1. The code addresses the anomaly detection problem by training an autoencoder neural network on normal chest X-ray images. The autoencoder learns to reconstruct normal images with minimal reconstruction error. After training, the encoder part of the autoencoder is extracted, and a kernel density estimator (KDE) is fitted on the encoded representations (latent space) of the normal images. For a new test image, the code computes its reconstruction error from the autoencoder and its density score from the KDE model. If either the reconstruction error is high or the density score is low compared to predefined thresholds, the image is classified as an anomaly (potentially pneumonia). This approach leverages the autoencoder's ability to reconstruct normal data well while struggling with anomalies, combined with the density estimation of the normal data distribution in the latent space to detect outliers or anomalies.
2. The anomaly detection design consists of an autoencoder neural network architecture and a kernel density estimation (KDE) model. The autoencoder is trained to reconstruct normal chest X-ray images, with the encoder part learning to compress the input images into a lower-dimensional latent space representation. After training, the encoder is extracted, and a KDE model is fitted on the encoded representations of the normal training data. For a new test image, its reconstruction error from the autoencoder and its density score from the KDE model are computed. If either the reconstruction error exceeds a threshold or the density score falls below a threshold, the image is classified as an anomaly. The autoencoder's ability to reconstruct normal data well while struggling with anomalies, combined with the density estimation of the normal data distribution in the latent space, enables the detection of anomalous or outlier images.
3. The experimental setup involves training an autoencoder model on normal chest X-ray images from the training set, and evaluating its performance on separate validation and anomaly (pneumonia) test sets. The autoencoder is trained to minimize the reconstruction error, measured by the mean squared error loss function. During the evaluation phase, two key metrics are computed: reconstruction error and density score. The reconstruction error is calculated as the mean squared error between the input image and its reconstructed counterpart from the autoencoder. The density score is obtained by feeding the encoded representation (latent space) of the input image into a kernel density estimation (KDE) model fitted on the encoded normal training data. Lower density scores indicate a higher likelihood of the input being an anomaly. To classify an image as normal or anomalous, predefined thresholds are set for both the reconstruction error and density score. If either metric exceeds its respective threshold, the image is classified as an anomaly (pneumonia). The code also provides a function to calculate the average and standard deviation of the reconstruction error and density scores for both normal and anomaly batches, which can aid in setting appropriate thresholds.