In [ ]:
```
import torch
from torchvision import datasets, transforms
from torch.utils.data import DataLoader
from sklearn.decomposition import PCA
from sklearn.metrics import mean_squared_error
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from matplotlib import pyplot as plt
```

Importing Data

In [ ]:
```
# Transform to convert images to PyTorch tensors and normalize them
transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))  # Normalize around the mean 0.5
])

# Download and load the training data
trainset = datasets.MNIST(root='./data', download=True, train=True, transform=transfor
trainloader = DataLoader(trainset, batch_size=64, shuffle=True)

# Download and load the test data
testset = datasets.MNIST(root='./data', download=True, train=False, transform=transfor
testloader = DataLoader(testset, batch_size=64, shuffle=True)
```

```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz to ./data/MNI
ST/raw/train-images-idx3-ubyte.gz
100%|██████████| 9912422/9912422 [00:00<00:00, 219483760.03it/s]
Extracting ./data/MNIST/raw/train-images-idx3-ubyte.gz to ./data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz to ./data/MNI
ST/raw/train-labels-idx1-ubyte.gz
100%|██████████| 28881/28881 [00:00<00:00, 49503757.18it/s]
Extracting ./data/MNIST/raw/train-labels-idx1-ubyte.gz to ./data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz to ./data/MNIS
T/raw/t10k-images-idx3-ubyte.gz
100%|██████████| 1648877/1648877 [00:00<00:00, 78595926.91it/s]
Extracting ./data/MNIST/raw/t10k-images-idx3-ubyte.gz to ./data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz to ./data/MNIS
T/raw/t10k-labels-idx1-ubyte.gz
100%|██████████| 4542/4542 [00:00<00:00, 16638016.39it/s]
Extracting ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz to ./data/MNIST/raw
```

