**Answer 2**

**Connection between Linear Autoencoder and Principal Component Analysis (PCA)**

**Linear autoencoders and Principal Component Analysis (PCA) are closely related in terms of purpose and operations; especially in reducing their dimensionality.**

1. **Linear Transformations: A linear autoencoder includes encoding as well as decoding which are linear transformations. When trained it transform input data points into a latent form while preserving their structural properties and in the process it will resemble PCA, which transform data in to a new lower dimensional linear subspace.**
2. **Mean Squared Error: PCA also tries to minimize the reconstruction error, which is typically quantified by the mean squared error (MSE); Likewise, for Linear autoencoder. This kind of error in PCA is minimized through an eigenvalue decomposition of the covariance of the data. On the other hand, Linear autoencoders reduce the reconstruction loss through backpropagation techniques.**
3. **Latent Space Representation: The authors point out that the learned latent space of a linear autoencoder is similar to PCA because it extracts the main components of the given input data. The dimensions in this latent space are in fact the most important in decreasing order and hence enable efficient data representation and compression.**

**Answer 4**

**1. Model Architecture**

* **Dense Autoencoder**:
  + This model fully connected (dense) layers and hence the model lacks capability to extract higher level hierarchies from the spatial location data. The neurons in a dense layer are connected to neurons in the next layer, and hence their parameters are many.
* **Vanilla CNN Auto encoder**:
  + This model incorporates convolution layers and these layers are meant for handling data structures with a grid like structure for instance images. Convolutional layers convolution to locate features and motifs as well as employing filters that maintain spatial structure.

**2. Performance Metrics**

* **Loss (Mean Squared Error)**:
  + The CNN Auto encoder typically exhibits a lower reconstruction loss (MSE) compared to the Dense Auto encoder. This indicates that the CNN is better at reconstructing the original images from the compressed representations.
* **Visual Reconstruction Quality**:
  + When comparing the original and reconstructed images, the CNN Auto encoder generally produces higher quality reconstructions with clearer edges and more detailed features, while the Dense Auto encoder may produce blurrier or less defined images.

**3. Training Dynamics**

* **Convergence Speed**:
  + CNNs often converge faster than dense networks due to their ability to extract and learn relevant features early in training. The structure of convolutions allows the model to learn hierarchies of features progressively, which can lead to faster reductions in loss during training.
* **Generalization**:
  + CNNs tend to generalize better to unseen data because they can learn translational invariance and local features. This is particularly beneficial in image processing tasks where slight variations in images should not affect the output.

**4. Reasons for Improvements**

* **Feature Learning**:
  + CNNs are inherently better at learning hierarchical feature representations. The filters in convolutional layers capture patterns at different scales, making them more suitable for image data.
* **Parameter Efficiency**:
  + CNNs utilize weight sharing and local connectivity, which results in fewer parameters compared to dense networks. This not only reduces computational complexity but also helps in avoiding overfitting, particularly when the training dataset is limited.
* **Robustness**:
  + Convolutional architectures provide robustness against translation and distortion in the input data, enabling better performance in real-world scenarios where images can vary significantly in appearance.

**Answer 6**

### Observing Model Performance Improvements: Image Denoising AE vs. Vanilla CNN AE

When comparing the performance of the Image Denoising Autoencoder (AE) and the Vanilla CNN AE, several key observations can be made:

#### Performance Improvements

1. **Denoising Capability**: The Image Denoising AE is specifically trained to reconstruct clean images from noisy inputs. This targeted approach allows it to learn more robust features of the data, leading to better reconstruction quality, especially when noise is present in real-world scenarios.
2. **Generalization**: And because the Denoising AE is trained on noisy data it can better generalise and will not fit the images in training set too well. The generalization is made better as the model is able to recognize the patterns in the images other than learning the training images by heart.
3. **Visual Quality**: In a case where the images are reconstructed through the two models, the results seem to be better, cleaner, and even aesthetically pleasing from the Denoising AE. The reconstruction from the Vanilla CNN AE may still be noisy or look like an artifact, specially when assessed against noisy inputs.
4. **Mean Squared Error (MSE)**: The loss values (MSE) presented in Table 4 show that the Denoising AE generally has lower MSE values for noisy images than Vanilla CNN AE martyr that the Denoising AE can better reconstruct the clean images.

#### Reasons for Improvements

* **Training on Noisy Data**: The Denoising AE learns to distinguish between noise and the underlying signal during training. This capability allows the model to generalize better to unseen images, particularly those that may contain noise.
* **Architecture Optimization**: Since both models employed convolutional layers it meant that they were well-equipped to identify spatial hierarchies in the streams of data. But the fundamental design of Denoising AE is much closer to how noise is handled, making the Denoising AE much more suitable for noisy environments.
* **Loss Function**: While their loss function is mean squared error (MSE), the Denoising AE model is trained differently from the other model to reduce the effects of noise when learning. It directly targets the gap between the clean and reconstructed images and this is the right approach for image denoising.

**Answer 7**  
  
Differences Between Autoencoders (AE) and Variational Autoencoders (VAE)

#### Conceptual Differences

1. **Output Distribution**:
   * **Autoencoder (AE)**: An AE’ goal is to learn deterministic model that maps an input to output in order to reconstruct the input. That is, it maps the input into a space and reconstructs it from the map.
   * **Variational Autoencoder (VAE)**: In a VAE, the data is mapped into a particular probability distribution in a lower dimensionality space – usually, the Gaussian distribution. Rather than associating inputs with specific points in the latent space it encodes them as distributions (mean and variance) which permits sample generation of the new data.
2. **Loss Function**:
   * **AE**: The loss function is often defined just on the reconstruction error by means of some metrics (e.g., Mean Squared Error). An aim is to achieve the smallest difference between the input and the output reconstructed by the network.
   * **VAE**: The loss function consists of two parts: the reconstruction loss, which is similar to that of AE, and the Kullback-Leibler divergence term, forcing the learned distribution of the latent code to be close to a prior distribution, such as a standard normal distribution. The second approach makes the model to generate more reasonable and systematic latent vectors.
3. **Generative Capability**:
   * **AE**: Although an AE can reconstruct inputs, it is not optimally programmed for the generation of new data samples. Its principal application is dedicated to dimensionality reduction and reconstruction.
   * **VAE**: VAEs are specifically designed for generation of data. They can obtain new data from the same distribution of the training data by sampling from the latent space. This makes VAEs useful when one requires to generate new samples for instance when synthesizing images.