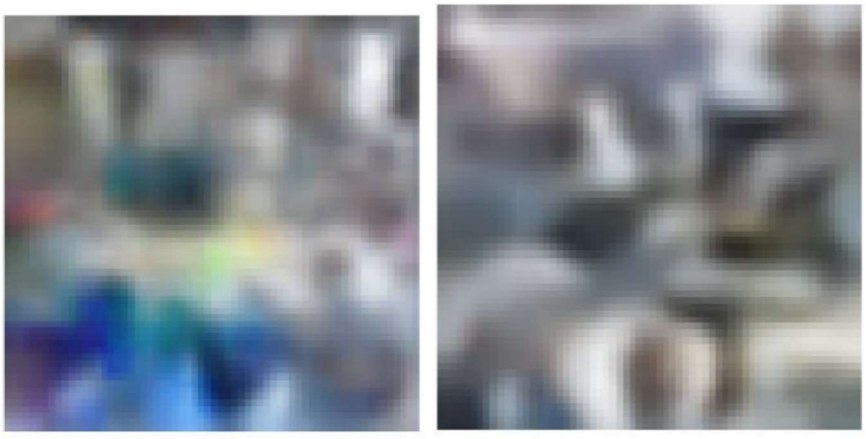
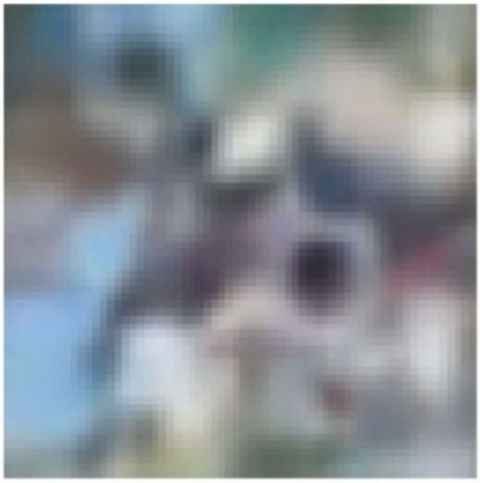
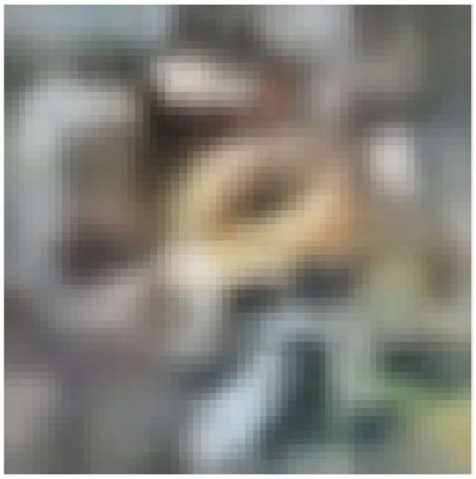
```
        self.rec_loss_tracker = tf.keras.metrics.Mean(name="recon_loss")
        self.kl_loss_tracker = tf.keras.metrics.Mean(name="kl_loss")

    @property
    def metrics(self):
        return [self.total_loss_tracker, self.rec_loss_tracker, self.kl_loss_tracker]

    def train_step(self, data):
        with tf.GradientTape() as tape:
            z_mean, z_log_var, z = self.encoder(data)
            reconstruction = self.decoder(z)
            rec_loss = tf.reduce_mean(tf.keras.losses.binary_crossentropy(data, reconstruction))
            rec_loss *= self.img_shape[0] * self.img_shape[1] * self.img_shape[2]
            kl_loss = -0.5 * tf.reduce_mean(1 + z_log_var - tf.square(z_mean) - tf.exp(z_log_var))
            total_loss = rec_loss + kl_loss
        grads = tape.gradient(total_loss, self.trainable_weights)
        self.optimizer.apply_gradients(zip(grads, self.trainable_weights))
        self.total_loss_tracker.update_state(total_loss)
        self.rec_loss_tracker.update_state(rec_loss)
        self.kl_loss_tracker.update_state(kl_loss)
        return {"loss": self.total_loss_tracker.result(),
                "recon_loss": self.rec_loss_tracker.result(),
                "kl_loss": self.kl_loss_tracker.result()}

# Instantiate
encoder = build_encoder(img_shape, latent_dim)
decoder = build_decoder(latent_dim, img_shape)
vae = VAE(encoder, decoder, img_shape)
```

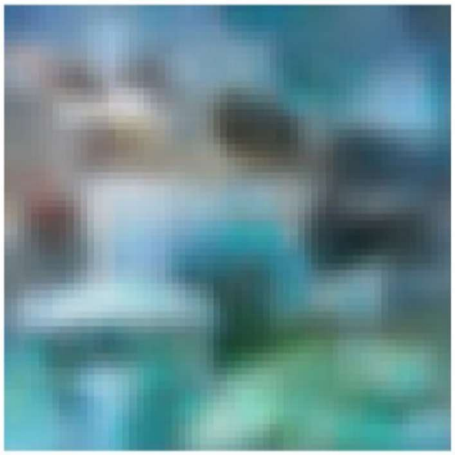
```
# 5) Compile & 6) Train
vae.compile(optimizer=tf.keras.optimizers.Adam())
vae.fit(x_train, epochs=50, batch_size=64)

# 7) Generate images
z_sample = tf.random.normal(shape=(5, latent_dim))
generated = vae.decoder.predict(z_sample)
for i in range(len(generated)):
    plt.imshow(np.clip(generated[i], 0, 1))
    plt.axis('off')
    plt.show()
```

OUTPUT:









RESULT: The trained VAE learned meaningful latent structure and generated realistic-looking images when sampling from the latent prior.

EXP NO: 09 DATE: 04/10/2025	**Text Generation using LSTM**

AIM: To train an LSTM-based recurrent neural network on the Shakespeare corpus to generate coherent and fluent English-like text sequences.

ALGORITHM:

- Load and preprocess the Shakespeare dataset (convert to lowercase, tokenize characters).
- Create input sequences of fixed length for training (each sequence predicts the next character).
- Build a Sequential LSTM model with embedding and dense output layers.
- Compile the model with categorical cross-entropy loss and Adam optimizer.
- Train the model on text sequences for several epochs.
- Generate new text by seeding the model with a random starting string and predicting next characters iteratively.

CODE:

```
# Text Generation with LSTM (Shakespeare Corpus)

import tensorflow as tf

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import LSTM, Dense, Embedding

import numpy as np

import random, sys


# Load dataset

path = tf.keras.utils.get_file("shakespeare.txt",

   "https://storage.googleapis.com/download.tensorflow.org/data/shakespeare.txt")

text = open(path, "r", encoding="utf-8").read().lower()

print(f"Corpus length: {len(text)} characters")
```

```
# Create character mappings
chars = sorted(list(set(text)))
char2idx = {c:i for i, c in enumerate(chars)}
idx2char = {i:c for i, c in enumerate(chars)}

# Prepare sequences
seq_len = 60
step = 3
sentences = []
next_chars = []
for i in range(0, len(text) - seq_len, step):
    sentences.append(text[i: i + seq_len])
    next_chars.append(text[i + seq_len])
print("Number of sequences:", len(sentences))

x = np.zeros((len(sentences), seq_len, len(chars)), dtype=bool)
y = np.zeros((len(sentences), len(chars)), dtype=bool)
for i, sentence in enumerate(sentences):
    for t, char in enumerate(sentence):
        x[i, t, char2idx[char]] = 1
    y[i, char2idx[next_chars[i]]] = 1

# Build model
model = Sequential([
    LSTM(128, input_shape=(seq_len, len(chars))),
    Dense(len(chars), activation='softmax')
])
model.compile(loss='categorical_crossentropy',  optimizer='adam')
```

```
model.fit(x, y, batch_size=128, epochs=20)

# Function to sample next character
def sample(preds, temperature=1.0):
    preds = np.asarray(preds).astype('float64')
    preds = np.log(preds + 1e-8) / temperature
    exp_preds = np.exp(preds)
    preds = exp_preds / np.sum(exp_preds)
    probas = np.random.multinomial(1, preds, 1)
    return np.argmax(probas)

# Generate text
start_index = random.randint(0, len(text) - seq_len - 1)
seed_text = text[start_index:start_index + seq_len]
print("Seed:\n", seed_text)
print("\nGenerated Text:\n")

generated = seed_text
for i in range(500):
    x_pred = np.zeros((1, seq_len, len(chars)))
    for t, char in enumerate(seed_text):
        x_pred[0, t, char2idx[char]] = 1
    preds = model.predict(x_pred, verbose=0)[0]
    next_index = sample(preds, temperature=0.5)
    next_char = idx2char[next_index]
    generated += next_char
    seed_text = seed_text[1:] + next_char
```