In [ ]:

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python docker image: https://github.com/kaggle/docker-
# For example, here's several helpful packages to load in

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the "../input/" directory.
# For example, running this (by clicking run or pressing Shift+Enter) will list all

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# Any results you write to the current directory are saved as output.
```

In [1]:

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Dropout, Conv2D, MaxPooling2D, B
from tensorflow.keras.utils import to_categorical, plot_model

import matplotlib.pyplot as plt
```

In [2]:

```
train = pd.read_csv('/kaggle/input/digit-recognizer/train.csv')
test = pd.read_csv('/kaggle/input/digit-recognizer/test.csv')
```

In [3]:

```
train.head(2)
```

Out[3]:

| | label | pixel0 | pixel1 | pixel2 | pixel3 | pixel4 | pixel5 | pixel6 | pixel7 | pixel8 | ... | pixel774 | pixel77 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | |
| **1** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | |

2 rows × 785 columns

In [4]:

```
test.head(2)
```

Out[4]:

| | pixel0 | pixel1 | pixel2 | pixel3 | pixel4 | pixel5 | pixel6 | pixel7 | pixel8 | pixel9 | ... | pixel774 | pixel7 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | |
| **1** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | ... | 0 | |

2 rows × 784 columns

In [7]:

```
train = np.array(train)
test = np.array(test)

train_x = train[:, 1:]
train_y = train[:, 0]

# Normalize the data
```

```
train_x = train_x / 255.0
test = test / 255.0
```

In [8]:
```
train_x
```

Out[8]:
```
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.]])
```

In [10]:
```
#Reshape
train_x = train_x.reshape(-1,28,28,1)
test = test.reshape(-1,28,28,1)
```

In [12]:
```
train_y
```

Out[12]:
```
array([1, 0, 1, ..., 7, 6, 9])
```

In [13]:
```
train_y = to_categorical(train_y)
```

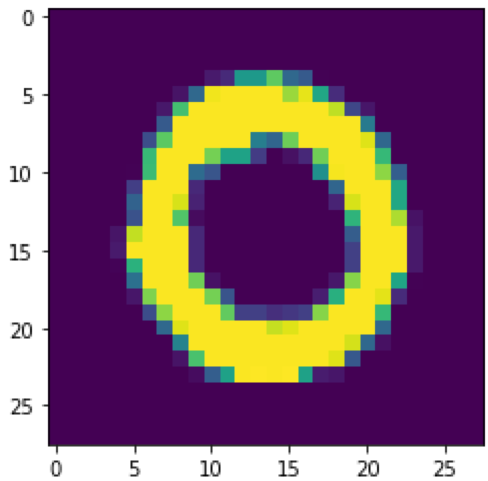
In [14]:
```
train_y
```

Out[14]:
```
array([[0., 1., 0., ..., 0., 0., 0.],
       [1., 0., 0., ..., 0., 0., 0.],
       [0., 1., 0., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 1., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 1.]], dtype=float32)
```

In [15]:
```
print(train_x.shape)
```

```
(42000, 28, 28, 1)
```

In [19]:
```
g = plt.imshow(train_x[1][:,:,0])
```




In [22]:
```
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(MaxPooling2D(pool_size=(2,2)))
model.add(Dropout(0.25))
```

```python
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(MaxPooling2D(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"))
```

In [27]:

```python
from tensorflow.keras.optimizers import RMSprop
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.callbacks import ReduceLROnPlateau
#Trying RMSProp optimizer

optimizer_rms = RMSprop(lr=0.001, rho=0.9, epsilon=1e-08, decay=0.0)
# Compile the model
model.compile(optimizer = optimizer_rms , loss = "categorical_crossentropy", metrics
```

In [28]:

```python
BATCH_SIZE=64
EPOCH=5
```

In [29]:

```python
history = model.fit(train_x, train_y, batch_size=BATCH_SIZE, epochs=EPOCH, validatio
```

```
Train on 33600 samples, validate on 8400 samples
Epoch 1/5
33600/33600 [==============================] - 126s 4ms/sample - loss: 0.2354 - accu
racy: 0.9255 - val_loss: 0.0603 - val_accuracy: 0.9800
Epoch 2/5
33600/33600 [==============================] - 124s 4ms/sample - loss: 0.0771 - accu
racy: 0.9762 - val_loss: 0.0441 - val_accuracy: 0.9873
Epoch 3/5
33600/33600 [==============================] - 124s 4ms/sample - loss: 0.0578 - accu
racy: 0.9822 - val_loss: 0.0423 - val_accuracy: 0.9873
Epoch 4/5
33600/33600 [==============================] - 124s 4ms/sample - loss: 0.0507 - accu
racy: 0.9854 - val_loss: 0.0366 - val_accuracy: 0.9894
Epoch 5/5
33600/33600 [==============================] - 124s 4ms/sample - loss: 0.0450 - accu
racy: 0.9870 - val_loss: 0.0354 - val_accuracy: 0.9907
```

In [31]:

```python
from tensorflow.keras.optimizers import Adam
optimizer_adam = Adam(learning_rate=0.001, beta_1=0.9, beta_2=0.999, epsilon=1e-07,n
# Compile the model
model.compile(optimizer = optimizer_adam , loss = "categorical_crossentropy", metric
# Since target variable has multiple classes, loss fnctn can be categorical cross en
history_adam = model.fit(train_x, train_y, batch_size=BATCH_SIZE, epochs=EPOCH, vali
```

```
Train on 33600 samples, validate on 8400 samples
Epoch 1/5
33600/33600 [==============================] - 123s 4ms/sample - loss: 0.0391 - accu
racy: 0.9879 - val_loss: 0.0333 - val_accuracy: 0.9895
Epoch 2/5
33600/33600 [==============================] - 123s 4ms/sample - loss: 0.0352 - accu
racy: 0.9895 - val_loss: 0.0350 - val_accuracy: 0.9902
Epoch 3/5
33600/33600 [==============================] - 124s 4ms/sample - loss: 0.0324 - accu
racy: 0.9900 - val_loss: 0.0328 - val_accuracy: 0.9913
Epoch 4/5
33600/33600 [==============================] - 123s 4ms/sample - loss: 0.0278 - accu
racy: 0.9917 - val_loss: 0.0348 - val_accuracy: 0.9910
```

```
Epoch 5/5
33600/33600 [==============================] - 129s 4ms/sample - loss: 0.0260 - accu
racy: 0.9921 - val_loss: 0.0275 - val_accuracy: 0.9921
```

In [32]:

```
#Stochastic gradient with momentum and Nesterov
#we can slo use momentum optimzer (sgd+momentum)
from tensorflow.keras.optimizers import SGD
optimizer_sgd=SGD(learning_rate=0.01, momentum=0.9, nesterov=True, name='SGD')
model.compile(optimizer = optimizer_sgd , loss = "categorical_crossentropy", metrics
history_sgd = model.fit(train_x, train_y, batch_size=BATCH_SIZE, epochs=EPOCH, valid
```

```
Train on 33600 samples, validate on 8400 samples
Epoch 1/5
33600/33600 [==============================] - 124s 4ms/sample - loss: 0.0180 - accu
racy: 0.9943 - val_loss: 0.0333 - val_accuracy: 0.9927
Epoch 2/5
33600/33600 [==============================] - 123s 4ms/sample - loss: 0.0156 - accu
racy: 0.9953 - val_loss: 0.0410 - val_accuracy: 0.9927
Epoch 3/5
33600/33600 [==============================] - 123s 4ms/sample - loss: 0.0113 - accu
racy: 0.9965 - val_loss: 0.0361 - val_accuracy: 0.9931
Epoch 4/5
33600/33600 [==============================] - 134s 4ms/sample - loss: 0.0124 - accu
racy: 0.9958 - val_loss: 0.0382 - val_accuracy: 0.9931
Epoch 5/5
33600/33600 [==============================] - 123s 4ms/sample - loss: 0.0099 - accu
racy: 0.9965 - val_loss: 0.0328 - val_accuracy: 0.9931
```

**SGD Optimizer proves to be the best one, Loss consistently reduced during each iteration**