Deep Learning on Computational Accelerators 236781 Mini-Project

WET ASSIGNMENT

Muhammad Ghanayem

Ahmad Ghanayem

Chosen Architecture

For our project, we selected the U-Net architecture to tackle the MRI image reconstruction challenge. U-Net is well-regarded for its encoder-decoder structure with skip connections, which are useful in retaining important details needed for accurate image reconstruction. Each run was defined with batch size equal to 64, learning rate of 0.001 and a total number of 25 epochs.

- U-Net Architecture: We chose U-Net because it's known for handling images at different scales effectively, which is crucial for the detailed reconstruction required in MRI scans.
- Integration of Provided Subsampling Layer: The "SubsamplingLayer" was provided in our course materials. We incorporated it into our model to help simulate different MRI scan resolutions.

Loss Criteria Used:

We focused on Peak Signal-to-Noise Ratio (PSNR) to measure the quality of our reconstructions. PSNR is a common metric in medical imaging because it gives a good indication of how the reconstructed image compares to the original, which is critical for clinical applications.

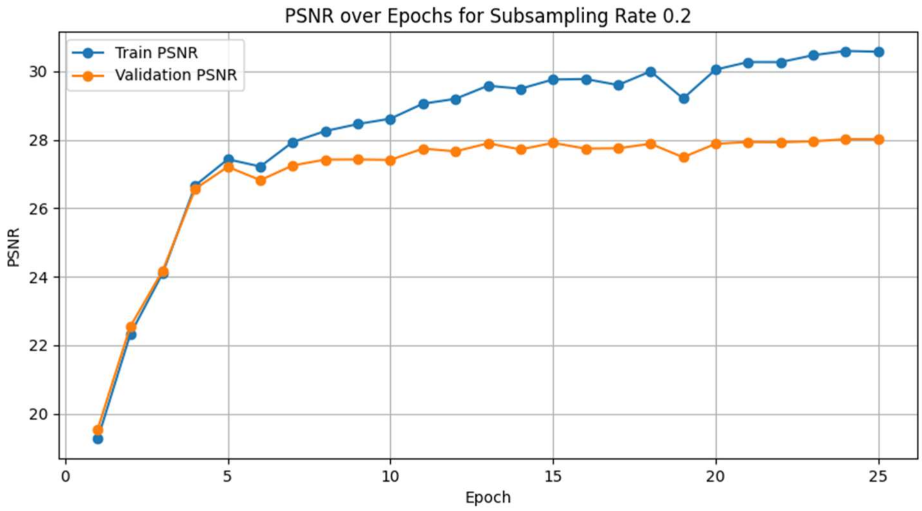
Additional Considerations:

- We made sure to include detailed tracking and visualization of our model's training process. By plotting metrics like PSNR across training epochs and comparing them between training and validation phases, we could fine-tune our model effectively and ensure it wasn’t overfitting.
- We introduced early stopping to try and prevent overfitting(though we defined it to happen after 10 epochs of no improvement which we should've reduced a bit, say to 5).

Overall, our approach uses a proven architecture adapted for MRI data specifics, ensuring that our model is robust and reliable for different imaging conditions.

Learning mask not applied:

- Drop rate of 0.2:



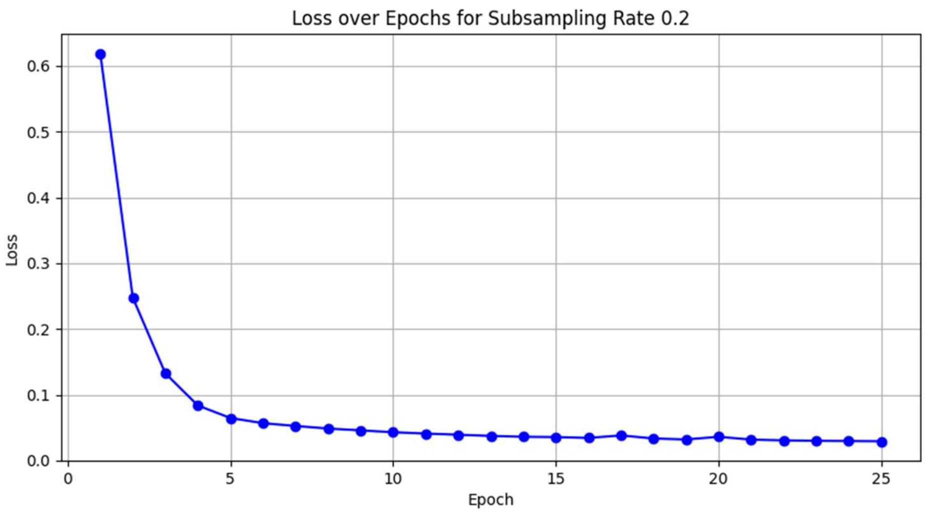
- The PSNR for both training and validation shows a consistent increase until around the 13th epoch, after which it stabilizes for the validation. The training PSNR is slightly higher than the validation PSNR, suggesting some degree of overfitting after the 13th epoch but generally indicating good model performance.

Train:

