In [66]: In [67]:	<pre>import pandas as pd import numpy as np import matplotlib.pyplot as plt from tensorflow.keras.datasets import mnist</pre>
In [68]:	<pre>(x_train,y_train),(x_test,y_test) = mnist.load_data() print(x_train.shape) print(y_train.shape) print(x_test.shape) print(y_test.shape)</pre>
In [69]:	<pre>(60000, 28, 28) (60000,) (10000, 28, 28) (10000,) plt.figure(figsize=(20,20)) for i in range(49): plt.subplot(7,7,i+1) plt.xticks([])</pre>
	plt.vticks([]) plt.imshow(x_train[i], 'gray') plt.title(y_train[i], fontdict={'size': 25}) plt.show() 5 0 4 1 9 2 1
	5 0 1 1 2 3 3 3
	3 1 4 3 5 6
In [70]:	<pre>x_train = x_train[:10000,:,:] x_test = x_test[:5000,:,:]</pre>
	<pre>y_train = y_train[:10000] y_test = y_test[:5000] print(x_train.shape) print(x_test.shape) print(y_train.shape) print(y_test.shape)</pre> (10000, 28, 28)
In [71]: Out[71]:	(5000, 28, 28) (10000,) (5000,) x_train[0] array([[0, 0, 0, 0, 0, 0, 0, 0, 0, 0
	$ \begin{bmatrix} 0, & 0, & 0, & 0, & 0, & 0, & 0, & 0,$
	0, 0], [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
	0, 0], [0, 0, 0, 0, 0, 0, 0, 49, 238, 253, 253, 253, 253, 253, 253, 253, 253
	0, 0], [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 14, 1, 154, 253, 90, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0], [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 139, 253, 190, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0], [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
	0, 0], [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
	0, 0], [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
	0, 0], [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
	0, 0], [0, 0, 0, 0, 0, 0, 18, 171, 219, 253, 253, 253, 253, 195, 80, 9, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
	0, 0], [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
In [72]:	0, 0]], dtype=uint8) 1. Normalization of Images x_train = x_train/255 x_test = x_test/255 print(x_train.shape)
In [73]:	(10000, 28, 28) (5000, 28, 28) 2. Building CNN Architecture from tensorflow.keras.models import Sequential
In [74]:	<pre>from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Dropout s1 = Sequential() s1.add(Conv2D(48, (3,3), activation='relu', input_shape=(28,28,1))) s1.add(MaxPooling2D(pool_size=(2,2))) s1.add(Conv2D(48, (3,3), activation='relu')) s1.add(MaxPooling2D(pool_size=(2,2)))</pre>
	<pre>s1.add(Conv2D(48,(3,3),activation='relu')) s1.add(MaxPooling2D(pool_size=(2,2))) s1.add(Platten()) s1.add(Dense(24,activation='relu')) s1.add(Dense(12,activation='relu')) s1.add(Dense(10,activation='softmax'))</pre>
In [75]:	3. Executing Model For Appropriate Number of Epochs t1 = s1.fit(x_train,y_train,epochs=30,validation_data=(x_test,y_test)) Epoch 1/30
	313/313 [===================================
	Epoch 6/30 313/313 [===================================
	313/313 [===================================
	Epoch 15/30 313/313 [===================================
	313/313 [===================================
	Epoch 24/30 313/313 [===================================
In [76]:	313/313 [===================================
Out[76]:	loss acc val_loss val_acc Epochs 25 0.009501 0.9965 0.231871 0.9510 25 26 0.011834 0.9962 0.180473 0.9630 26 27 0.019162 0.9936 0.175431 0.9642 27
In [84]:	28 0.006474 0.9979 0.171185 0.9672 28 29 0.001899 0.9994 0.216790 0.9602 29 4. Depicting loss Vs val_loss plt.plot(q1['Epochs'], q1['loss'], label='Training loss') plt.plot(q1['Epochs'], q1['val_loss'], label='Training loss')
	plt.xlabel('Epochs') plt.ylabel('Loss') plt.title('Epochs Vs Loss') plt.legend() plt.show() Epochs Vs Loss
	0.8 - Training loss
	5. Depicting acc Vs val_acc
In [85]:	<pre>plt.plot(q1['Epochs'],q1['acc'],label='Training acc') plt.plot(q1['Epochs'],q1['val_acc'],label='Testing acc') plt.xlabel('Epochs') plt.ylabel('Acc') plt.title('Epochs vs Acc') plt.title('Epochs vs Acc') plt.legend() plt.show()</pre>
	Epochs vs Acc 0.95 0.90 0.85
	0.80 - 0.75 - Training acc Testing acc Testing acc Epochs
In [86]:	6. Generating Predictions on Test Data pred = s1.predict(x_test) print(pred[:3]) 157/157 [===========] - 0s 2ms/step [[1.9028212e-10 7.7226536e-09 8.6162286e-09 2.0768140e-07 4.8074524e-15 2.7230345e-15 4.9577699e-22 9.999976e-01 8.4127915e-14 1.7721449e-12]
In [87]:	2.7230345e-15 4.9577699e-22 9.9999976e-01 8.4127915e-14 1.7721449e-12] [2.5479605e-07 5.5944944e-14 9.9999976e-01 8.2995416e-13 4.6933997e-12 1.0601382e-22 1.3950309e-14 1.4420688e-12 5.8752551e-12 4.8577564e-13] [4.6709991e-07 9.9995470e-01 3.2356027e-05 8.7650838e-09 3.6273659e-06 3.7590563e-11 8.1373713e-10 8.4762924e-06 2.5162467e-07 5.2624419e-08]] pred_s1 = [np.argmax(i) for i in pred] print(pred_s1[:10])
In [88]: In [89]:	Trom skiedini.metries import confusion_matrix, classification_report
[- v] .	<pre>class_m = confusion_matrix(y_test, pred_s1) print(class_m) print(classification_report(y_test, pred_s1)) [[456</pre>
	[3 0 0 8 0 434 0 1 8 2] [29 3 0 0 8 2 415 0 5 0] [1 3 15 1 0 0 0 487 1 4] [5 0 6 0 1 0 0 3 469 5] [4 0 1 0 1 0 0 1 7 506]]
	2 0.94 0.96 0.95 530 3 0.97 0.94 0.96 500 4 0.97 0.99 0.98 500 5 0.98 0.95 0.97 456 6 1.00 0.90 0.94 462 7 0.93 0.95 0.94 512 8 0.95 0.96 0.96 489 9 0.97 0.97 0.97 520
	accuracy 0.96 5000 macro avg 0.96 0.96 5000 weighted avg 0.96 0.96 5000