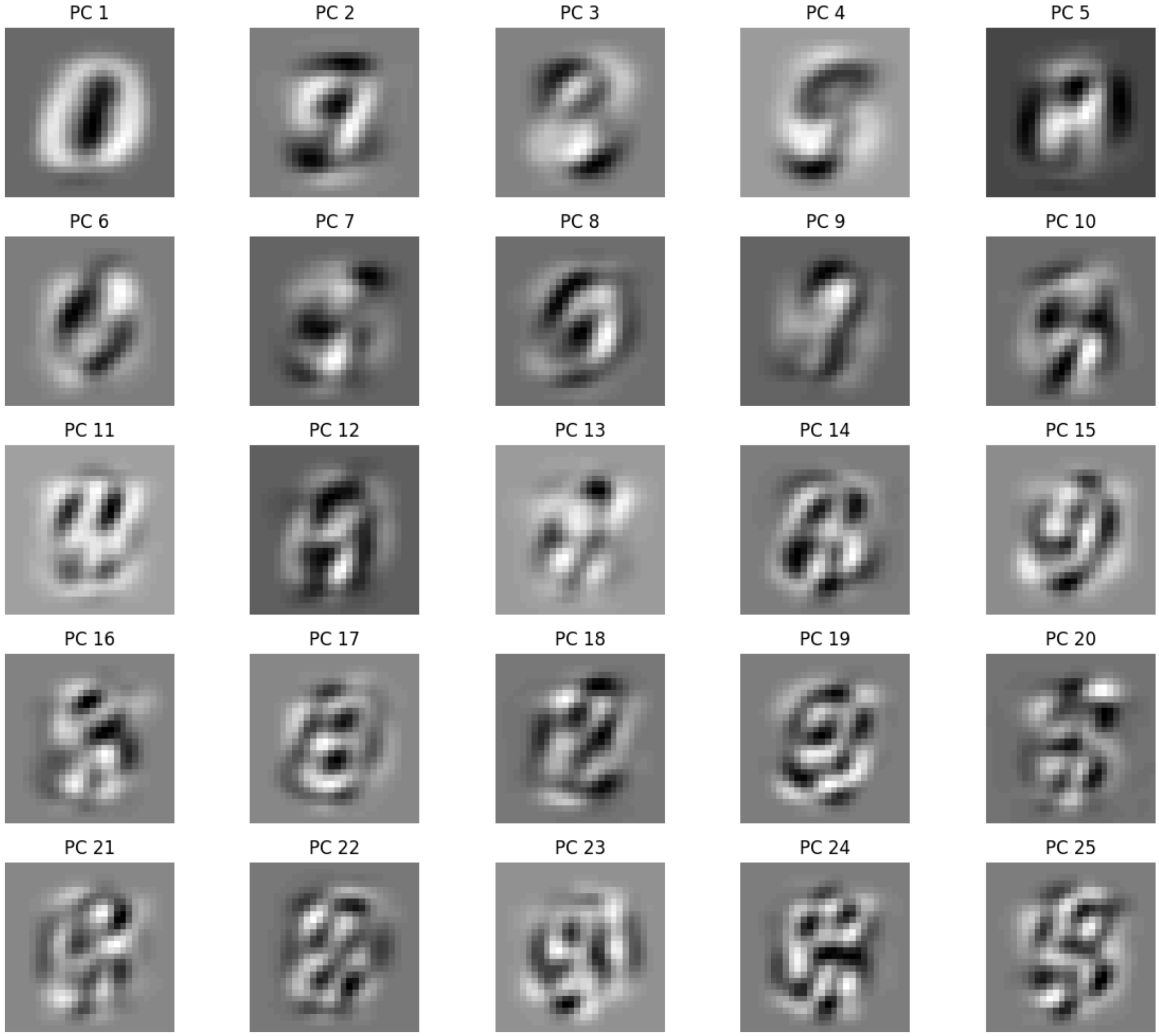
PCA

In [ ]:
```
# Flatten the images for PCA
X_train_flattened = trainset.data.view(len(trainset), -1).numpy()
X_test_flattened = testset.data.view(len(testset), -1).numpy()

# Normalize data
X_train_flattened = X_train_flattened / 255.0
X_test_flattened = X_test_flattened / 255.0

# PCA with different number of components
components = [50, 100, 150, 200]
for n_components in components:
    pca = PCA(n_components=n_components)
    pca.fit(X_train_flattened)
    X_train_pca = pca.transform(X_train_flattened)
    X_test_pca = pca.transform(X_test_flattened)
    X_reconstructed_pca = pca.inverse_transform(X_train_pca)
    reconstruction_loss = mean_squared_error(X_train_flattened, X_reconstructed_pca)

    # Logistic regression classifier to classify our reconstructed images
    lr = LogisticRegression(max_iter=1000, solver='sag', multi_class='multinomial')
    lr.fit(X_train_pca, trainset.targets.numpy())

    # Evaluating on a subset of the test set
    validation_index = np.random.choice(len(testset), 1000, replace=False)
    validation_images_pca = X_test_pca[validation_index]
    validation_labels = testset.targets.numpy()[validation_index]

    validation_predictions = lr.predict(validation_images_pca)
    accuracy = accuracy_score(validation_labels, validation_predictions)
    print(f'Reconstruction loss for PCA with {n_components} components: {reconstructic
```

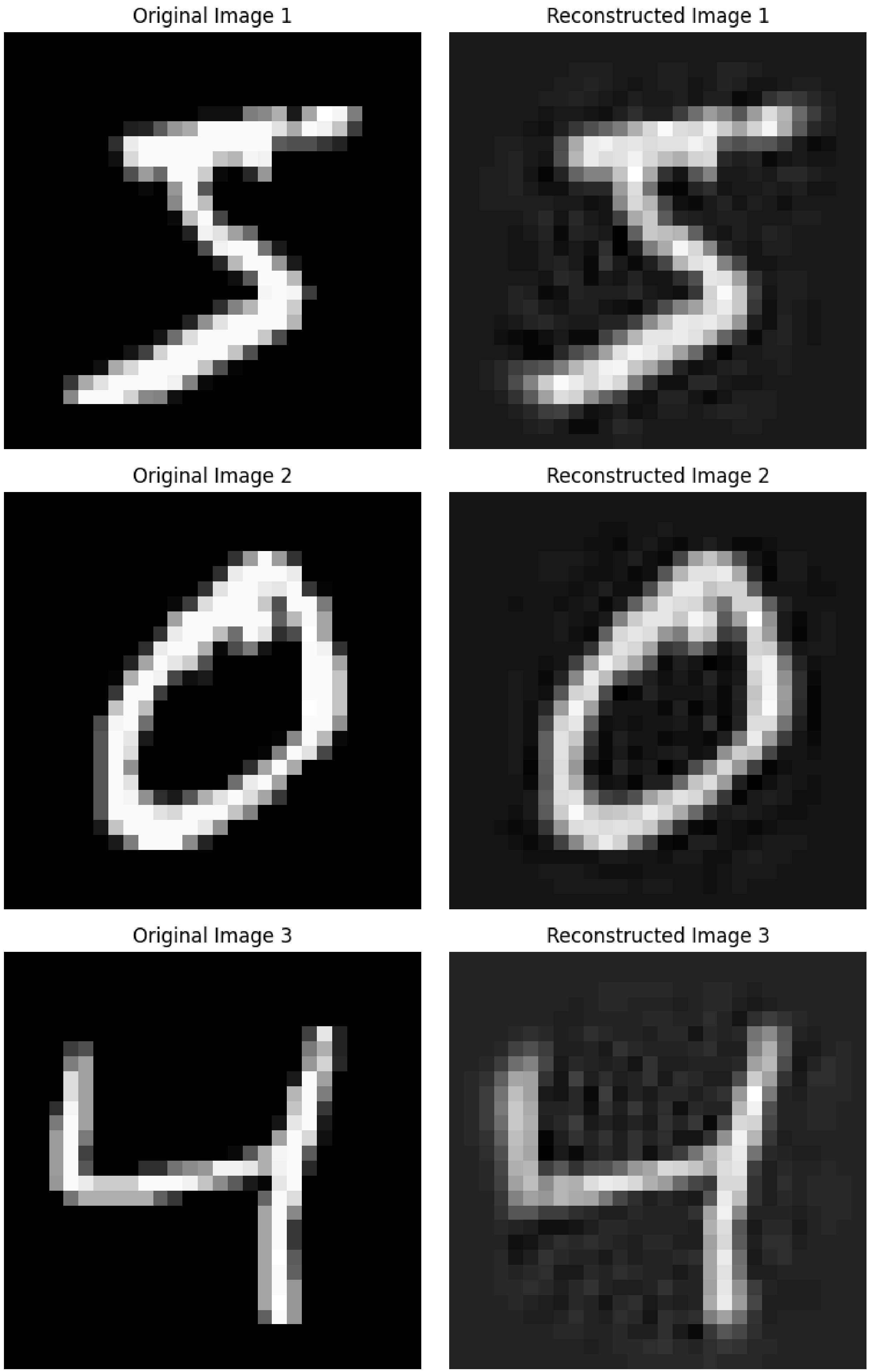
```
Reconstruction loss for PCA with 50 components: 0.011795084610364161 Classification A
ccuracy: 0.924
Reconstruction loss for PCA with 100 components: 0.005756633405031867 Classification
Accuracy: 0.93
Reconstruction loss for PCA with 150 components: 0.0034891502018314425 Classification
Accuracy: 0.924
Reconstruction loss for PCA with 200 components: 0.0022767954728689765 Classification
Accuracy: 0.926
```

