Part 1: Comprehension Questions

1. Generative Adversarial Networks (GANs):

1) Theory and Objective of GANs:
   a. Explain the objective function used in GANs. Why is it structured as a min-max optimization problem between the generator and the discriminator?
   b. Define the role of the generator and discriminator in GANs. How do they interact to improve the generated samples?
   c. In what scenario does the discriminator in GANs become too powerful, and what impact does this have on the training process? How can this problem be mitigated?

2) Training Strategies for GANs:
   a. Outline the steps involved in training a GAN. Include how the losses of both the generator and discriminator are optimized.
   b. Deep Convolutional GANs (DCGANs) modify traditional GANs by introducing strided convolutions. Explain how this modification benefits GAN training and stability.

3) Applications of GANs:
   a. List three real-world imaging applications of GANs and describe the specific advantages they bring to those applications (e.g., data augmentation, image generation).
   b. GANs are often used for generating realistic images. Explain how latent space interpolation works in GANs and provide an example of how it is used to generate different variations of an image.

2. Variational Autoencoders (VAEs)

1) Theory of VAEs:
   a. Explain the primary differences between a standard autoencoder and a variational autoencoder. What role does the latent variable z play in the VAE architecture?
   b. VAEs use the reparameterization trick. What is the purpose of this trick, and how does it help in training VAEs?
2) Loss Function of VAEs:
   a. Derive the evidence lower bound (ELBO) used as the objective function in VAEs. Explain how this loss function balances reconstruction accuracy and the Kullback-Leibler divergence between the approximate posterior and the prior.
   b. Why is the KL-divergence important in VAEs? How does minimizing KL-divergence help in generating high-quality samples?
3) Applications of VAEs:
   a. Explain how VAEs can be used for anomaly detection. What makes them particularly suited for this task?
   b. Compare the use of VAEs and GANs for image generation. In what scenarios would you choose a VAE over a GAN?

Part 2: Application to Imaging Science

1. GANs (Generative Adversarial Networks):

1) GAN Implementation:
   a. Implement a simple GAN to generate images from the MNIST dataset. Use a fully connected generator and discriminator network. Train the model and plot the loss curves for both the generator and discriminator.
   b. Visualize the output of the generator at various stages of training (e.g., after 10, 50, 100 epochs) to show how the generated images evolve over time.

2) DCGAN for Image Generation:
   Implement a Deep Convolutional GAN (DCGAN) to generate images from the CIFAR-10 dataset. Apply the following best practices during training:
   - Use strided convolutions instead of pooling layers.
   - Apply batch normalization in both the generator and the discriminator.
   - Use the ReLU activation function in the generator and Leaky ReLU in the discriminator.

   After training, visualize the generated images and compare them to the real CIFAR-10 images.

3) Latent Space Interpolation in GANs:
   Implement latent space interpolation between two generated images. Select two distinct latent vectors, interpolate between them using linear interpolation, and visualize the resulting images. Comment on how smooth or realistic the transitions are.

2. VAEs (Variational Autoencoders)

1) VAE Implementation for Image Generation:
   a. Implement a Variational Autoencoder (VAE) for the MNIST dataset. Train the model to reconstruct input images and generate new images by sampling from the learned latent space.
   b. Visualize both the reconstruction and the newly generated images. Plot the ELBO (Evidence Lower Bound) loss and KL-divergence during training.

2) VAE for Anomaly Detection
   Implement a VAE and train it on the MNIST dataset. Use the trained model to detect anomalies by evaluating the reconstruction error. Test your model on a set of anomalous images (e.g., noisy or corrupted MNIST digits) and plot the distribution of reconstruction errors. Set a threshold to classify images as "anomalous" or "normal".

3) VAE Latent Space Visualization
   After training a VAE on MNIST, visualize the latent space by performing 2D scatter plots of the latent vectors. Color the points based on their digit class (0-9). Discuss how well the latent space clusters based on the digit classes.

Submission Requirements:
Part 1: A written report (minimum 2 pages and maximum 4 pages) following IEEE formatting guidelines, including citations from peer-reviewed sources.

Part 2: Organize all your codes for Part 2 in your GitHub account in one repository and make it public. Please add the link to this repository to your report.

In the report for part 2, include your graphs, images with captions, and a brief analysis of your findings for each implementation. (short paragraph).

Due Date: Friday, November 01.

Evaluation Criteria:
- Understanding of Concepts: Demonstrated through the clarity and depth of your answers and theoretical discussion.
- Application: Insightfulness and relevance of your analysis to real-world imaging science applications.
- Presentation: Adherence to IEEE formatting and overall clarity of writing.
- Implementation: The clarity of your code, figures and analysis.