In [1]:
```
from tensorflow.keras.datasets import mnist
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
d:\Study\ML2\Practicals\.venv\Lib\site-
packages\keras\src\export\tf2onnx_lib.py:8: FutureWarning: In the future
`np.object` will be defined as the corresponding NumPy scalar.
  if not hasattr(np, "object"):
```

In [2]:
```
data = mnist.load_data()
(train_images, train_labels), (test_images, test_labels) = data
```

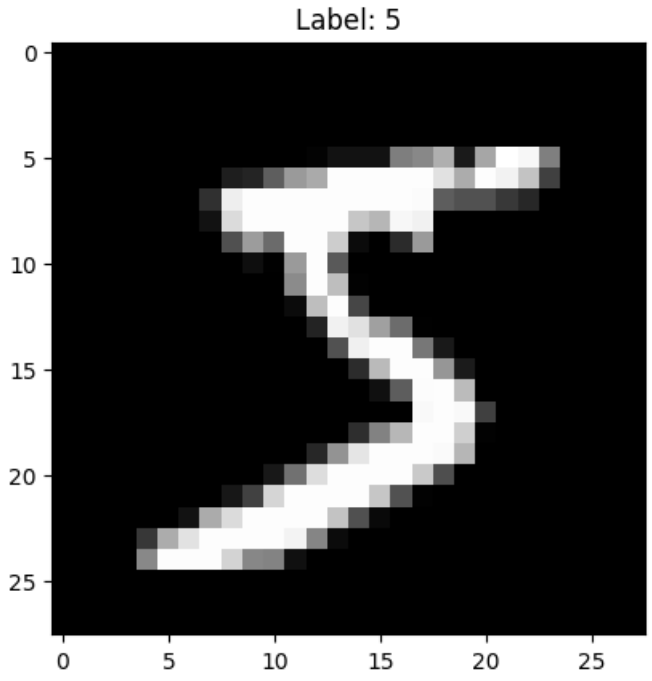
In [3]:
```
img_size =  train_images[0].shape[0]
```

In [4]:
```
num_classes = 10
```

In [5]:
```
train_images = train_images.astype("float32") / 255.0
test_images = test_images.astype("float32") / 255.0
```

In [6]:
```
plt.imshow(train_images[0], cmap='gray')
plt.title(f'Label: {train_labels[0]}')
```

Out[6]: Text(0.5, 1.0, 'Label: 5')



In [7]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Input, Flatten,RandomRotation,
GaussianNoise
```

In [8]:
```
from tensorflow.keras.optimizers import SGD, Adam
```

In [9]:
```
Gen_model = Sequential([
    Input(shape =(img_size,img_size) ),
    RandomRotation(0.1),
    GaussianNoise(0.05),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(32, activation='relu'),
    Dense(num_classes, activation='softmax')
])

Gen_model.compile(optimizer = 'adam', loss =
'sparse_categorical_crossentropy',metrics=['accuracy'])
Gen_history = Gen_model.fit(train_images,train_labels, epochs = 50)
```

```
Epoch 1/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m3s[0m 1ms/step - accuracy:
0.3938 - loss: 1.7054
Epoch 2/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.4798 - loss: 1.4601
Epoch 3/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5083 - loss: 1.3811
Epoch 4/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5291 - loss: 1.3313
Epoch 5/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5398 - loss: 1.2957
Epoch 6/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5440 - loss: 1.2850
Epoch 7/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5451 - loss: 1.2708
Epoch 8/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5602 - loss: 1.2313
Epoch 9/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5610 - loss: 1.2281
Epoch 10/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5728 - loss: 1.1981
Epoch 11/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5705 - loss: 1.2038
Epoch 12/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5727 - loss: 1.1991
Epoch 13/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5790 - loss: 1.1842
Epoch 14/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m3s[0m 1ms/step - accuracy:
0.5786 - loss: 1.1856
Epoch 15/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m6s[0m 3ms/step - accuracy:
0.5743 - loss: 1.1883
Epoch 16/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.5725 - loss: 1.1940
Epoch 17/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m11s[0m 3ms/step -
accuracy: 0.5872 - loss: 1.1574
Epoch 18/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5897 - loss: 1.1496
Epoch 19/50
```

```
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5861 - loss: 1.1570
Epoch 20/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5861 - loss: 1.1479
Epoch 21/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5925 - loss: 1.1452
Epoch 22/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5919 - loss: 1.1437
Epoch 23/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5925 - loss: 1.1472
Epoch 24/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5900 - loss: 1.1542
Epoch 25/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5982 - loss: 1.1285
Epoch 26/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5911 - loss: 1.1443
Epoch 27/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5961 - loss: 1.1337
Epoch 28/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5957 - loss: 1.1276
Epoch 29/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5977 - loss: 1.1221
Epoch 30/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6000 - loss: 1.1242
Epoch 31/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5894 - loss: 1.1514
Epoch 32/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6029 - loss: 1.1165
Epoch 33/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6114 - loss: 1.0892
Epoch 34/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.5997 - loss: 1.1240
Epoch 35/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6125 - loss: 1.0880
Epoch 36/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6073 - loss: 1.1020
Epoch 37/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6128 - loss: 1.0876
Epoch 38/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6019 - loss: 1.1106
Epoch 39/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6105 - loss: 1.0882
Epoch 40/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6041 - loss: 1.1055
Epoch 41/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6065 - loss: 1.1052
Epoch 42/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
```

```
0.6087 - loss: 1.0956
Epoch 43/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6043 - loss: 1.1026
Epoch 44/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6150 - loss: 1.0815
Epoch 45/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6099 - loss: 1.0965
Epoch 46/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6083 - loss: 1.0938
Epoch 47/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6087 - loss: 1.0910
Epoch 48/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6047 - loss: 1.0979
Epoch 49/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6123 - loss: 1.0816
Epoch 50/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 1ms/step - accuracy:
0.6183 - loss: 1.0709
```

Without Generalization

In [10]:
```
data = mnist.load_data()
(train_images, train_labels), (test_images, test_labels) = data
img_size =  train_images[0].shape[0]
num_classes = 10
```

In [11]:
```
NonGen_model = Sequential([
    Input(shape =(img_size,img_size) ),
    Flatten(),
    Dense(128, activation='relu'),
    Dense(32, activation='relu'),
    Dense(num_classes, activation='softmax')
])
callbacks = tensorflow.k
NonGen_model.compile(optimizer = 'adam', loss =
'sparse_categorical_crossentropy',metrics=['accuracy'])
NonGen_history = NonGen_model.fit(train_images,train_labels, epochs = 50)
```

```
Epoch 1/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 807us/step -
accuracy: 0.5947 - loss: 1.6090
Epoch 2/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 956us/step -
accuracy: 0.8255 - loss: 0.5957
Epoch 3/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m4s[0m 2ms/step - accuracy:
0.9061 - loss: 0.3591
Epoch 4/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m6s[0m 3ms/step - accuracy:
0.9401 - loss: 0.2342
Epoch 5/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m6s[0m 3ms/step - accuracy:
0.9553 - loss: 0.1715
Epoch 6/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m9s[0m 3ms/step - accuracy:
0.9633 - loss: 0.1411
Epoch 7/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 782us/step -
accuracy: 0.9685 - loss: 0.1208
Epoch 8/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 777us/step -
accuracy: 0.9728 - loss: 0.1006
Epoch 9/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 773us/step -
accuracy: 0.9751 - loss: 0.0959
Epoch 10/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 776us/step -
accuracy: 0.9774 - loss: 0.0889
Epoch 11/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 776us/step -
accuracy: 0.9793 - loss: 0.0810
Epoch 12/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 809us/step -
accuracy: 0.9814 - loss: 0.0773
Epoch 13/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 800us/step -
accuracy: 0.9819 - loss: 0.0726
Epoch 14/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 851us/step -
accuracy: 0.9834 - loss: 0.0680
Epoch 15/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 817us/step -
accuracy: 0.9842 - loss: 0.0632
Epoch 16/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 845us/step -
accuracy: 0.9842 - loss: 0.0635
Epoch 17/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 831us/step -
accuracy: 0.9851 - loss: 0.0601
Epoch 18/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 820us/step -
accuracy: 0.9862 - loss: 0.0571
Epoch 19/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 839us/step -
accuracy: 0.9859 - loss: 0.0589
```

```
Epoch 20/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 822us/step -
accuracy: 0.9864 - loss: 0.0583
Epoch 21/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 831us/step -
accuracy: 0.9883 - loss: 0.0507
Epoch 22/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 774us/step -
accuracy: 0.9861 - loss: 0.0634
Epoch 23/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 808us/step -
accuracy: 0.9884 - loss: 0.0502
Epoch 24/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 855us/step -
accuracy: 0.9883 - loss: 0.0527
Epoch 25/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 2ms/step - accuracy:
0.9882 - loss: 0.0523
Epoch 26/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m6s[0m 2ms/step - accuracy:
0.9884 - loss: 0.0546
Epoch 27/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 838us/step -
accuracy: 0.9891 - loss: 0.0510
Epoch 28/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m4s[0m 2ms/step - accuracy:
0.9899 - loss: 0.0455
Epoch 29/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m6s[0m 2ms/step - accuracy:
0.9895 - loss: 0.0504
Epoch 30/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 2ms/step - accuracy:
0.9894 - loss: 0.0511
Epoch 31/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.9907 - loss: 0.0441
Epoch 32/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m4s[0m 2ms/step - accuracy:
0.9901 - loss: 0.0514
Epoch 33/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m7s[0m 3ms/step - accuracy:
0.9918 - loss: 0.0438
Epoch 34/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m10s[0m 3ms/step -
accuracy: 0.9906 - loss: 0.0480
Epoch 35/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m4s[0m 2ms/step - accuracy:
0.9907 - loss: 0.0485
Epoch 36/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m6s[0m 3ms/step - accuracy:
0.9905 - loss: 0.0487
Epoch 37/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m10s[0m 3ms/step -
accuracy: 0.9918 - loss: 0.0406
Epoch 38/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m11s[0m 3ms/step -
accuracy: 0.9911 - loss: 0.0431
Epoch 39/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.9915 - loss: 0.0469
Epoch 40/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.9918 - loss: 0.0461
Epoch 41/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.9924 - loss: 0.0400
Epoch 42/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.9922 - loss: 0.0415
Epoch 43/50
```

```
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 778us/step -
accuracy: 0.9911 - loss: 0.0446
Epoch 44/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.9922 - loss: 0.0450
Epoch 45/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m5s[0m 3ms/step - accuracy:
0.9913 - loss: 0.0509
Epoch 46/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m8s[0m 1ms/step - accuracy:
0.9926 - loss: 0.0375
Epoch 47/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 814us/step -
accuracy: 0.9926 - loss: 0.0415
Epoch 48/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 868us/step -
accuracy: 0.9925 - loss: 0.0404
Epoch 49/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m2s[0m 794us/step -
accuracy: 0.9933 - loss: 0.0384
Epoch 50/50
[1m1875/1875[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m1s[0m 777us/step -
accuracy: 0.9913 - loss: 0.0547
```

In [12]:

```
import matplotlib.pyplot as plt
epochs = range(1, len(NonGen_history.history['loss']) + 1)

plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
plt.plot(epochs, Gen_history.history['loss'], label='Gen loss')
plt.plot(epochs, NonGen_history.history['loss'], label='Non-gen loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Training Loss')
plt.legend()

plt.subplot(1,2,2)
plt.plot(epochs, Gen_history.history['accuracy'], label='Gen acc')
plt.plot(epochs, NonGen_history.history['accuracy'], label='Non-gen acc')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('Training Accuracy')
plt.legend()

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