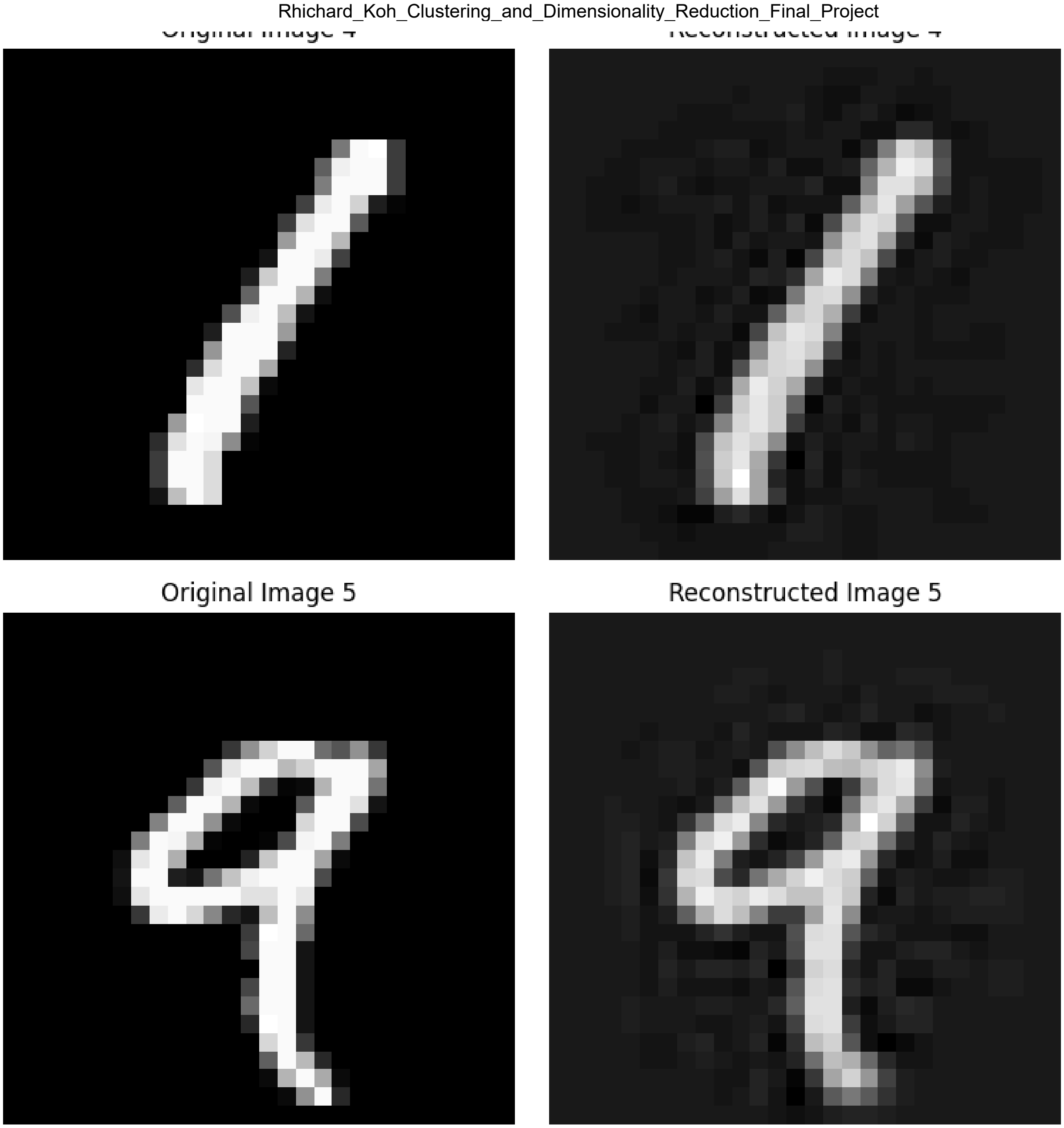
The best scoring minimal components is 100 as it has the highest accuracy and a decent reconstruction loss.

In [ ]:
```
# Visualizing the first 25 PCA'S
fig, axes = plt.subplots(5, 5, figsize=(12, 10))

for i in range(25):
    row = i // 5
    col = i % 5
    pc_image = pca.components_[i].reshape(28, 28)  # Reshape the principal component t
    axes[row, col].imshow(pc_image, cmap='gray')
    axes[row, col].set_title(f'PC {i+1}')
    axes[row, col].axis('off')

plt.tight_layout()
plt.show()
```



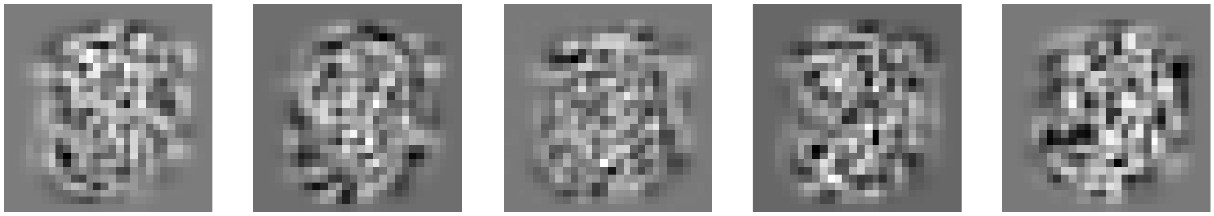
In [ ]:
```python
# Comparing the reconstructed images to the original images
fig, axes = plt.subplots(5, 2, figsize=(8, 4 * 5))

for i in range(5):
    # Original image
    original_image = X_train_flattened[i].reshape(28, 28)

    # Reconstructed image after PCA
    reconstructed_image = pca.inverse_transform(X_train_pca[i]).reshape(28, 28)

    # Plot original image
    axes[i, 0].imshow(original_image, cmap='gray')
    axes[i, 0].set_title(f'Original Image {i+1}')
    axes[i, 0].axis('off')

    # Plot reconstructed image
    axes[i, 1].imshow(reconstructed_image, cmap='gray')
    axes[i, 1].set_title(f'Reconstructed Image {i+1}')
    axes[i, 1].axis('off')

plt.tight_layout()
plt.show()
```


Original Image 1
Reconstructed Image 1
Original Image 2
Reconstructed Image 2
Original Image 3
Reconstructed Image 3



In [ ]:
```
def generate_digits(n_digits):
    fig, axes = plt.subplots(1, n_digits, figsize=(10, 2))
    for i in range(n_digits):
        # Randomly sample from the distribution of the PCA coefficients
        random_sample = np.random.normal(0, 1, pca.n_components)

        # Generate new data by inverse transforming the random sample
        new_digit = pca.inverse_transform(random_sample)

        # Rescale to original range and reshape to 28x28
        new_digit_image = new_digit.reshape(28, 28)

        # Plot
        ax = axes[i]
        ax.imshow(new_digit_image, cmap='gray')
        ax.axis('off')
    plt.show()
```

```
# Generate and display 5 new digits
generate_digits(5)
```



The images were generated by selecting random points within a space transformed by Principal Component Analysis (PCA) and then converting these points back into the format of the original images. As a result, these images might not look exactly like any specific digits from the MNIST dataset. Instead, they display variations based on the major trends or features identified by the PCA.

Autoencoder

In [ ]:

```
import torch.nn as nn
import torch.optim as optim

class Autoencoder(nn.Module):
    def __init__(self, input_size, hidden_size):
        super(Autoencoder, self).__init__()
        self.encoder = nn.Linear(input_size, hidden_size)
        self.decoder = nn.Linear(hidden_size, input_size)

    def forward(self, x):
        x = torch.flatten(x, start_dim=1)
        encoded = torch.relu(self.encoder(x))
        decoded = torch.sigmoid(self.decoder(encoded))
        return decoded

# Train autoencoder
def train_autoencoder(hidden_size, results={}):

    model = Autoencoder(784, hidden_size)
    criterion = nn.MSELoss()
    optimizer = optim.Adam(model.parameters(), lr=1e-3)

    # Training Loop
    num_epochs = 8
    for epoch in range(num_epochs):
        total_loss = 0
        for images, _ in trainloader:
            optimizer.zero_grad()
            outputs = model(images)
            loss = criterion(outputs, torch.flatten(images, start_dim=1))
            loss.backward()
            optimizer.step()
            total_loss += loss.item()
        average_loss = total_loss / len(trainloader)

    results[hidden_size] = {'reconstruction_loss': average_loss}
```

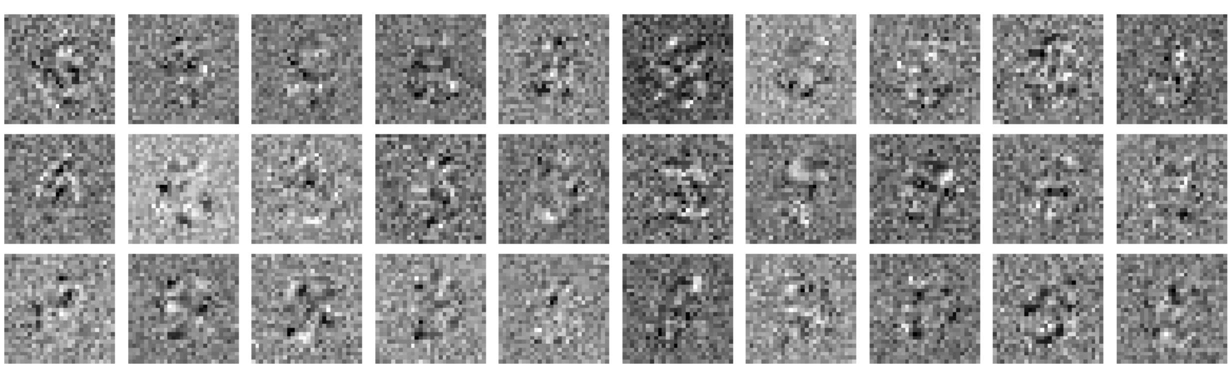
```
    encoded_train = []
    train_labels = []
    for data, target in trainloader:
        encoded = model(data)
        encoded_train.append(encoded.detach().cpu().numpy())
        train_labels.append(target.numpy())
    encoded_train = np.concatenate(encoded_train, axis=0)
    train_labels = np.concatenate(train_labels, axis=0)

    clf = LogisticRegression(max_iter=1000, solver='sag', multi_class='multinomial')
    clf.fit(encoded_train, train_labels)

    encoded_val = []
    val_labels = []
    for data, target in testloader:
        encoded = model(data)
        encoded_val.append(encoded.detach().cpu().numpy())
        val_labels.append(target.numpy())
    encoded_val = np.concatenate(encoded_val, axis=0)
    val_labels = np.concatenate(val_labels, axis=0)
    val_predictions = clf.predict(encoded_val)
    accuracy = accuracy_score(val_labels, val_predictions)

    results[hidden_size]['classification_accuracy'] = accuracy
    print(f'Encoding Dim: {hidden_size}, Classification Accuracy: {accuracy}')

    return model, loss.item(), results

hidden_sizes = [50, 100, 150, 200]
results = {}
for hidden_size in hidden_sizes:
    model, loss, results = train_autoencoder(hidden_size,results)
    print(f'Reconstruction loss for Autoencoder with {hidden_size} hidden units:', los
for encoding_dim, metrics in results.items():
    print(f'{encoding_dim}: Reconstruction Loss: {metrics["reconstruction_loss"]}, Cla
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_sag.py:350: Convergence
Warning: The max_iter was reached which means the coef_ did not converge
  warnings.warn(
Encoding Dim: 50, Classification Accuracy: 0.8038
Reconstruction loss for Autoencoder with 50 hidden units: 0.9075490236282349
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_sag.py:350: Convergence
Warning: The max_iter was reached which means the coef_ did not converge
  warnings.warn(
Encoding Dim: 100, Classification Accuracy: 0.8621
Reconstruction loss for Autoencoder with 100 hidden units: 0.8906221985816956
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_sag.py:350: Convergence
Warning: The max_iter was reached which means the coef_ did not converge
  warnings.warn(
Encoding Dim: 150, Classification Accuracy: 0.8531
Reconstruction loss for Autoencoder with 150 hidden units: 0.8868787884712219
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_sag.py:350: Convergence
Warning: The max_iter was reached which means the coef_ did not converge
  warnings.warn(
```

```
Encoding Dim: 200, Classification Accuracy: 0.8583
Reconstruction loss for Autoencoder with 200 hidden units: 0.883091390132904
50: Reconstruction Loss: 0.9358660034152236, Classification Accuracy: 0.8038
100: Reconstruction Loss: 0.9164198400623509, Classification Accuracy: 0.8621
150: Reconstruction Loss: 0.9233703469035468, Classification Accuracy: 0.8531
200: Reconstruction Loss: 0.9157706576623896, Classification Accuracy: 0.8583
```

The best minimum hidden encoding dimmension was 100 because it had the highest classification accuracy while still having the 2nd lowest reconstruction loss.

In [ ]:
```python
hidden_size = 100
autoencoder = Autoencoder(784, hidden_size)
criterion = nn.MSELoss()
optimizer = optim.Adam(autoencoder.parameters(), lr=0.001)

for epoch in range(8):
    for data, _ in trainloader:
        optimizer.zero_grad()
        output = autoencoder(data)
        loss = criterion(output, torch.flatten(data, start_dim=1))
        loss.backward()
        optimizer.step()


# Generate new handwritten digits using the trained autoencoder
np.random.seed(42)
random_noise = np.random.normal(0,1,(30, hidden_size))
random_noise = torch.tensor(random_noise, dtype=torch.float32)
generated_images = autoencoder.decoder(random_noise).detach().cpu().numpy()

# Plot the generated images
fig, axes = plt.subplots(3, 10, figsize=(15, 4.5))  # Adjusted for 3 rows and 10 colum
for i, ax in enumerate(axes.flatten()):
    ax.imshow(generated_images[i].reshape(28, 28), cmap='gray')
    ax.axis('off')
plt.tight_layout()
plt.show()
```



RBN

In [11]:
```python
# Load the MNIST dataset
transform = transforms.Compose([transforms.ToTensor(),
                                transforms.Normalize((0.5,), (0.5,))])
train = datasets.MNIST(root='./data', train=True, download=True, transform=transform)
test = datasets.MNIST(root='./data', train=False, download=True, transform=transform)
```

```
trainloader = torch.utils.data.DataLoader(train, batch_size=64, shuffle=True)
testloader = torch.utils.data.DataLoader(test, batch_size=64, shuffle=False)
```

In [ ]:

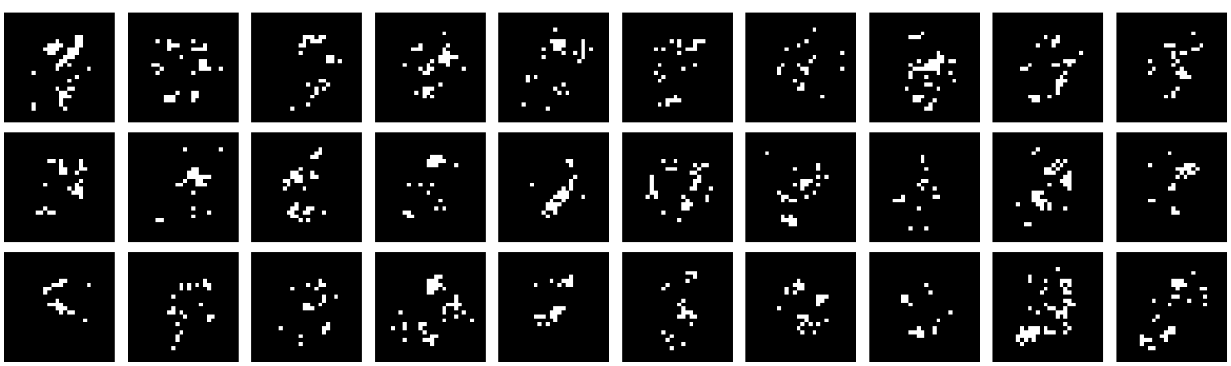
```
# Define the RBM class
class RBM(torch.nn.Module):
    def __init__(self, input, hiddensize):
        super(RBM, self).__init__()
        self.W = torch.nn.Parameter(torch.randn(hiddensize, input) * 0.01)
        self.v_bias = torch.nn.Parameter(torch.zeros(input))
        self.h_bias = torch.nn.Parameter(torch.zeros(hiddensize))

    def sample_h(self, v):
        h_prob = torch.sigmoid(torch.matmul(v, self.W.t()) + self.h_bias)
        h_sample = torch.bernoulli(h_prob)
        return h_sample

    def sample_v(self, h):
        v_prob = torch.sigmoid(torch.matmul(h, self.W) + self.v_bias)
        v_sample = torch.bernoulli(v_prob)
        return v_sample

    def free_energy(self, v):
        vbias_term = torch.matmul(v, self.v_bias)
        wx_b = torch.matmul(v, self.W.t()) + self.h_bias
        hidden_term = torch.sum(torch.log(1 + torch.exp(wx_b)), dim=1)
        return -vbias_term - hidden_term

    def forward(self, v):
        h = self.sample_h(v)
        v_recon = self.sample_v(h)
        return v_recon

# List of encoding dimensions to test
hidden_size = [50, 100, 150, 200]
results_dict = {}

for size in hidden_size:
    rbm = RBM(input=784, hiddensize=size)
    optimizer = torch.optim.SGD(rbm.parameters(), lr=0.1)

    # Training Loop for RBM
    for epoch in range(8):  # Adjust the number of epochs if necessary
        loss_sum = 0
        for data, _ in trainloader:
            data = data.view(-1, 784)  # Flatten the images
            data = torch.clamp(data, 0.0, 1.0)
            data = (data > 0.5).float()  # Convert to binary using thresholding
            v_recon = rbm(data)
            loss = torch.mean(rbm.free_energy(data)) - torch.mean(rbm.free_energy(v_re
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
            loss_sum += loss.item()
        average_loss = loss_sum / len(trainloader)
    results_dict[size] = {'reconstruction_loss': average_loss}

    # Extract features from the training set
    encoded_train = []
    train_labels = []
```

```
    for data, target in trainloader:
        data = data.view(-1, 784)
        data = torch.clamp(data, 0.0, 1.0)
        data = (data > 0.5).float()  # Convert to binary using thresholding
        encoded = rbm.sample_h(data)  # Get encoded (hidden) representations
        encoded_train.append(encoded.detach().numpy())
        train_labels.append(target.numpy())
    encoded_train = np.concatenate(encoded_train, axis=0)
    train_labels = np.concatenate(train_labels, axis=0)

    # Train a softmax classifier
    lr = LogisticRegression(max_iter=1000, solver='lbfgs', multi_class='multinomial')
    lr.fit(encoded_train, train_labels)

    # Evaluate classification accuracy on the test set
    encoded_test = []
    test_labels = []
    for data, target in testloader:
        data = data.view(-1, 784)
        data = torch.clamp(data, 0.0, 1.0)
        data = (data > 0.5).float()  # Convert to binary using thresholding
        encoded = rbm.sample_h(data)
        encoded_test.append(encoded.detach().numpy())
        test_labels.append(target.numpy())
    encoded_test = np.concatenate(encoded_test, axis=0)
    test_labels = np.concatenate(test_labels, axis=0)
    test_predictions = lr.predict(encoded_test)
    accuracy = accuracy_score(test_labels, test_predictions)

    # Record the classification accuracy
    results_dict[size]['classification_accuracy'] = accuracy
    print(f'Hidden Size: {size}, Reconstruction Loss: {average_loss}, Classification A

# Print the results for all encoding dimensions
print("Results for different Hidden Size:")
for size, metrics in results_dict.items():
    print(f'{size}: Reconstruction Loss: {metrics["reconstruction_loss"]}, Classificat
```

```
Encoding Dim: 50, Reconstruction Loss: -19.923210117608498, Classification Accuracy:
0.8439
Encoding Dim: 75, Reconstruction Loss: -18.55157110787658, Classification Accuracy:
0.8666
Encoding Dim: 100, Reconstruction Loss: -17.291857076860442, Classification Accuracy:
0.8758
Encoding Dim: 150, Reconstruction Loss: -15.531131760652132, Classification Accuracy:
0.8845
Encoding Dim: 200, Reconstruction Loss: -14.382853977715792, Classification Accuracy:
0.8889
Results for different Encoding Dimensions:
50: Reconstruction Loss: -19.923210117608498, Classification Accuracy: 0.8439
75: Reconstruction Loss: -18.55157110787658, Classification Accuracy: 0.8666
100: Reconstruction Loss: -17.291857076860442, Classification Accuracy: 0.8758
150: Reconstruction Loss: -15.531131760652132, Classification Accuracy: 0.8845
200: Reconstruction Loss: -14.382853977715792, Classification Accuracy: 0.8889
```

The best minimum hidden encoding dimmension was 150 because it had the 2nd highest classification and the 2nd lowest reconstruction loss but it is about the same as our max value which is 200. When trying to go for efficiency and the smallest size we can go, 150 is better than 200.

In [ ]:
```
# Set the number of hidden dimensions
hiddensize = 150

# Train an RBM with 150 hidden dimensions (assuming train_loader is defined)
rbm = RBM(n_vis=784, n_hid=hiddensize)
optimizer = torch.optim.SGD(rbm.parameters(), lr=0.1)

for epoch in range(8):  # Adjust the number of epochs if necessary
    for data, _ in trainloader:
        data = data.view(-1, 784)
        data = torch.clamp(data, 0.0, 1.0)
        data = (data > 0.5).float()  # Convert to binary using thresholding
        v_recon = rbm(data)
        loss = torch.mean(rbm.free_energy(data)) - torch.mean(rbm.free_energy(v_recon.
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

# Generate 30 new images using the trained RBM
np.random.seed(42)  # Set a seed for reproducibility
random_hidden = torch.bernoulli(torch.rand(30, hiddensize))  # Randomly sample the hid
generated_images = rbm.sample_v(random_hidden).detach().numpy()  # Reconstruct the vis

# Plot the generated images
fig, axes = plt.subplots(3, 10, figsize=(15, 4.5))  # Adjusted for 3 rows and 10 colum
for i, ax in enumerate(axes.flatten()):
    ax.imshow(generated_images[i].reshape(28, 28), cmap='gray')
    ax.axis('off')
plt.tight_layout()
plt.show()
```



DBN

In [4]:
```
!pip install keras-tuner
```

```
Collecting keras-tuner
  Downloading keras_tuner-1.4.7-py3-none-any.whl (129 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 129.1/129.1 kB 1.9 MB/s eta 0:00:00
Requirement already satisfied: keras in /usr/local/lib/python3.10/dist-packages (from keras-tuner) (3.2.1)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from keras-tuner) (24.0)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from keras-tuner) (2.31.0)
Collecting kt-legacy (from keras-tuner)
  Downloading kt_legacy-1.0.5-py3-none-any.whl (9.6 kB)
Requirement already satisfied: absl-py in /usr/local/lib/python3.10/dist-packages (from keras->keras-tuner) (1.4.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from keras->keras-tuner) (1.25.2)
Requirement already satisfied: rich in /usr/local/lib/python3.10/dist-packages (from keras->keras-tuner) (13.7.1)
Requirement already satisfied: namex in /usr/local/lib/python3.10/dist-packages (from keras->keras-tuner) (0.0.7)
Requirement already satisfied: h5py in /usr/local/lib/python3.10/dist-packages (from keras->keras-tuner) (3.9.0)
Requirement already satisfied: optree in /usr/local/lib/python3.10/dist-packages (from keras->keras-tuner) (0.11.0)
Requirement already satisfied: ml-dtypes in /usr/local/lib/python3.10/dist-packages (from keras->keras-tuner) (0.2.0)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests->keras-tuner) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->keras-tuner) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests->keras-tuner) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests->keras-tuner) (2024.2.2)
Requirement already satisfied: typing-extensions>=4.0.0 in /usr/local/lib/python3.10/dist-packages (from optree->keras->keras-tuner) (4.11.0)
Requirement already satisfied: markdown-it-py>=2.2.0 in /usr/local/lib/python3.10/dist-packages (from rich->keras->keras-tuner) (3.0.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /usr/local/lib/python3.10/dist-packages (from rich->keras->keras-tuner) (2.16.1)
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.10/dist-packages (from markdown-it-py>=2.2.0->rich->keras->keras-tuner) (0.1.2)
Installing collected packages: kt-legacy, keras-tuner
Successfully installed keras-tuner-1.4.7 kt-legacy-1.0.5
```

In [7]:

```python
import tensorflow as tf
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.models import Sequential
from tensorflow.keras.datasets import mnist
from tensorflow.keras.utils import to_categorical
from kerastuner.tuners import RandomSearch

def load_data():
    # Load and preprocess the MNIST dataset
    (x_train, y_train), (x_test, y_test) = mnist.load_data()
    x_train = x_train.reshape(-1, 784).astype('float32') / 255
    x_test = x_test.reshape(-1, 784).astype('float32') / 255
    y_train = to_categorical(y_train, 10)
    y_test = to_categorical(y_test, 10)
    return x_train, y_train, x_test, y_test
```

```
def build_model(hp):
    model = Sequential()
    # Hyperparameters to tune
    units = hp.Choice('units', values=[50, 100, 150, 200])
    dropout_rate = hp.Float('dropout_rate', min_value=0.0, max_value=0.5, step=0.1)

    # Model architecture
    model.add(Dense(units=units, activation='relu', input_shape=(784,)))
    model.add(Dropout(dropout_rate))
    model.add(Dense(units=units, activation='relu'))
    model.add(Dropout(dropout_rate))
    model.add(Dense(10, activation='softmax'))

    model.compile(optimizer='adam',
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
    return model

def main():
    x_train, y_train, x_test, y_test = load_data()
    tuner = RandomSearch(
        build_model,
        objective='val_accuracy',
        max_trials=10,  # Adjust the number of trials to cover the grid
        executions_per_trial=1,
        directory='tuner_dir',
        project_name='DBN_grid_search')

    tuner.search(x_train, y_train, epochs=10, validation_data=(x_test, y_test))

    # Get the optimal hyperparameters
    best_hps = tuner.get_best_hyperparameters()[0]
    print(f"Best number of units: {best_hps.get('units')}")
    print(f"Best dropout rate: {best_hps.get('dropout_rate')}")

    # Build the model with the best hyperparameters and train it
    model = tuner.hypermodel.build(best_hps)
    model.fit(x_train, y_train, epochs=50, validation_data=(x_test, y_test))

if __name__ == "__main__":
    main()
```

```
Trial 10 Complete [00h 02m 04s]
val_accuracy: 0.9815000295639038

Best val_accuracy So Far: 0.9815000295639038
Total elapsed time: 00h 17m 30s
Best number of units: 200
Best dropout rate: 0.1
Epoch 1/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.8755 - loss: 0.4115 - val_accuracy: 0.9603 - val_loss: 0.1234
Epoch 2/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9654 - loss: 0.1124 - val_accuracy: 0.9710 - val_loss: 0.0889
Epoch 3/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 11s 6ms/step - accuracy: 0.9755 - loss: 0.0782 - val_accuracy: 0.9777 - val_loss: 0.0756
Epoch 4/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9810 - loss: 0.0575 - val_accuracy: 0.9805 - val_loss: 0.0625
Epoch 5/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 9s 4ms/step - accuracy: 0.9847 - loss: 0.0481 - val_accuracy: 0.9744 - val_loss: 0.0827
Epoch 6/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9865 - loss: 0.0425 - val_accuracy: 0.9797 - val_loss: 0.0668
Epoch 7/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9885 - loss: 0.0359 - val_accuracy: 0.9804 - val_loss: 0.0721
Epoch 8/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9894 - loss: 0.0323 - val_accuracy: 0.9797 - val_loss: 0.0726
Epoch 9/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 8s 5ms/step - accuracy: 0.9908 - loss: 0.0277 - val_accuracy: 0.9788 - val_loss: 0.0816
Epoch 10/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 11s 5ms/step - accuracy: 0.9911 - loss: 0.0266 - val_accuracy: 0.9777 - val_loss: 0.0896
Epoch 11/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9926 - loss: 0.0230 - val_accuracy: 0.9808 - val_loss: 0.0795
Epoch 12/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9921 - loss: 0.0238 - val_accuracy: 0.9812 - val_loss: 0.0801
Epoch 13/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 9s 5ms/step - accuracy: 0.9925 - loss: 0.0237 - val_accuracy: 0.9808 - val_loss: 0.0876
Epoch 14/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9933 - loss: 0.0199 - val_accuracy: 0.9793 - val_loss: 0.0890
Epoch 15/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9931 - loss: 0.0199 - val_accuracy: 0.9803 - val_loss: 0.0853
Epoch 16/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9933 - loss: 0.0202 - val_accuracy: 0.9818 - val_loss: 0.0849
Epoch 17/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 9s 5ms/step - accuracy: 0.9944 - loss: 0.0198 - val_accuracy: 0.9817 - val_loss: 0.0842
Epoch 18/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 9s 5ms/step - accuracy: 0.9944 - loss: 0.0165 - val_ac
```

```
curacy: 0.9806 - val_loss: 0.0949
Epoch 19/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 12s 5ms/step - accuracy: 0.9929 - loss: 0.0225 - val_a
ccuracy: 0.9807 - val_loss: 0.0915
Epoch 20/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9945 - loss: 0.0173 - val_a
ccuracy: 0.9827 - val_loss: 0.0871
Epoch 21/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9945 - loss: 0.0172 - val_a
ccuracy: 0.9826 - val_loss: 0.0843
Epoch 22/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 9s 5ms/step - accuracy: 0.9947 - loss: 0.0173 - val_ac
curacy: 0.9808 - val_loss: 0.1027
Epoch 23/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9947 - loss: 0.0182 - val_a
ccuracy: 0.9827 - val_loss: 0.1024
Epoch 24/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9949 - loss: 0.0160 - val_a
ccuracy: 0.9806 - val_loss: 0.1109
Epoch 25/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 11s 6ms/step - accuracy: 0.9952 - loss: 0.0162 - val_a
ccuracy: 0.9838 - val_loss: 0.0914
Epoch 26/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 18s 4ms/step - accuracy: 0.9953 - loss: 0.0150 - val_a
ccuracy: 0.9832 - val_loss: 0.0974
Epoch 27/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9968 - loss: 0.0102 - val_a
ccuracy: 0.9803 - val_loss: 0.1123
Epoch 28/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9955 - loss: 0.0157 - val_a
ccuracy: 0.9824 - val_loss: 0.1187
Epoch 29/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 9s 5ms/step - accuracy: 0.9958 - loss: 0.0151 - val_ac
curacy: 0.9766 - val_loss: 0.1487
Epoch 30/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 9s 5ms/step - accuracy: 0.9951 - loss: 0.0185 - val_ac
curacy: 0.9814 - val_loss: 0.1170
Epoch 31/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9958 - loss: 0.0148 - val_a
ccuracy: 0.9823 - val_loss: 0.1115
Epoch 32/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9957 - loss: 0.0151 - val_a
ccuracy: 0.9809 - val_loss: 0.1226
Epoch 33/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9954 - loss: 0.0158 - val_a
ccuracy: 0.9808 - val_loss: 0.1267
Epoch 34/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 8s 4ms/step - accuracy: 0.9965 - loss: 0.0122 - val_ac
curacy: 0.9823 - val_loss: 0.1396
Epoch 35/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 11s 5ms/step - accuracy: 0.9951 - loss: 0.0191 - val_a
ccuracy: 0.9840 - val_loss: 0.1247
Epoch 36/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9963 - loss: 0.0144 - val_a
ccuracy: 0.9823 - val_loss: 0.1289
Epoch 37/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9956 - loss: 0.0169 - val_a
ccuracy: 0.9827 - val_loss: 0.1220
Epoch 38/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9966 - loss: 0.0112 - val_a
```

```
ccuracy: 0.9849 - val_loss: 0.1187
Epoch 39/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 9s 5ms/step - accuracy: 0.9963 - loss: 0.0149 - val_ac
curacy: 0.9815 - val_loss: 0.1373
Epoch 40/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9963 - loss: 0.0115 - val_a
ccuracy: 0.9839 - val_loss: 0.1292
Epoch 41/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9971 - loss: 0.0104 - val_a
ccuracy: 0.9839 - val_loss: 0.1237
Epoch 42/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 8s 4ms/step - accuracy: 0.9965 - loss: 0.0116 - val_ac
curacy: 0.9823 - val_loss: 0.1377
Epoch 43/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9960 - loss: 0.0145 - val_a
ccuracy: 0.9808 - val_loss: 0.1488
Epoch 44/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9957 - loss: 0.0149 - val_a
ccuracy: 0.9806 - val_loss: 0.1445
Epoch 45/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9966 - loss: 0.0119 - val_a
ccuracy: 0.9816 - val_loss: 0.1456
Epoch 46/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 8s 5ms/step - accuracy: 0.9959 - loss: 0.0153 - val_ac
curacy: 0.9832 - val_loss: 0.1369
Epoch 47/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 11s 5ms/step - accuracy: 0.9966 - loss: 0.0116 - val_a
ccuracy: 0.9823 - val_loss: 0.1363
Epoch 48/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9964 - loss: 0.0121 - val_a
ccuracy: 0.9830 - val_loss: 0.1331
Epoch 49/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 10s 5ms/step - accuracy: 0.9967 - loss: 0.0144 - val_a
ccuracy: 0.9817 - val_loss: 0.1473
Epoch 50/50
1875/1875 ━━━━━━━━━━━━━━━━━━━━ 9s 5ms/step - accuracy: 0.9967 - loss: 0.0114 - val_ac
curacy: 0.9807 - val_loss: 0.1792
```

After completing the grid search the best value for our hidden size is 200 has it gave us the lowest loss and highest accuracy.