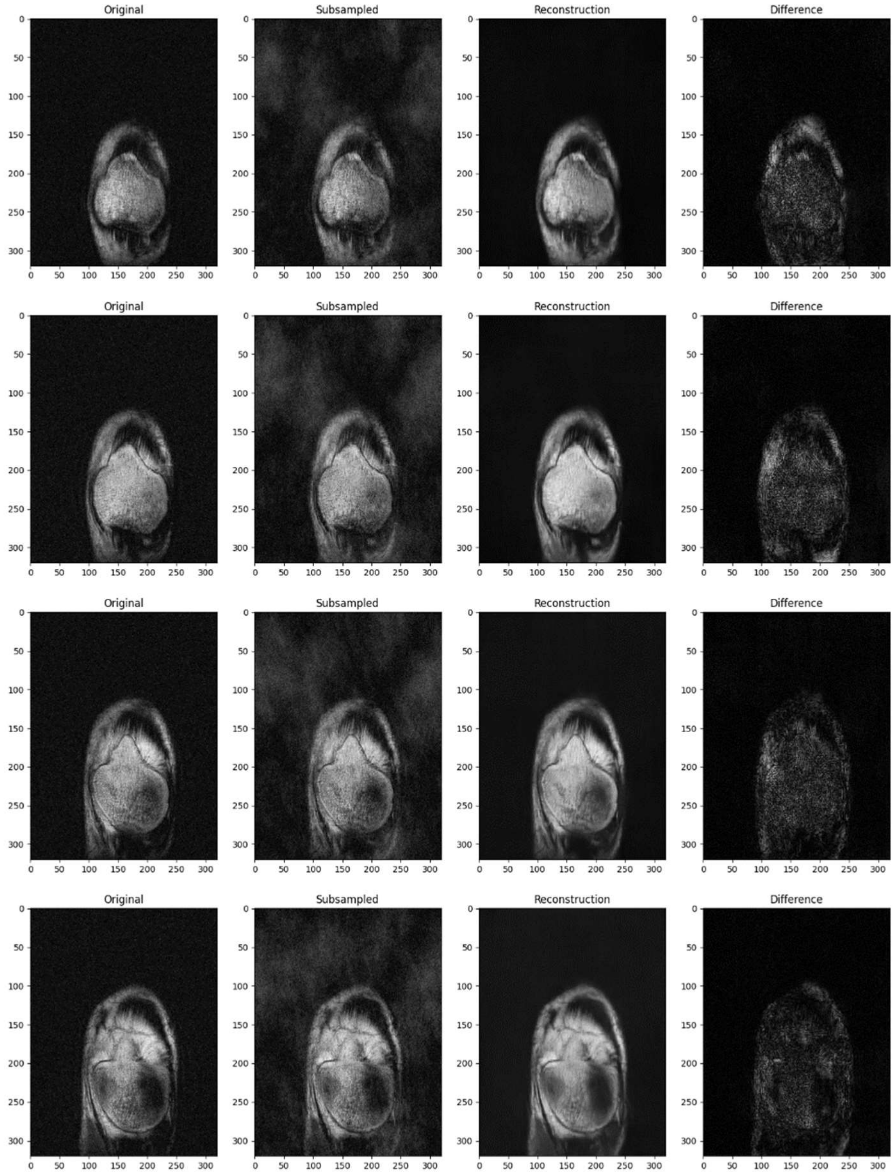
- Mean PSNR: 28.22
- Standard Deviation: 2.77

Validation:

- Mean PSNR: 27.00
- Standard Deviation: 2.03

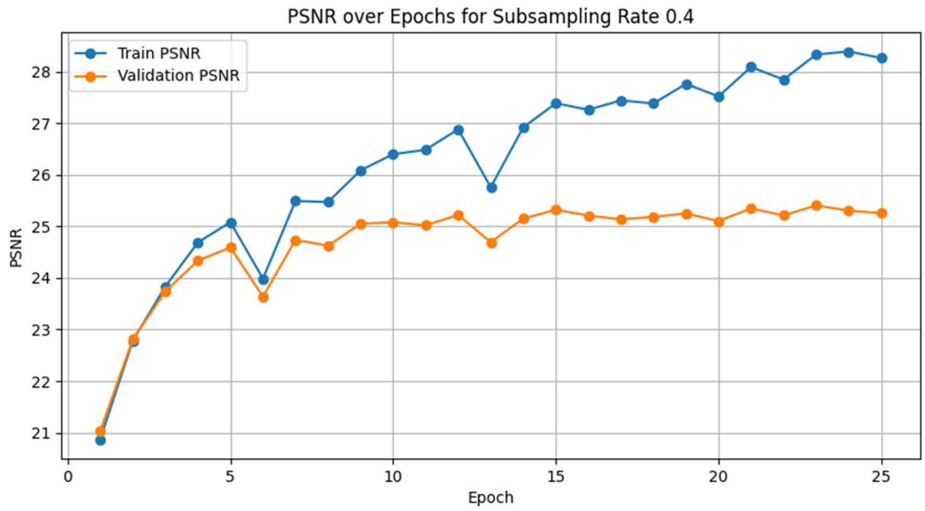


- The loss starts high at around 0.6 but quickly drops to below 0.1 within the first 4 epochs and continues to decrease slowly, leveling off as the epochs progress. This rapid decline followed by a plateau suggests that the model quickly learned the essential features necessary for reconstruction and then fine-tuned those features slowly over time.



- Quality of Reconstruction: The reconstructed images at this dropout rate closely resemble the original, with only minor artifacts and noise in the difference images.
- Detail Preservation: Fine details of the original images are well preserved in the reconstruction, which correlates with the high PSNR values observed in the graphs.
- Difference Analysis: The difference images mostly show low-intensity variations, indicating that the reconstruction is quite accurate.

- Drop rate of 0.4:



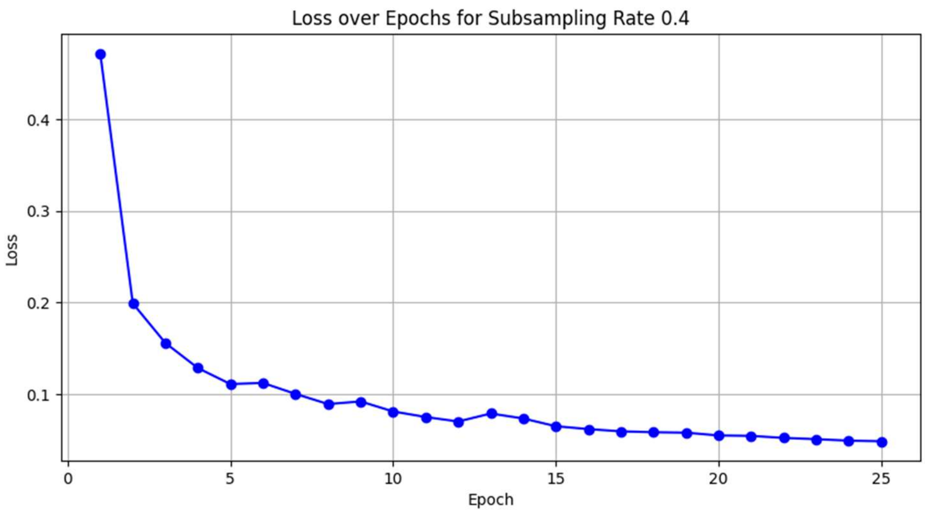
- The PSNR for both training and validation increases steadily but levels off at lower values in the validation compared to the 0.2 rate. The validation PSNR particularly shows a greater disparity from the training PSNR, indicating more pronounced overfitting at this dropout rate.

Train:

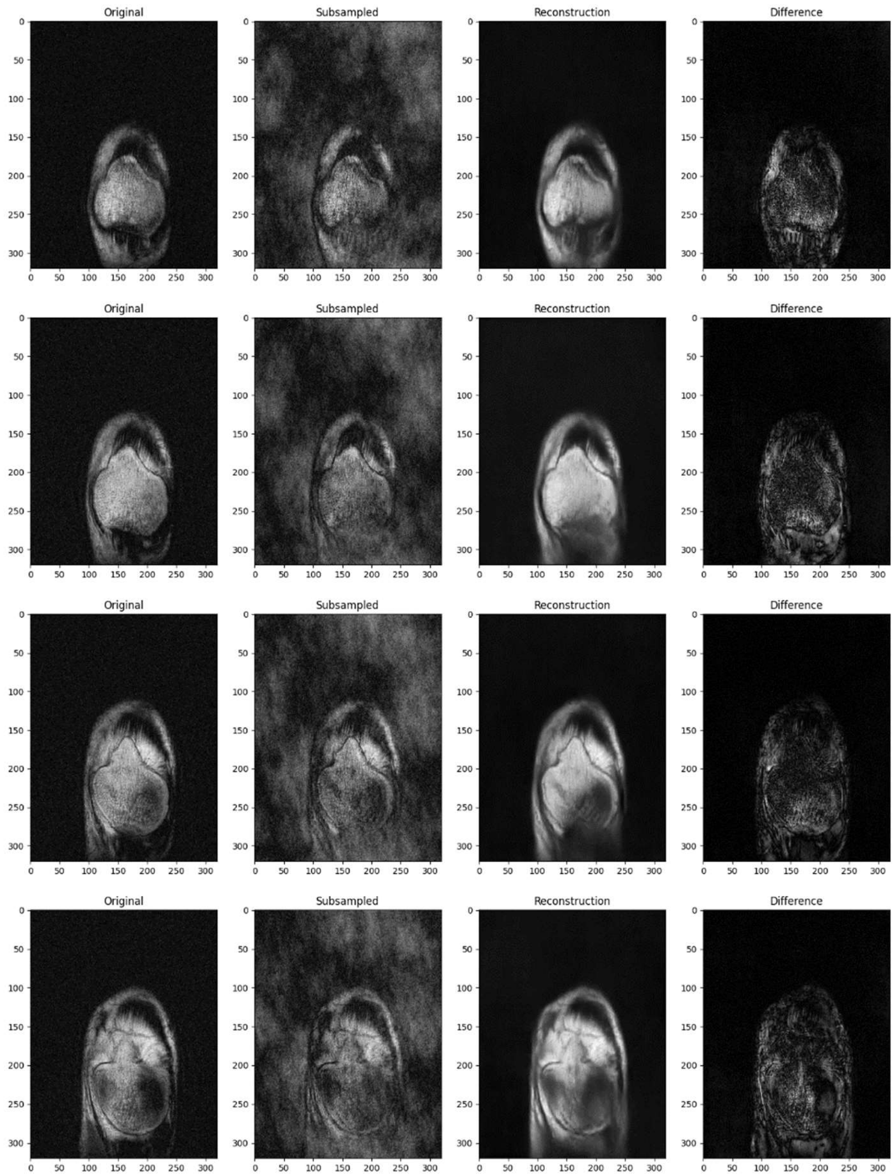
- Mean PSNR: 26.29
- Standard Deviation: 1.80

Validation:

- Mean PSNR: 24.66
- Standard Deviation: 0.96

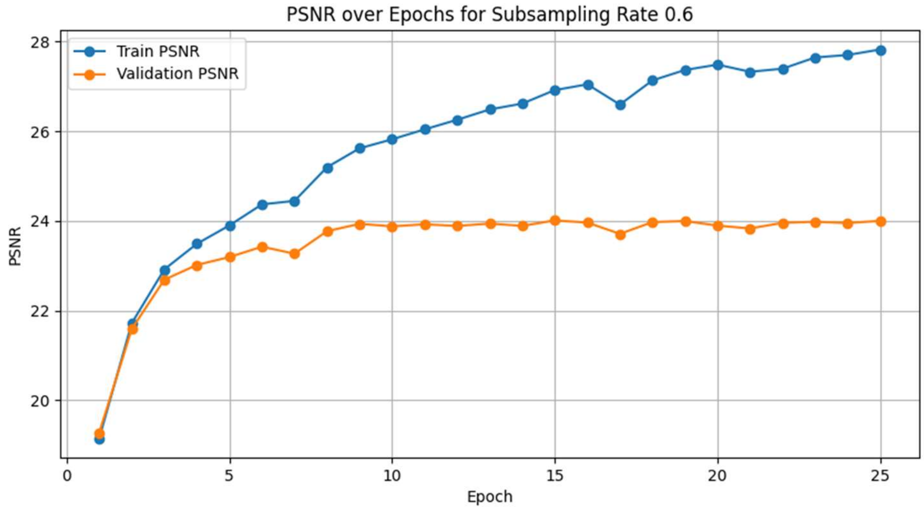


- The initial loss is slightly lower than in the 0.2 rate, starting just above 0.4, and follows a similar rapid decrease. The loss levels off a bit higher compared to the 0.2 rate, suggesting that increasing the dropout rate slightly impairs the model's ability to reduce error as effectively.



- Quality of Reconstruction: There is a noticeable decline in the quality of the reconstructed images compared to the 0.2 dropout rate, with more visible artifacts and noise.
- Detail Preservation: The model struggles slightly more to capture finer details, particularly in complex areas, which is consistent with the lower PSNR values.
- Difference Analysis: The difference images show higher intensity areas, suggesting more significant discrepancies between the original and reconstructed images.

- Drop rate of 0.6:



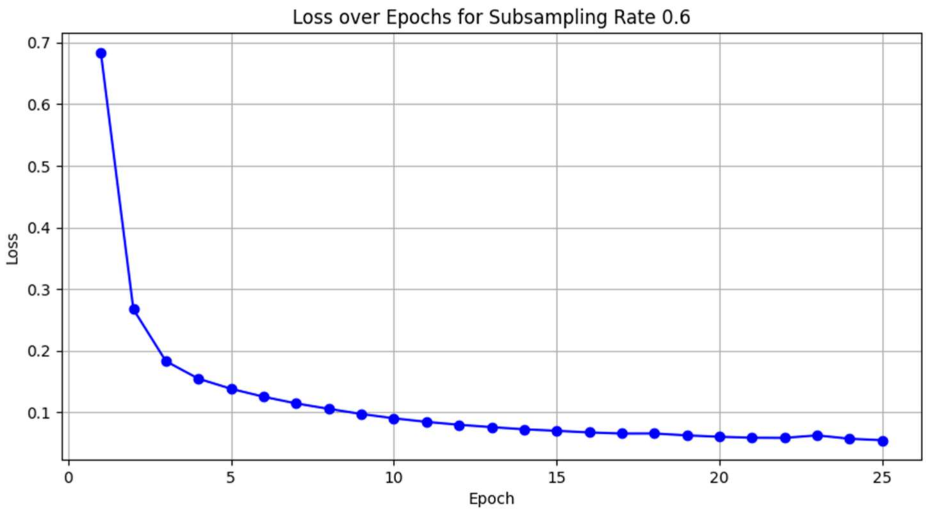
- The PSNR trajectory is quite different, with the training PSNR continuing to increase while the validation PSNR starts low and plateaus much lower than the other rates. This significant divergence suggests the model is heavily overfitting the training data and generalizes poorly.

Train:

- Mean PSNR: 25.76
- Standard Deviation: 2.09

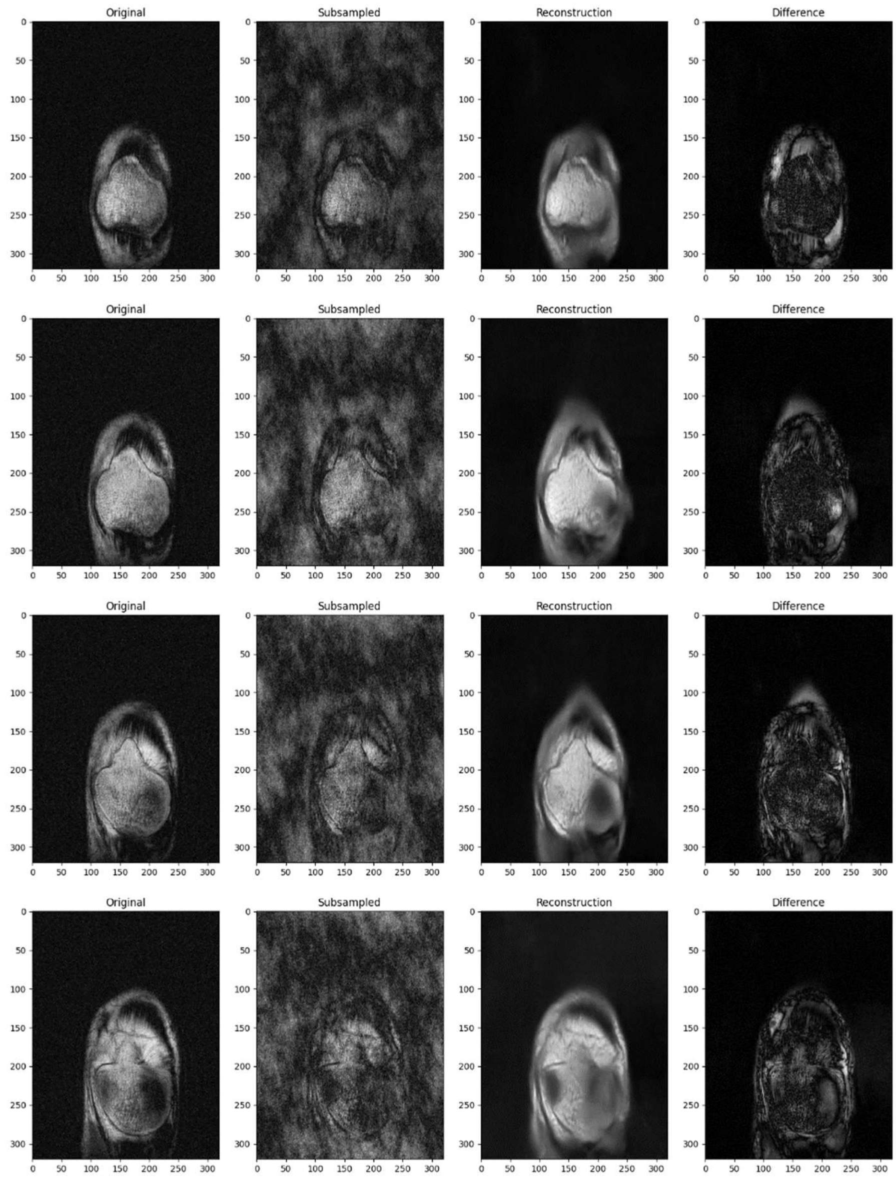
Validation:

- Mean PSNR: 23.54
- Standard Deviation: 0.99



- The loss starts the highest among the three rates at nearly 0.7 but decreases similarly, indicating the model can still learn despite the high dropout rate. The loss flattens out comparable to the 0.4 rate.

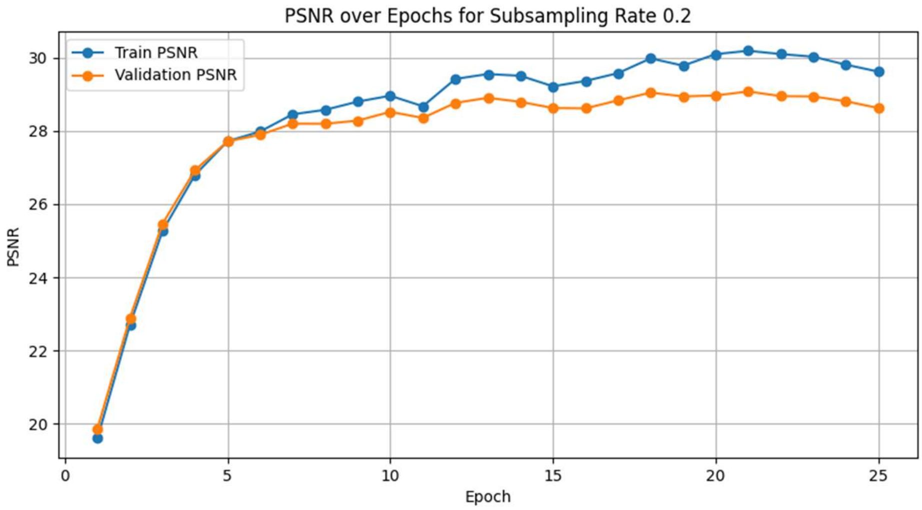
- The high dropout rate has substantially impacted the model's generalization ability, as seen in the significant divergence between training and validation PSNR. The model learns enough to reduce training loss but fails to apply this effectively to unseen data.



- Quality of Reconstruction: The quality further declines, with the reconstructions appearing blurrier and less defined compared to lower dropout rates.
- Detail Preservation: Many details are lost or inaccurately reconstructed, which aligns with the even lower PSNR values and the wide gap between training and validation PSNR, indicating overfitting.
- Difference Analysis: The difference images are more intense, displaying significant deviations from the original, which underscores the model's reduced effectiveness at this dropout rate.

Learning mask applied:

- ## Drop rate of 0.2:



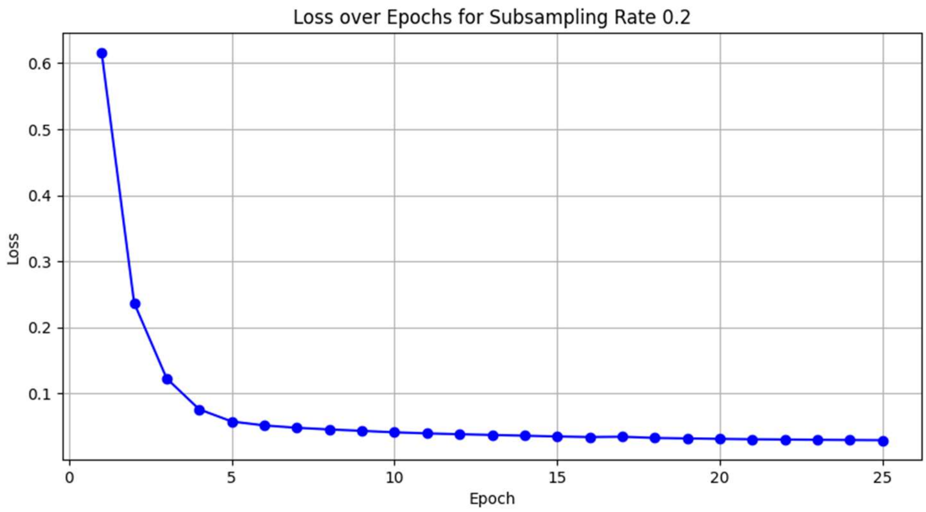
- The PSNR for both training and validation shows steady improvement, with the training PSNR slightly higher throughout the run. This indicates a strong reconstruction capability that maintains throughout the epochs.

Train:

- Mean PSNR: 28.40
- Standard Deviation: 2.42

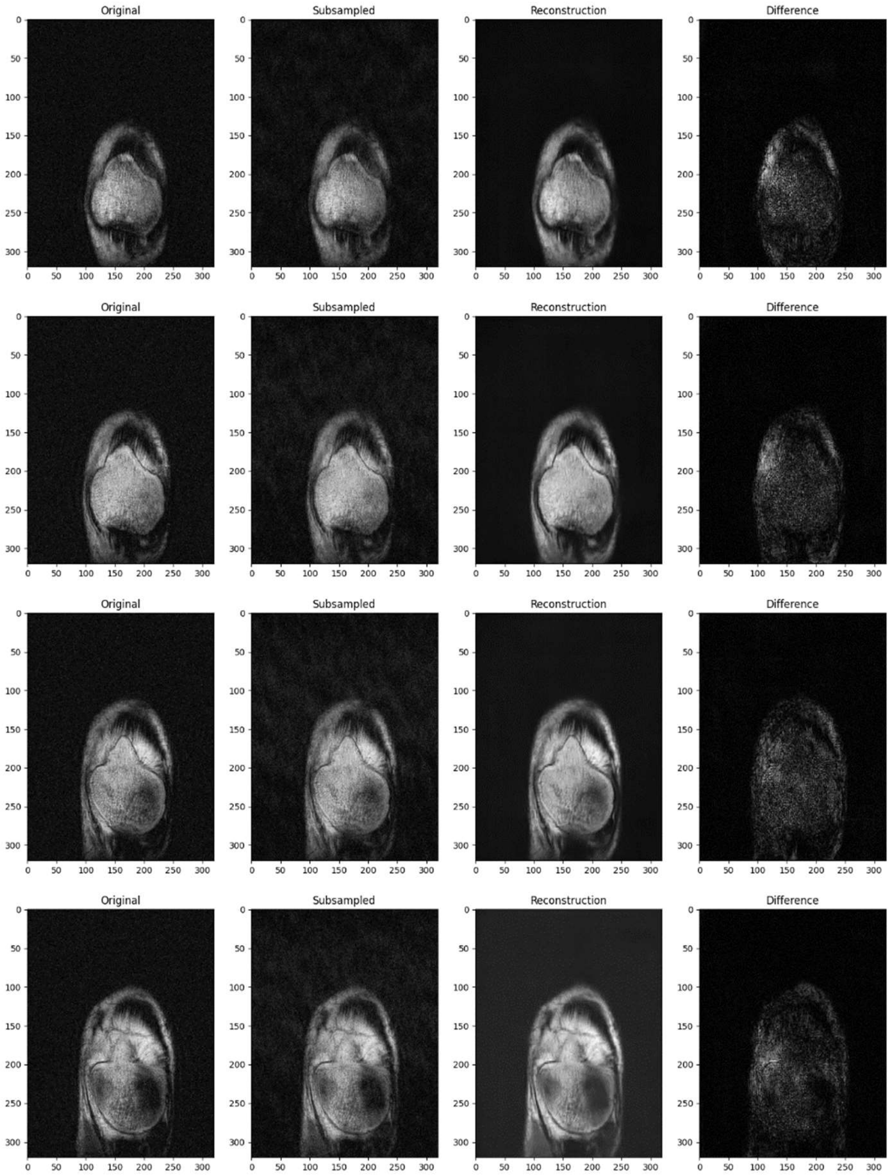
Validation:

- Mean PSNR: 27.85
- Standard Deviation: 2.09



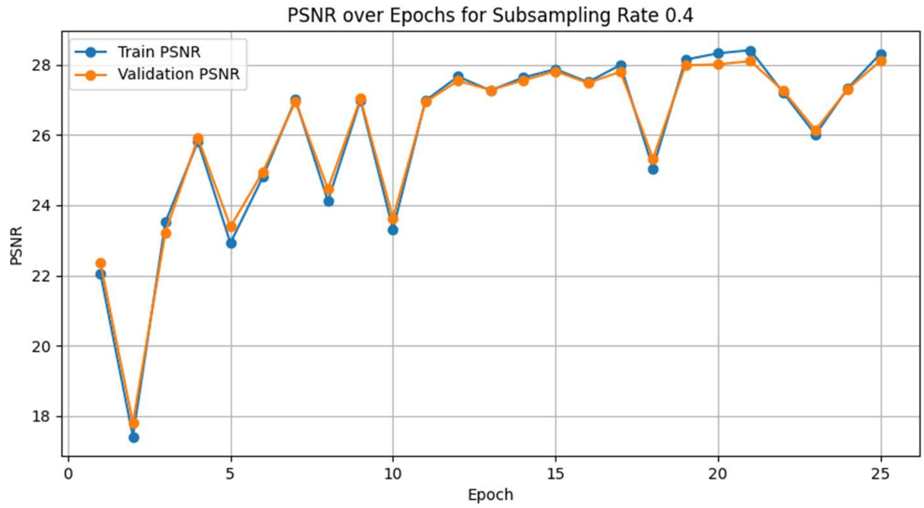
- The loss decreases rapidly from around 0.6 to below 0.1 within the initial few epochs, then gradually levels off, showing effective learning and stabilization without overfitting.

- This dropout rate coupled with the learned mask exhibits strong performance, quickly reducing error and achieving high reconstruction quality as evidenced by the high and stable PSNR values. The close alignment between training and validation PSNR also suggests effective generalization.



- Reconstruction Quality: The reconstructed images are very close to the original, showing excellent quality. This suggests the model is working really well at this dropout rate.
- Detail Preservation: The model captures most of the small details in the images, which matches with the high PSNR values seen in the plots.
- Difference Analysis: The difference images have very little visible changes from the original, indicating that the reconstruction is very accurate.

- ## Drop rate of 0.4:



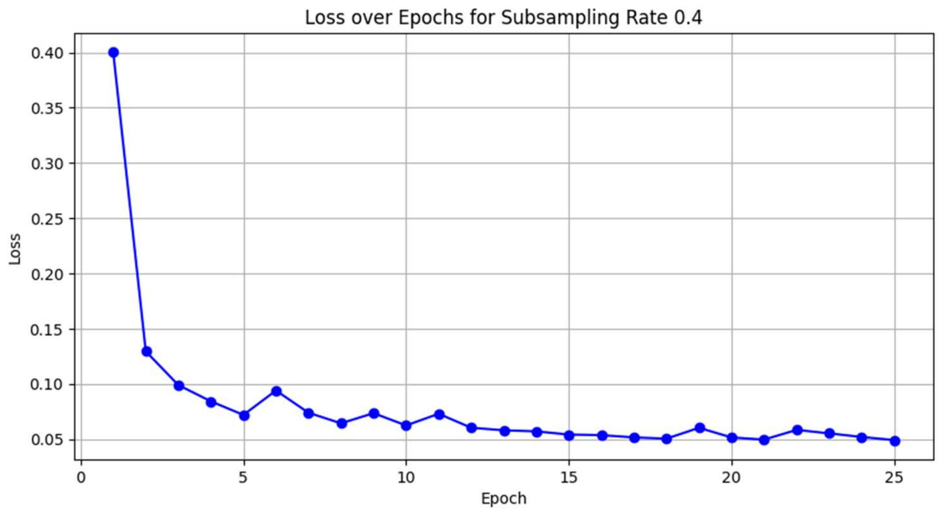
- Both training and validation PSNR improve significantly after a sharp initial increase. However, the PSNR exhibits more fluctuations compared to the 0.2 rate, which may indicate some variability in learning stability across epochs.

Train:

- Mean PSNR: 25.91
- Standard Deviation: 2.66

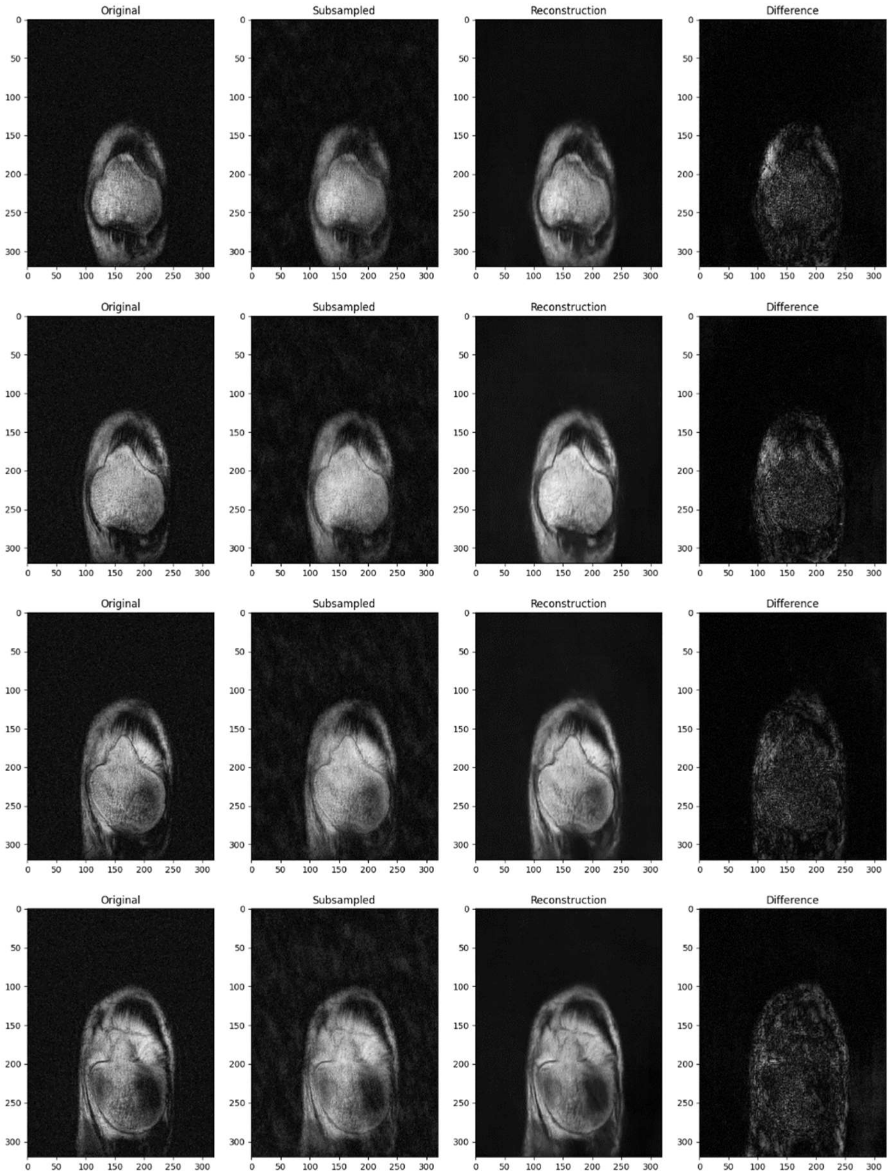
Validation:

- Mean PSNR: 26.04
- Standard Deviation: 2.39



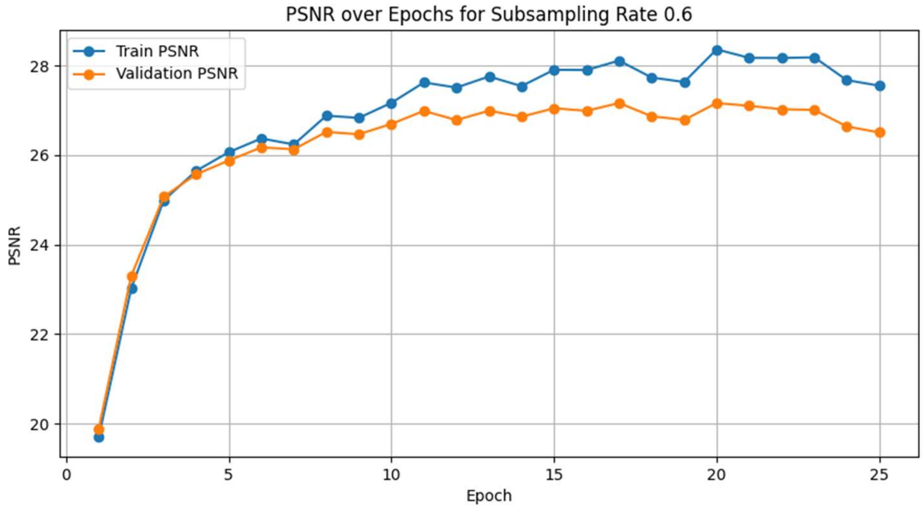
- The loss exhibits a swift decline from around 0.4 and stabilizes at a slightly higher value than for the 0.2 dropout rate, indicating less optimal but still effective learning.

- With a higher dropout rate, the performance slightly deteriorates, evidenced by the higher stabilized loss and more volatile PSNR. The variability in PSNR suggests that the model could be sensitive to the dropout settings, impacting its ability to consistently learn from the data.



- Reconstruction Quality: The quality drops a bit compared to the 0.2 rate, with some blurring of features. This matches with slightly lower PSNR values.
- Detail Preservation: While most key details are still visible, the images lose a bit of sharpness, especially in complex areas.
- Difference Analysis: The difference images show more noticeable differences from the original than at 0.2, but they're still quite good, showing that the reconstruction is decent but not perfect.

- <u>Drop rate of 0.6:</u>



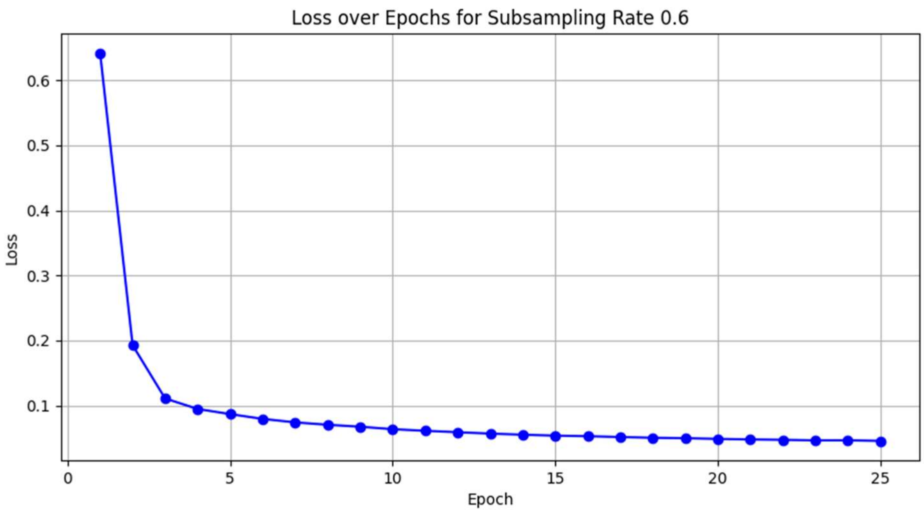
- The validation PSNR remains fairly stable and close to the training PSNR throughout later epochs, suggesting that the model has good generalization to unseen data. There is some fluctuation in the training PSNR which is higher than the validation PSNR, particularly in the latter epochs, but this is minimal and does not suggest severe overfitting.

Train:

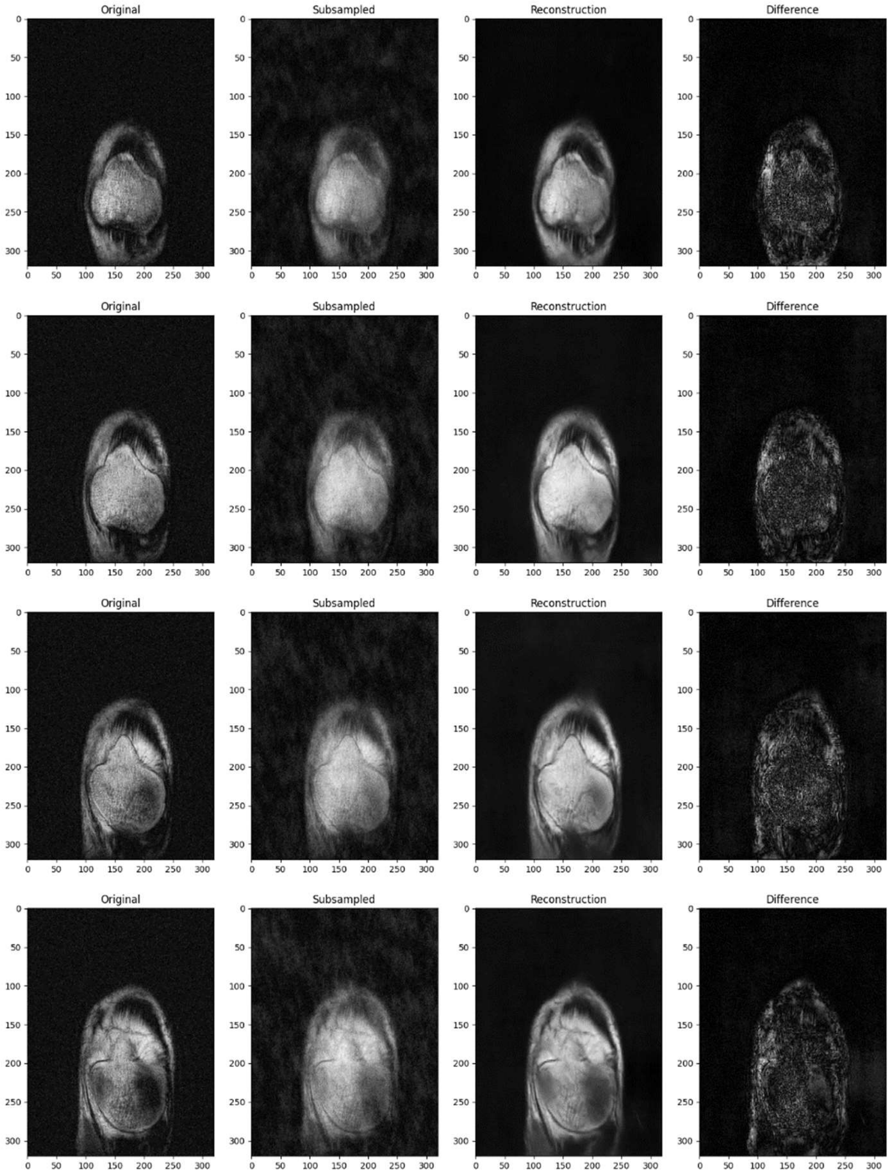
- Mean PSNR: 26.86
- Standard Deviation: 1.87

Validation:

- Mean PSNR: 26.16
- Standard Deviation: 1.57



- The initial loss is the highest, starting around 0.6, and follows a similar trend of rapid decrease. The curve flattens at a level comparable to the 0.4 rate, again showing good learning but with limitations due to higher dropout.



- Quality of Reconstruction: The quality of reconstruction deteriorates further at this rate. The images are blurrier and less defined, indicating decreased effectiveness in the reconstruction process.
- Detail Preservation: The reconstructions lose considerable detail, particularly in finer structures, which aligns with the larger gap observed between training and validation PSNR.
- Difference Analysis: The difference images are significantly more intense and widespread, demonstrating substantial deviations from the original images and highlighting issues with model generalization at this higher dropout rate.

Conclusions:

Among the six configurations tested three dropout rates each with and without a learned mask the **best performing** model is the one with a **Dropout Rate of 0.2 using a Learned Mask.** Here's why this model stands out:

- **Loss and PSNR Metrics:** It shows the quickest and most consistent reduction in loss, suggesting efficient learning, and the highest PSNR values, which indicate better image reconstruction quality.
- **Visual Quality:** The reconstructed images from this model are very close to the original images, showing that it captures details well and produces fewer errors, as seen in the very minimal differences in the difference images.
- **Stability and Generalization:** This setup not only performs well in training but also shows good generalization to validation data, which is crucial for practical use.

Among the six configurations tested three dropout rates each with and without a learned mask the **least effective** model is the one with a **Dropout Rate of 0.6 without a Learned Mask.** Here's why this model underperforms significantly:

- **Loss and PSNR Metrics:** Although there is a reduction in loss, it's not as effective as in other configurations, indicating less successful learning. The PSNR values, especially in validation, are significantly lower compared to other models, which points to poor image reconstruction quality. The substantial gap between training and validation PSNR illustrates severe overfitting; the model memorizes the training data but fails to generalize this learning effectively to new data.
- **Visual Quality:** The reconstructed images from this model are markedly worse than those from other configurations. They show significant blurring and loss of detail, indicating that the model struggles to accurately capture and reproduce the features of the original images. The difference images are also much more pronounced, highlighting greater reconstruction errors and discrepancies compared to the original.
- **Stability and Generalization:** This model displays poor stability and generalization capabilities. Its performance on validation data is substantially worse than on training data, suggesting that it is not well-suited for practical use where effective generalization to new data is crucial.

Why Our Model Performed Best with Drop Rate 0.2 and Learning Mask:

- Optimal Data Utilization: With a drop rate of 0.2, our model could access a larger portion of the original image data, enabling it to learn more detailed and nuanced features of the MRI scans.
- Enhanced Adaptability: The learning mask facilitated a more focused and efficient learning process by enabling the model to prioritize the most informative features of the data, rather than treating all data uniformly.

Why Our Model Performed Worst with Drop Rate 0.6 and No Learning Mask:

- Insufficient Data for Learning: The high drop rate significantly limited the amount of data available for training, preventing our model from learning essential features necessary for accurate image reconstruction.
- Lack of Adaptability: Operating without the learning mask, our model was unable to differentiate between more and less relevant parts of the data, treating all input uniformly. This approach is less effective, especially when a substantial portion of potentially valuable data is discarded due to the high drop rate.

Improvements:

Given a year to work on this project and unlimited hardware resources, we would focus on several key strategies to enhance the image reconstruction model:

1. Deepening the Network: We would experiment with adding more layers to the network. A deeper network could potentially capture more complex patterns in the data, which is crucial for improving the quality of the reconstructed images.

2. Data Augmentation: To help the model generalize better to unseen data, we'd implement more extensive data augmentation techniques. This could include transformations like rotations, scaling, and elastic deformations, which would make the model robust to various distortions it might encounter in real-world MRI data.

3. Expanding the Dataset: With more resources, we could train and test the model on a much larger dataset. This would not only enhance the model's ability to learn diverse features but also improve its generalization capabilities across different MRI images.