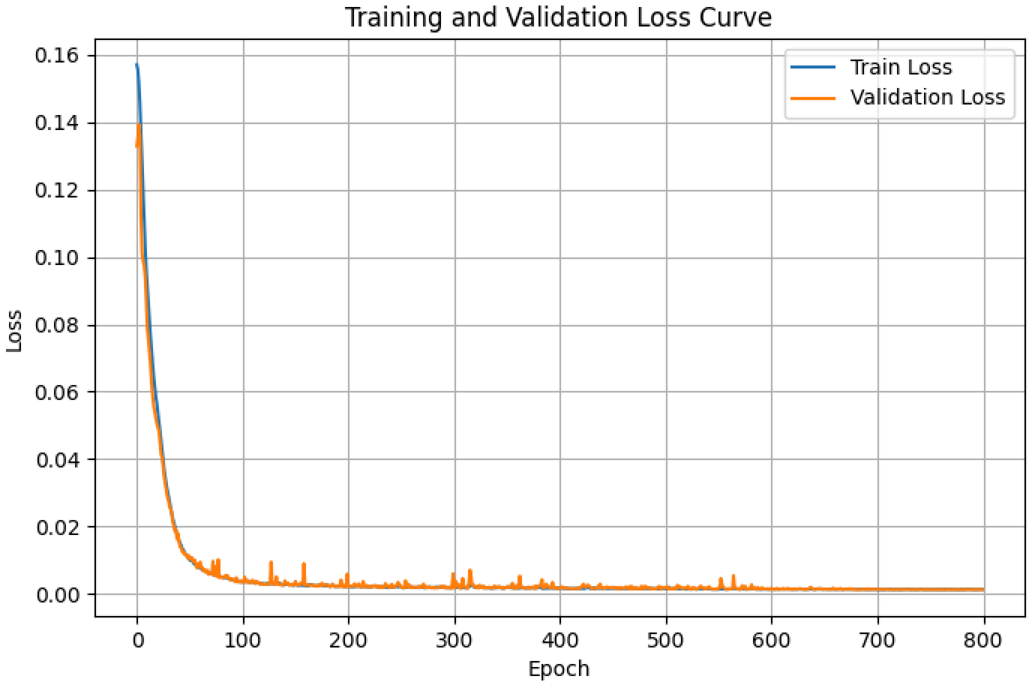
Training Setup

- **Data Splitting:** Train (114), Validation (29), Test (57) sets.
- **Loss Function:** Mean Squared Error (MSE) or L1 Loss (`criterion`).
- **Optimizer:** Adam optimizer with weight decay.
- **Learning Rate Scheduler:** Warmup phase followed by cosine decay.

```
lr = lr_scheduler(epoch, warmup_epochs, warmup_lr, initial_lr, num_epochs)
```

- **Logging:** TensorBoard for tracking loss curves. Output logs saved to `output/output.txt`.

Results & Conclusion




```
Loss: mean = 0.00134656, std = 0.00054760
PSNR: mean = 29.08446121, std = 1.93235576
SSIM: mean = 0.84434632, std = 0.03711063
```

Impact of Dropout and Dynamic Learning Rate

TODO: Compared to the baseline, this improves PSNR and SSIM by ....

Compare L1 with L2

TODO: The L1-trained model ... in PSNR and SSIM, suggesting ...

Unrolled Deep Learning Reconstruction Network

TODO: