Importing requred librabries

these are useful as they are needed to run all the fuctions in our notebook

In [1]:
```
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.preprocessing import image
from tensorflow.keras.optimizers import RMSprop
from tensorflow.keras.layers import Conv2D, Flatten, Dense, Dropout, Input
from tensorflow.keras.models import Model
import tensorflow as tf
import matplotlib.pyplot as plt
from skimage import io
from tqdm import tqdm
import numpy as np
import os
import shutil
import random
import pandas as pd
import cv2 as cv
# from PIL import Image
```

Generating xtrain and ytrain

Here we are generating xtrain, for that we have to go through the following steps -

1)locate to the train folder

2)convert the images to grayscale, we ae converting to grayscale as other colors aren't present in our dataset, black and white are the colors available

3)resize the image to 28,28. We are doing this as the standard MNIST dataset is also in 28,28. also cause 28x28 pixels are enough to train ou model

4)appending the image pixels value and label in an array to finally get our xtrain

In [90]:
```
train_dir = os.listdir(r'E:\Internship\IIITD MIDAS\Task 2.2\Dataset\train')
root_dir = r'E:\Internship\IIITD MIDAS\Task 2.2\Dataset'

X = []
f=0
for cls in train_dir:
  src = root_dir+ '\\train\\' + cls
  allFileNames = os.listdir(src)
  a = cls
  a = a[-2:]
  p = int(a)
  p
  # print(cls)
  # # print(src + '/'+ allFileNames)

  for img in allFileNames:
    # ytrain.append(p)
    IMG_LOC=src+'\\'+img
    # image = io.imread(IMG_LOC)
    image=cv.imread(IMG_LOC, cv.IMREAD_GRAYSCALE)
    image=cv.resize(image,(28,28))
    print(f)
    f=f+1
    # testing_data.append([np.array(img),img_num])
    X.append([np.array(image),np.array(p)])
  # print(X)
  # print(ytrain)
    # print(image)
```

```
320
321
322
323
324
325
326
327
328
329
330
331
332
333
334
335
336
337
338
339
```

Reshaping the array X and dividing it in Xtrain and Ytrain. We need xtrain and y train to train our model

In [91]:
```
x_train = np.array([i[0] for i in X]).reshape(-1,28,28,1)
y_train = np.array([i[1] for i in X])
```

Printing the shape of Xtrain and Ytrain, to verify if its same as what we need in our model

In [92]:
```
print(x_train.shape)
print(y_train.shape)
```

```
(340, 28, 28, 1)
(340,)
```

Generating Xtest and Ytest

Following the same steps as we did for xtrain and ytrain

In [93]:
```
train_dir = os.listdir(r'E:\Internship\IIITD MIDAS\Task 2.2\Dataset\test')
# img=cv.imread("/content/drive/MyDrive/IIITD/data/Sample027/img027-004.png", cv.IMREAD_GRAYSCALE)
root_dir = r'E:\Internship\IIITD MIDAS\Task 2.2\Dataset'
# os.makedirs(root_dir + '/train')

y = []
# ytrain = []
f=0
for cls in train_dir:
    src = root_dir+ '\\test\\' + cls
    allFileNames = os.listdir(src)
    a = cls
    a = a[-2:]
    p = int(a)
    p
#     print(cls)
    # # print(src + '/'+ allFileNames)
    for img in allFileNames:
        # ytrain.append(p)
        IMG_LOC=src+'\\'+img
        # image = io.imread(IMG_LOC)
        image=cv.imread(IMG_LOC, cv.IMREAD_GRAYSCALE)
        image=cv.resize(image,(28,28))
        # testing_data.append([np.array(img),img_num])
        y.append([np.array(image),np.array(p)])
        print(f)
        f=f+1
# print(y)
  # print(ytrain)
    # print(image)
```

```
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
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39
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41
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45
46
47
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49
50
51
52
53
54
55
56
57
58
59
```

In [94]:
```
x_test = np.array([i[0] for i in y]).reshape(-1,28,28,1)
y_test = np.array([i[1] for i in y])
```

In [95]:
```
print(x_test.shape)
print(y_test.shape)
print(x_train.shape)
print(y_train.shape)
```

```
(60, 28, 28, 1)
(60,)
(340, 28, 28, 1)
(340,)
```

Data Normalization

As the CNN algorithm converge faster on the [0..1] data than on [0..255]

In [96]:
```
x_train, x_test=x_train/255.0, x_test/255.0
y_train, y_test=y_train.flatten(), y_test.flatten()
```

In [97]:
```
y_train
```

Out[97]:
```
array([ 1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
```

```
 2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,
 2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,  2,
 3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,
 3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,
 4,  4,  4,  4,  4,  4,  4,  4,  4,  4,  4,  4,  4,  4,  4,  4,  4,
 4,  4,  4,  4,  4,  4,  4,  4,  4,  4,  4,  4,  4,  4,  4,  4,  4,
 5,  5,  5,  5,  5,  5,  5,  5,  5,  5,  5,  5,  5,  5,  5,  5,  5,
 5,  5,  5,  5,  5,  5,  5,  5,  5,  5,  5,  5,  5,  5,  5,  5,  5,
 6,  6,  6,  6,  6,  6,  6,  6,  6,  6,  6,  6,  6,  6,  6,  6,  6,
 6,  6,  6,  6,  6,  6,  6,  6,  6,  6,  6,  6,  6,  6,  6,  6,  6,
 7,  7,  7,  7,  7,  7,  7,  7,  7,  7,  7,  7,  7,  7,  7,  7,  7,
 7,  7,  7,  7,  7,  7,  7,  7,  7,  7,  7,  7,  7,  7,  7,  7,  7,
 8,  8,  8,  8,  8,  8,  8,  8,  8,  8,  8,  8,  8,  8,  8,  8,  8,
 8,  8,  8,  8,  8,  8,  8,  8,  8,  8,  8,  8,  8,  8,  8,  8,  8,
 9,  9,  9,  9,  9,  9,  9,  9,  9,  9,  9,  9,  9,  9,  9,  9,  9,
 9,  9,  9,  9,  9,  9,  9,  9,  9,  9,  9,  9,  9,  9,  9,  9,  9,
10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10,
10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10])
```

Label encoding

We need to give the y test and train in one hot encoded form

used this article for Label encoding - https://www.geeksforgeeks.org/ml-label-encoding-of-datasets-in-python/

it basically converts all the labels from 0 to the end. so that it becomes easier in one hot encoding.

In [98]:
```
# Import label encoder
from sklearn import preprocessing

# label_encoder object knows how to understand word labels.
label_encoder = preprocessing.LabelEncoder()

# Encode labels in column 'species'.
y_train= label_encoder.fit_transform(y_train)
y_train
# y_train.unique()
```

Out[98]:
```
array([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, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 3, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6,
       6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6, 7, 7, 7,
       7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7,
       7, 7, 7, 7, 7, 7, 7, 7, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8,
       8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 8, 9, 9,
       9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9, 9,
       9, 9, 9, 9, 9, 9, 9, 9, 9, 9], dtype=int64)
```

Used the to_categorical function to convert the data to one hot encoded form

In [99]:
```
from numpy import array
from numpy import argmax
from keras.utils import to_categorical
# define example
data = array(y_train)
print(data)
# one hot encode
encoded = to_categorical(data)
print(encoded)
y_train = encoded
```

```
[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
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3
 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4 4
 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5 5
 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6 6
 7 7 7 7 7 7 7 7 7 7 7 7 7 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8
 8 8 8 8 8 8 8 8 8 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9 9
 9 9 9 9 9 9 9]
[[1. 0. 0. ... 0. 0. 0.]
 [1. 0. 0. ... 0. 0. 0.]
 [1. 0. 0. ... 0. 0. 0.]
 ...
 [0. 0. 0. ... 0. 0. 1.]
 [0. 0. 0. ... 0. 0. 1.]
 [0. 0. 0. ... 0. 0. 1.]]
```

Same for Y test

In [100]:
```
label_encoder = preprocessing.LabelEncoder()
y_test= label_encoder.fit_transform(y_test)
```

In [101]:
```
y_test
```

Out[101]:
```
array([0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 3, 3, 3, 3,
       3, 3, 4, 4, 4, 4, 4, 4, 5, 5, 5, 5, 5, 5, 6, 6, 6, 6, 6, 6, 7, 7,
       7, 7, 7, 8, 8, 8, 8, 8, 8, 9, 9, 9, 9, 9, 9], dtype=int64)
```

In [102]:
```
data = array(y_test)
print(data)
# one hot encode
encoded = to_categorical(data)
print(encoded)
y_test = encoded
```

```
[0 0 0 0 0 0 1 1 1 1 1 1 2 2 2 2 2 2 3 3 3 3 3 3 4 4 4 4 4 4 5 5 5 5 5 5 6
 6 6 6 6 6 7 7 7 7 7 7 8 8 8 8 8 8 9 9 9 9 9 9]
[[1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
```

```
[0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]
[0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]
[0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]
[0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]
[0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]
[0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]
[0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
[0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
[0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
[0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
[0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
[0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
[0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]
[0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]
[0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]
[0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]
[0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]
[0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]
[0. 0. 0. 0. 1. 0. 0. 0. 0. 0.]
[0. 0. 0. 0. 1. 0. 0. 0. 0. 0.]
[0. 0. 0. 0. 1. 0. 0. 0. 0. 0.]
[0. 0. 0. 0. 1. 0. 0. 0. 0. 0.]
[0. 0. 0. 0. 1. 0. 0. 0. 0. 0.]
[0. 0. 0. 0. 1. 0. 0. 0. 0. 0.]
[0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
[0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
[0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
[0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
[0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
[0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
[0. 0. 0. 0. 0. 0. 1. 0. 0. 0.]
[0. 0. 0. 0. 0. 0. 1. 0. 0. 0.]
[0. 0. 0. 0. 0. 0. 1. 0. 0. 0.]
[0. 0. 0. 0. 0. 0. 1. 0. 0. 0.]
[0. 0. 0. 0. 0. 0. 1. 0. 0. 0.]
[0. 0. 0. 0. 0. 0. 1. 0. 0. 0.]
[0. 0. 0. 0. 0. 0. 0. 1. 0. 0.]
[0. 0. 0. 0. 0. 0. 0. 1. 0. 0.]
[0. 0. 0. 0. 0. 0. 0. 1. 0. 0.]
[0. 0. 0. 0. 0. 0. 0. 1. 0. 0.]
[0. 0. 0. 0. 0. 0. 0. 1. 0. 0.]
[0. 0. 0. 0. 0. 0. 0. 1. 0. 0.]
[0. 0. 0. 0. 0. 0. 0. 0. 1. 0.]
[0. 0. 0. 0. 0. 0. 0. 0. 1. 0.]
[0. 0. 0. 0. 0. 0. 0. 0. 1. 0.]
[0. 0. 0. 0. 0. 0. 0. 0. 1. 0.]
[0. 0. 0. 0. 0. 0. 0. 0. 1. 0.]
[0. 0. 0. 0. 0. 0. 0. 0. 1. 0.]
[0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]
[0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]
[0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]
[0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]
[0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]
[0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]]
```

In [103]:

```
print(x_test.shape)
print(y_test.shape)
print(x_train.shape)
print(y_train.shape)
```

```
(60, 28, 28, 1)
(60, 10)
(340, 28, 28, 1)
(340, 10)
```

SAVING CHECKPOINTS

We need to save the checkpoints of our model, in case any error occurs in between our training

i refered this article to save checkpoints - https://towardsdatascience.com/checkpointing-deep-learning-models-in-keras-a652570b8de6

In [106]:

```
checkpoint_path = "E:\Internship\IIITD MIDAS\Task 2.2\checkpoints\cp-{epoch:04d}.ckpt"
```

In [107]:

```
cp_callback = tf.keras.callbacks.ModelCheckpoint(
    filepath=checkpoint_path,
    save_weights_only=True,
    save_freq=20,
    verbose=1)
```

Model

Importing required libraries

In [119]:

```
from sklearn.metrics import confusion_matrix
import itertools

from keras.utils.np_utils import to_categorical # convert to one-hot-encoding
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten, Conv2D, MaxPool2D
from keras.optimizers import RMSprop
from keras.preprocessing.image import ImageDataGenerator
from keras.callbacks import ReduceLROnPlateau
```

Here we have created a function to create a CNN model by adding the following Layers

I have added 2 convolution layers, with filer size as 32. Padding as Same, and activation function as relu

one Max Pooling layer with pool size 2,2 and 1 Droupout to prevent overfitting

I have repeated the above archetecture with a filter size of 64, as with more layers, the model might perform better

Finally i have added a flatten layer to flatten the input, so that i can feed it to the dense layer.

I have then added the dense layer with relu as activation function.

At last i have added another dense layer with softmax as activation function because my final output has 62 classes.

After this i have added the required optimizers and i have finally compiled the model

In [120]:

```
def create_model():
    model = Sequential()

    model.add(Conv2D(filters = 32, kernel_size = (5,5),padding = 'Same',
```

```
                 activation ='relu', input_shape = (28,28,1)))
model.add(Conv2D(filters = 32, kernel_size = (5,5),padding = 'Same',
                 activation ='relu'))
model.add(MaxPool2D(pool_size=(2,2)))
model.add(Dropout(0.25))


model.add(Conv2D(filters = 64, kernel_size = (3,3),padding = 'Same',
                 activation ='relu'))
model.add(Conv2D(filters = 64, kernel_size = (3,3),padding = 'Same',
                 activation ='relu'))
model.add(MaxPool2D(pool_size=(2,2), strides=(2,2)))
model.add(Dropout(0.25))


model.add(Flatten())
model.add(Dense(256, activation = "relu"))
model.add(Dropout(0.5))
model.add(Dense(10, activation = "softmax"))

optimizer = RMSprop(lr=0.001,
                    rho=0.9,
                    epsilon=1e-08,
                    decay=0.0)

model.compile(optimizer = optimizer ,
              loss = "categorical_crossentropy",
              metrics=["accuracy"])
return model
```

Creating a Model

In [121]:
```
model_ckpt= create_model()
```

Setting the number of epochs and batch size

In [122]:
```
epochs = 300 # Turn epochs to 30 to get 0.9967 accuracy
batch_size = 86
```

Data Augmentation

In data augmentation, we add a few image to the training dataset, with a little variation such as rotation or whitening and fliping of images. We do so, so that our model do not over fit.

Getting over fit means our model will get so much used to our training dataset, that its prediction on new images will be very faulty

In [123]:
```
datagen = ImageDataGenerator(
        featurewise_center=False,  # set input mean to 0 over the dataset
        samplewise_center=False,  # set each sample mean to 0
        featurewise_std_normalization=False,  # divide inputs by std of the dataset
        samplewise_std_normalization=False,  # divide each input by its std
        zca_whitening=False,  # apply ZCA whitening
        rotation_range=10,  # randomly rotate images in the range (degrees, 0 to 180)
        zoom_range = 0.1, # Randomly zoom image
        width_shift_range=0.1,  # randomly shift images horizontally (fraction of total width)
        height_shift_range=0.1,  # randomly shift images vertically (fraction of total height)
        horizontal_flip=False,  # randomly flip images
        vertical_flip=False)  # randomly flip images


datagen.fit(x_train)
```

We are finally running the model we have built, by giving all the attributes to the model.fit_generator function

In [124]:
```
history = model_ckpt.fit_generator(datagen.flow(x_train,y_train, batch_size=batch_size),
                                   epochs = epochs,
                                   validation_data = (x_test,y_test),
                                   verbose = 2,
                                   steps_per_epoch=x_train.shape[0] // batch_size
                                   , callbacks=[cp_callback])
```

```
3/3 - 1s - loss: 0.0338 - accuracy: 0.9882 - val_loss: 0.2446 - val_accuracy: 0.9500
Epoch 294/300

Epoch 00294: saving model to E:\Internship\IIITD MIDAS\Task 2.2\checkpoints\cp-0294.ckpt

3/3 - 1s - loss: 0.0353 - accuracy: 0.9843 - val_loss: 0.2216 - val_accuracy: 0.9333
Epoch 295/300
3/3 - 1s - loss: 0.0891 - accuracy: 0.9724 - val_loss: 0.2181 - val_accuracy: 0.9500
Epoch 296/300
3/3 - 1s - loss: 0.0307 - accuracy: 0.9921 - val_loss: 0.2114 - val_accuracy: 0.9333
Epoch 297/300
3/3 - 1s - loss: 0.0639 - accuracy: 0.9764 - val_loss: 0.2620 - val_accuracy: 0.9333
Epoch 298/300
3/3 - 1s - loss: 0.1347 - accuracy: 0.9488 - val_loss: 0.1802 - val_accuracy: 0.9333
Epoch 299/300
3/3 - 1s - loss: 0.0691 - accuracy: 0.9724 - val_loss: 0.2152 - val_accuracy: 0.9500
Epoch 300/300

Epoch 00300: saving model to E:\Internship\IIITD MIDAS\Task 2.2\checkpoints\cp-0300.ckpt
3/3 - 1s - loss: 0.0487 - accuracy: 0.9884 - val_loss: 0.4376 - val_accuracy: 0.9167
```

Calculating the final accuracy and loss

In [125]:
```
loss,acc = model_ckpt.evaluate(x_test,  y_test, verbose=2)
```

```
2/2 - 0s - loss: 0.4376 - accuracy: 0.9167
```

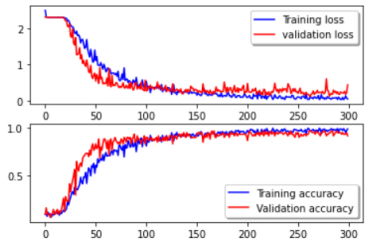
Evaluation

In [126]:
```
model = model_ckpt
```

Plotting the loss and accuracy curves for training and validation

In [127]:
```
# Plot the loss and accuracy curves for training and validation
fig, ax = plt.subplots(2,1)
```

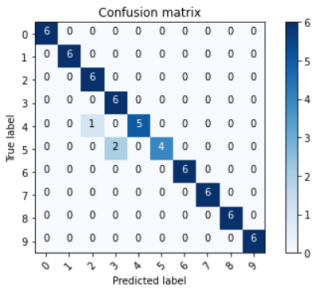
```
ax[0].plot(history.history['loss'], color='b', label="Training loss")
ax[0].plot(history.history['val_loss'], color='r', label="validation loss",axes =ax[0])
legend = ax[0].legend(loc='best', shadow=True)

ax[1].plot(history.history['accuracy'], color='b', label="Training accuracy")
ax[1].plot(history.history['val_accuracy'], color='r',label="Validation accuracy")
legend = ax[1].legend(loc='best', shadow=True)
```



In [87]:
```
model = model_ckpt
```

Plotting the Confusion matrix

In [88]:
```
# Look at confusion matrix

def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, cm[i, j],
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')

# Predict the values from the validation dataset
Y_pred = model.predict(x_test)
# Convert predictions classes to one hot vectors
Y_pred_classes = np.argmax(Y_pred,axis = 1)
# Convert validation observations to one hot vectors
Y_true = np.argmax(y_test,axis = 1)
# compute the confusion matrix
confusion_mtx = confusion_matrix(Y_true, Y_pred_classes)
# plot the confusion matrix
plot_confusion_matrix(confusion_mtx, classes = range(10))
```



loading pretrained

here we are loading the weights of the model which we have just trained so that we can train the MNIST data set on those predefined weights

In [44]:
```
checkpoint_dir = os.path.dirname(checkpoint_path)
latest = tf.train.latest_checkpoint(checkpoint_dir)
```

In [45]:
```
model_ckpt_MNIST = create_model()
model_ckpt_MNIST.load_weights(latest)
```

Out[45]:
```
<tensorflow.python.training.tracking.util.CheckpointLoadStatus at 0x243e92d2340>
```

In [46]:
```
loss,acc = model_ckpt_MNIST.evaluate(x_test,  y_test, verbose=2)
```

```
2/2 - 0s - loss: 0.3474 - accuracy: 0.9500
```

In [47]:
```
print("Restored model, accuracy: {:5.2f}%".format(100*acc))
```

```
Restored model, accuracy: 95.00%
```

Importing dataset

Here we are importing MNIST official dataset, so that e can train our model on it

We are also printing the sample train images to check if we have imported the correct dataset

I have used this to know how to import - https://www.askpython.com/python/examples/load-and-plot-mnist-dataset-in-python

In [49]:
```
from keras.datasets import mnist
```

In [50]:
```
#loading
(x_train, y_train), (x_test, y_test) = mnist.load_data()

#shape of dataset
print('X_train: ' + str(x_train.shape))
print('Y_train: ' + str(y_train.shape))
print('X_test:  '  + str(x_test.shape))
print('Y_test:  '  + str(y_test.shape))

#plotting
from matplotlib import pyplot
for i in range(9):
    pyplot.subplot(330 + 1 + i)
    pyplot.imshow(x_train[i], cmap=pyplot.get_cmap('gray'))
    pyplot.show()
```

```
X_train: (60000, 28, 28)
Y_train: (60000,)
X_test:  (10000, 28, 28)
Y_test:  (10000,)
```









Reshaping the array Xtrain and ytrain, so that it has the same dimension as the one required by our model

In [51]:
```
x_train = x_train.reshape(-1,28,28,1)
x_test = x_test.reshape(-1,28,28,1)
```

Printing the shape of Xtrain and Ytrain, to verify if its same as what we need in our model

In [52]:
```
#shape of dataset
print('X_train: ' + str(x_train.shape))
print('Y_train: ' + str(y_train.shape))
print('X_test:  '  + str(x_test.shape))
print('Y_test:  '  + str(y_test.shape))
```

```
X_train: (60000, 28, 28, 1)
Y_train: (60000,)
X_test:  (10000, 28, 28, 1)
Y_test:  (10000,)
```

Label encoding

We need to give the y test and train in one hot encoded form

used this article for Label encoding - https://www.geeksforgeeks.org/ml-label-encoding-of-datasets-in-python/

it basically converts all the labels from 0 to the end. so that it becomes easier in one hot encoding.

In [53]:
```
# Import label encoder
from sklearn import preprocessing

# Label encoder object knows how to understand word labels
```

```
# Label_encoder object knows how to understand word labels.
label_encoder = preprocessing.LabelEncoder()

# Encode labels in column 'species'.
y_train= label_encoder.fit_transform(y_train)
y_train
# y_train.unique()
```

Out[53]:
```
array([5, 0, 4, ..., 5, 6, 8], dtype=int64)
```

Used the to_categorical function to convert the data to one hot encoded form

In [54]:
```
from numpy import array
from numpy import argmax
from keras.utils import to_categorical
# define example
data = array(y_train)
print(data)
# one hot encode
encoded = to_categorical(data)
print(encoded)
y_train = encoded
```

```
[5 0 4 ... 5 6 8]
[[0. 0. 0. ... 0. 0. 0.]
 [1. 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. 1. 0.]]
```

Same for Y test

In [55]:
```
label_encoder = preprocessing.LabelEncoder()
y_test= label_encoder.fit_transform(y_test)
y_test
```

Out[55]:
```
array([7, 2, 1, ..., 4, 5, 6], dtype=int64)
```

In [56]:
```
# define example
data = array(y_test)
print(data)
# one hot encode
encoded = to_categorical(data)
print(encoded)
y_test = encoded
```

```
[7 2 1 ... 4 5 6]
[[0. 0. 0. ... 1. 0. 0.]
 [0. 0. 1. ... 0. 0. 0.]
 [0. 1. 0. ... 0. 0. 0.]
 ...
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]
 [0. 0. 0. ... 0. 0. 0.]]
```

In [57]:
```
print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
```

```
(60000, 28, 28, 1)
(60000, 10)
(10000, 28, 28, 1)
(10000, 10)
```

When trained on given dataset and tested on MNIST test data -

Now we have changed our xtest and ytest to the standard MNIST dataset

Here we are testing our already trained weights from the small dataset on the big MNIST test data

In [60]:
```
loss,acc = model_ckpt_MNIST.evaluate(x_test,  y_test, verbose=2)
print("Restored model, accuracy: {:5.2f}%".format(100*acc))
```

```
313/313 - 12s - loss: 2547.1548 - accuracy: 0.1588
Restored model, accuracy: 15.88%
```

As we can see the accuracy is just 15% as our dataset was very small

Train our Pre trained weights on MNIST Dataset

In [61]:
```
checkpoint_path = "E:\Internship\IIITD MIDAS\Task 2.2\checkpoints\withMNIST\cp-{epoch:04d}.ckpt"
```

In [62]:
```
cp_callback = tf.keras.callbacks.ModelCheckpoint(
    filepath=checkpoint_path,
    save_weights_only=True,
    save_freq=200,
    verbose=1)
```

In [63]:
```
# # model_ckpt2.fit(train_images,
#           train_labels,
#           batch_size=64,
#           epochs=10,
#           validation_data=(test_images,test_labels),
#           callbacks=[cp_callback])


history = model_ckpt_MNIST.fit_generator(datagen.flow(x_train,y_train, batch_size=batch_size),
                                epochs = 10,
                                validation_data = (x_test,y_test),
                                verbose = 2,
                                steps_per_epoch=x_train.shape[0] // batch_size
                                , callbacks=[cp_callback])
```

```
Epoch 1/10

Epoch 00001: saving model to E:\Internship\IIITD MIDAS\Task 2.2\checkpoints\withMNIST\cp-0001.ckpt

Epoch 00001: saving model to E:\Internship\IIITD MIDAS\Task 2.2\checkpoints\withMNIST\cp-0001.ckpt
```

```
Epoch 00001: saving model to E:\Internship\IIITD MIDAS\Task 2.2\checkpoints\withMNIST\cp-0001.ckpt
697/697 - 455s - loss: 10.6294 - accuracy: 0.7872 - val_loss: 0.1255 - val_accuracy: 0.9649
Epoch 2/10

Epoch 00002: saving model to E:\Internship\IIITD MIDAS\Task 2.2\checkpoints\withMNIST\cp-0002.ckpt

Epoch 00002: saving model to E:\Internship\IIITD MIDAS\Task 2.2\checkpoints\withMNIST\cp-0002.ckpt

Epoch 00002: saving model to E:\Internship\IIITD MIDAS\Task 2.2\checkpoints\withMNIST\cp-0002.ckpt
697/697 - 476s - loss: 0.2070 - accuracy: 0.9450 - val_loss: 0.0457 - val_accuracy: 0.9854
Epoch 3/10

Epoch 00003: saving model to E:\Internship\IIITD MIDAS\Task 2.2\checkpoints\withMNIST\cp-0003.ckpt
```

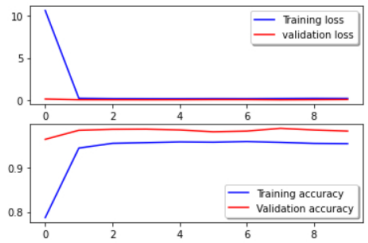
In [ ]:
```
loss,acc = model_ckpt_MNIST.evaluate(x_test,  y_test, verbose=2)
print("Restored model, accuracy: {:5.2f}%".format(100*acc))
```

2/2 - 0s - loss: 0.0717 - accuracy: 0.9836 Restored model, accuracy: 98.36%

Evaluation

Plotting the loss and accuracy curves for training and validation

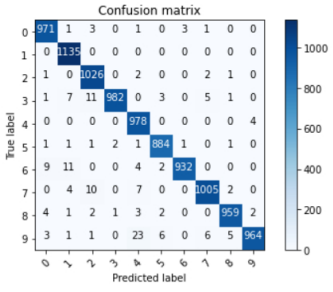
In [65]:
```
# Plot the loss and accuracy curves for training and validation
fig, ax = plt.subplots(2,1)
ax[0].plot(history.history['loss'], color='b', label="Training loss")
ax[0].plot(history.history['val_loss'], color='r', label="validation loss",axes =ax[0])
legend = ax[0].legend(loc='best', shadow=True)

ax[1].plot(history.history['accuracy'], color='b', label="Training accuracy")
ax[1].plot(history.history['val_accuracy'], color='r',label="Validation accuracy")
legend = ax[1].legend(loc='best', shadow=True)
```



In [69]:
```
model = model_ckpt_MNIST
```

Plotting the Confusion matrix

In [70]:
```
# Look at confusion matrix

def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, cm[i, j],
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')

# Predict the values from the validation dataset
Y_pred = model.predict(x_test)
# Convert predictions classes to one hot vectors
Y_pred_classes = np.argmax(Y_pred,axis = 1)
# Convert validation observations to one hot vectors
Y_true = np.argmax(y_test,axis = 1)
# compute the confusion matrix
confusion_mtx = confusion_matrix(Y_true, Y_pred_classes)
# plot the confusion matrix
plot_confusion_matrix(confusion_mtx, classes = range(10))
```



In [ ]: