Import dependencies and load the data

In [1]:
```
import tensorflow as tf
import matplotlib.pyplot as plt
import seaborn as sn
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import math
import datetime
import platform

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

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

# You can write up to 20GB to the current directory (/kaggle/working/) that gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the current session
```

In [2]:
```
print('Python version:', platform.python_version())
print('Tensorflow version:', tf.__version__)
print('Keras version:', tf.keras.__version__)
```

```
Python version: 3.9.12
Tensorflow version: 2.9.1
Keras version: 2.9.0
```

In [3]:
```
# Load the TensorBoard notebook extension.
# %reload_ext tensorboard
%load_ext tensorboard

# Clear any logs from previous runs.
!rm -rf ./.logs/
```

```
'rm' is not recognized as an internal or external command,
operable program or batch file.
```

Load MNIST data

In [4]:
```
train_mnist = pd.read_csv('train.csv')
test_mnist = pd.read_csv('test.csv')
```

In [5]:
```
test_mnist.shape
```

Out[5]:
```
(28000, 784)
```

In [6]:
```
train_mnist.shape
```

Out[6]:
```
(42000, 785)
```

In [7]:
```
from tensorflow.keras.datasets import mnist

# Load MNIST data
(X_train_mnist, y_train_mnist), (X_test_mnist, y_test_mnist) = mnist.load_data()
```

In [8]:
```
X_test_mnist.shape
X_test_mnist_re = X_test_mnist.reshape(10000,784)
X_test_mnist_re.shape
```

Out[8]:
```
(10000, 784)
```

In [9]:
```
X_train_mnist.shape
X_train_mnist_re = X_train_mnist.reshape(60000,784)
X_train_mnist_re.shape
pd.DataFrame(X_train_mnist_re).head()
```

Out[9]:

	0	1	2	3	4	5	6	7	8	9	...	774	775	776	777	778	779	780	781	782	783
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	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
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

5 rows × 784 columns

In [10]:
```
X_test_mnist.sum(axis=1)
```

Out[10]:
```
array([[  0,   0,   0, ...,   0,   0,   0],
       [  0,   0,   0, ..., 517, 190,   0],
       [  0,   0,   0, ...,   0,   0,   0],
       ...,
       [  0,   0,   0, ...,   0,   0,   0],
       [  0,   0,   0, ..., 648, 425,   0],
       [  0,   0,   0, ...,   0,   0,   0]], dtype=uint32)
```

In [11]:
```
X_train_mnist = train_mnist.iloc[:, 1:785]
y_train_mnist = train_mnist.iloc[:, 0]

X_test_mnist = test_mnist.iloc[:, 0:784]
```

In [12]:
```
X_train_mnist.shape, y_train_mnist.shape,type(X_train_mnist),type(y_train_mnist)
```

Out[12]:
```
((42000, 784),
 (42000,),
```

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```
 pandas.core.frame.DataFrame,
 pandas.core.series.Series)
```

In [13]:
```python
X_train_mnist.head()
```

Out[13]:

	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	pixel9	...	pixel774	pixel775	pixel776	pixel777	pixel778	pixel779	pixel780	pixel781	pixel782	pixel783
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	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
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

5 rows × 784 columns

QMNIST - The Extended MNIST Dataset (120k images)

Using to improve the performance of the digit recognition model with the expanded version of MNIST data

Load QMNIST data

In [14]:
```python
def unpickle(file):
    import pickle
    with open(file, 'rb') as fo:
        dict = pickle.load(fo, encoding='bytes')
    return dict
```

In [15]:
```python
# Read qmnist data
qmnist = unpickle("MNIST-120k")
X_train_qmnist = qmnist['data']

y_train_qmnist = pd.Series(qmnist['labels'].reshape(120000))
```

In [16]:
```python
X_train_qmnist.shape, y_train_qmnist.shape,type(X_train_qmnist),type(y_train_qmnist)
```

Out[16]:
```
((120000, 28, 28), (120000,), numpy.ndarray, pandas.core.series.Series)
```

In [17]:
```python
X_train_qmnist_re = X_train_qmnist.reshape(120000,784)
```

In [18]:
```python
X_train_qmnist_re = pd.DataFrame(X_train_qmnist_re)
```

In [19]:
```python
X_train_qmnist_re.shape, y_train_qmnist.shape,type(X_train_qmnist_re),type(y_train_qmnist)
```

Out[19]:
```
((120000, 784),
 (120000,),
 pandas.core.frame.DataFrame,
 pandas.core.series.Series)
```

In [20]:
```python
#X_train_mnist.columns
X_train_qmnist_re.columns = X_train_mnist.columns
X_train_qmnist_re.head()
```

Out[20]:

	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	pixel9	...	pixel774	pixel775	pixel776	pixel777	pixel778	pixel779	pixel780	pixel781	pixel782	pixel783
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	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
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

5 rows × 784 columns

Combine MNIST and QMNIST

In [21]:
```python
X_train_mnist.shape,X_train_qmnist_re.shape
```

Out[21]:
```
((42000, 784), (120000, 784))
```

In [22]:
```python
X_train = pd.concat([X_train_mnist,X_train_qmnist_re],axis=0)
```

In [23]:
```python
y_train_mnist.shape,y_train_qmnist.shape
```

Out[23]:
```
((42000,), (120000,))
```

In [24]:
```python
y_train = pd.concat([y_train_mnist,y_train_qmnist],axis=0)
X_train.shape, y_train.shape
```

Out[24]:
```
((162000, 784), (162000,))
```

3. Data Overview

3.1 Diamension of train and test data

In [25]:
```python
X_train.head()
```

Out[25]:

	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	pixel9	...	pixel774	pixel775	pixel776	pixel777	pixel778	pixel779	pixel780	pixel781	pixel782	pixel783
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	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
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

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4	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

5 rows × 784 columns

In [26]:
```
X_train.info(), X_train.shape
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 162000 entries, 0 to 119999
Columns: 784 entries, pixel0 to pixel783
dtypes: int64(784)
memory usage: 970.2 MB
```

Out[26]:
```
(None, (162000, 784))
```

In [27]:
```
X_test_mnist.info(),  X_test_mnist.shape
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 28000 entries, 0 to 27999
Columns: 784 entries, pixel0 to pixel783
dtypes: int64(784)
memory usage: 167.5 MB
```

Out[27]:
```
(None, (28000, 784))
```

3.2 Visualizing the data using TSNE

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TSNE - t-Distributed Stochastic Neighbor embedding. This is a dimensionality reduction algorithm that is designed to keep local structure in the high dimensional data set, but cares less about global structure. Here, we use it to go from the 784 pixel-dimension of the images to two dimensions. This makes plotting easier. The color scale is the original MNIST label and one can see that the separation of the labels is apparent.

In [28]:
```
# WARNING: running t-SNE on the full data set takes a while.
# X_tsn = X_train/255

# from sklearn.manifold import TSNE
# tsne = TSNE()

# tsne_res = tsne.fit_transform(X_tsn)
# plt.figure(figsize=(14, 12))
# plt.scatter(tsne_res[:,0], tsne_res[:,1], c=y, s=2)
# plt.xticks([])
# plt.yticks([])
# plt.colorbar()
```

Diamension of training data

In [29]:
```
print('X_train:', X_train.shape)
print('y_train:', y_train.shape)
# print('X_validation:', X_validation.shape)
# print('y_validation:', y_validation.shape)
```

```
X_train: (162000, 784)
y_train: (162000,)
```

Converting training, and testing data into array

In [30]:
```
pd.DataFrame(y_train).head()
```

Out[30]:

	0
0	1
1	0
2	1
3	4
4	0

In [31]:
```
x_train_re = X_train.to_numpy().reshape(162000, 28, 28)
y_train_re = y_train.values
#x_validation_re = X_validation.to_numpy().reshape(32400, 28, 28)
#y_validation_re = y_validation.values
x_test_re = X_test_mnist.to_numpy().reshape(28000, 28, 28)
```

Diamension of training, and testing data after reshape

In [32]:
```
print('x_train:', x_train_re.shape)
print('y_train:', y_train_re.shape)
#print('x_validation:', x_validation_re.shape)
#print('y_validation:', y_validation_re.shape)
print('x_test:', x_test_re.shape)
```

```
x_train: (162000, 28, 28)
y_train: (162000,)
x_test: (28000, 28, 28)
```

In [33]:
```
# Save image parameters to the constants that we will use later for data re-shaping and for model traning.
(_, IMAGE_WIDTH, IMAGE_HEIGHT) = x_train_re.shape
IMAGE_CHANNELS = 1

print('IMAGE_WIDTH:', IMAGE_WIDTH);
print('IMAGE_HEIGHT:', IMAGE_HEIGHT);
print('IMAGE_CHANNELS:', IMAGE_CHANNELS);
```

```
IMAGE_WIDTH: 28
IMAGE_HEIGHT: 28
IMAGE_CHANNELS: 1
```

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4. Explore the data

Here is how each image in the dataset looks like. It is a 28x28 matrix of integers (from 0 to 255) and each integer represents a color of a pixel.

In [34]:
```
pd.DataFrame(x_train_re[0])
```

Out[34]:

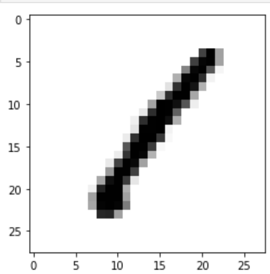
	0	1	2	3	4	5	6	7	8	9	...	18	19	20	21	22	23	24	25	26	27
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	...	0	0	188	255	94	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	...	0	191	250	253	93	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	...	123	248	253	167	10	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	...	247	253	208	13	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	...	253	235	77	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	...	253	88	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0	...	170	17	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	22	...	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	103	...	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	89	240	...	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	0	15	220	253	...	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	94	253	253	...	0	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	89	251	253	...	0	0	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	214	218	...	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

28 rows × 28 columns

4.1 Visualise how the digits were written

This number matrix may be drawn as follows:

In [35]:
```
plt.imshow(x_train_re[0], cmap=plt.cm.binary)
plt.show()
```



In [36]:
```
numbers_to_display = 12
num_cells = math.ceil(math.sqrt(numbers_to_display))
plt.figure(figsize=(10,10))
for i in range(numbers_to_display):
    plt.subplot(num_cells, num_cells, i+1)
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
    plt.imshow(x_train_re[i], cmap=plt.cm.binary)
    plt.xlabel(y_train_re[i])
plt.show()
```

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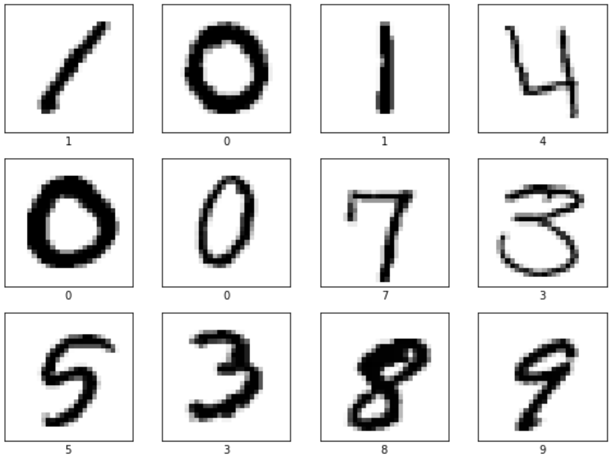

4.2 Reshaping train, test, and validation data

In order to use convolution layers we need to reshape our data and add a color channel to it. As you've noticed currently every digit has a shape of (28, 28) which means that it is a 28x28 matrix of color values form 0 to 255. We need to reshape it to (28, 28, 1) shape so that each pixel potentially may have multiple channels (like Red, Green and Blue).

In [37]:
```
x_train_with_chanels = x_train_re.reshape(
    x_train_re.shape[0],
    IMAGE_WIDTH,
    IMAGE_HEIGHT,
    IMAGE_CHANNELS
)

# x_validation_with_chanels = x_validation_re.reshape(
#     x_validation_re.shape[0],
#     IMAGE_WIDTH,
#     IMAGE_HEIGHT,
#     IMAGE_CHANNELS
# )

x_test_with_chanels = x_test_re.reshape(
    x_test_re.shape[0],
    IMAGE_WIDTH,
    IMAGE_HEIGHT,
    IMAGE_CHANNELS
)
```

In [38]:
```
print('x_train_with_chanels:', x_train_with_chanels.shape)
#print('x_validation_with_chanels:', x_validation_with_chanels.shape)
print('x_test_with_chanels:', x_test_with_chanels.shape)
```

```
x_train_with_chanels: (162000, 28, 28, 1)
x_test_with_chanels: (28000, 28, 28, 1)
```

4.3 Normalize train, test, and validation data

Here we're just trying to normalize from values range of [0...255] to [0...1].

In [39]:
```
x_train_normalized = x_train_with_chanels / 255
#x_validation_normalized = x_validation_with_chanels / 255
x_test_normalized = x_test_with_chanels / 255
```

In [40]:
```
# Let's check just one row from the 0th image to see color chanel values after normalization.
x_train_normalized[0][10]
```

Out[40]:
```
array([[0.        ],
       [0.        ],
       [0.        ],
       [0.        ],
       [0.        ],
       [0.        ],
       [0.        ],
       [0.        ],
       [0.        ],
       [0.        ],
       [0.        ],
       [0.        ],
       [0.        ],
       [0.        ],
       [0.36470588],
       [0.99607843],
       [0.99215686],
       [0.93333333],
       [0.66666667],
       [0.06666667],
       [0.        ],
       [0.        ],
       [0.        ],
       [0.        ],
       [0.        ],
       [0.        ],
       [0.        ],
       [0.        ]])
```

5. Build the CNN model to Classify Handwritten Digits

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We are using Sequential Keras model which have two pairs of Convolution2D and MaxPooling2D layers. The MaxPooling layer acts as a sort of downsampling using max values in a region instead of averaging.

After that we will use Flatten layer to convert multidimensional parameters to vector.

The last layer will be a Dense layer with 10 Softmax outputs. The output represents the network guess. The 0-th output represents a probability that the input digit is 0, the 1-st output represents a probability that the input digit is 1 and so on...

In [41]:
```
model = tf.keras.models.Sequential()

model.add(tf.keras.layers.Convolution2D(
    input_shape=(IMAGE_WIDTH, IMAGE_HEIGHT, IMAGE_CHANNELS),
    kernel_size=5,
    filters=8,
    strides=1,
    activation=tf.keras.activations.relu,
    kernel_initializer=tf.keras.initializers.VarianceScaling()
))

model.add(tf.keras.layers.MaxPooling2D(
    pool_size=(2, 2),
    strides=(2, 2)
))

model.add(tf.keras.layers.Convolution2D(
    kernel_size=5,
    filters=16,
    strides=1,
    activation=tf.keras.activations.relu,
    kernel_initializer=tf.keras.initializers.VarianceScaling()
))

model.add(tf.keras.layers.MaxPooling2D(
    pool_size=(2, 2),
    strides=(2, 2)
))

model.add(tf.keras.layers.Flatten())

model.add(tf.keras.layers.Dense(
    units=128,
    activation=tf.keras.activations.relu
));

model.add(tf.keras.layers.Dropout(0.2))

model.add(tf.keras.layers.Dense(
    units=10,
    activation=tf.keras.activations.softmax,
    kernel_initializer=tf.keras.initializers.VarianceScaling()
))
```

5.1 Summary of the training model

Here is our model summary so far.

In [42]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d (Conv2D)             (None, 24, 24, 8)         208       
                                                                 
 max_pooling2d (MaxPooling2D  (None, 12, 12, 8)        0         
 )                                                               
                                                                 
 conv2d_1 (Conv2D)           (None, 8, 8, 16)          3216      
                                                                 
 max_pooling2d_1 (MaxPooling  (None, 4, 4, 16)         0         
 2D)                                                             
                                                                 
 flatten (Flatten)           (None, 256)               0         
                                                                 
 dense (Dense)               (None, 128)               32896     
                                                                 
 dropout (Dropout)           (None, 128)               0         
                                                                 
 dense_1 (Dense)             (None, 10)                1290      
                                                                 
=================================================================
Total params: 37,610
Trainable params: 37,610
Non-trainable params: 0
_________________________________________________________________
```

5.2 Visualization of the model using graphviz

In order to plot the model the graphviz should be installed.

In [48]:
```
import tensorflow as tf
tf.keras.utils.plot_model(
    model,
    show_shapes=True,
    show_layer_names=True,
)
```

```
You must install pydot (`pip install pydot`) and install graphviz (see instructions at https://graphviz.gitlab.io/download/) for plot_model/model_to_dot to wor
k.
```

5.3 Compile the model using keras.optimizers.Adam

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In [45]:
```python
import tensorflow as tf
adam_optimizer = tf.keras.optimizers.Adam(learning_rate=0.001)

model.compile(
    optimizer=adam_optimizer,
    loss=tf.keras.losses.sparse_categorical_crossentropy,
    metrics=['accuracy']
)
```

5.4 Train the model

Data Augmentation We will use Data Augmentation to provide more data during the training process.

In [49]:
```python
datagen = tf.keras.preprocessing.image.ImageDataGenerator(
    rotation_range=20,
    width_shift_range=0.20,
    shear_range=15,
    zoom_range=0.10,
    validation_split=0.25,
    horizontal_flip=False
)

train_generator = datagen.flow(
    x_train_normalized,
    y_train_re,
    batch_size=256,
    subset='training',
)

validation_generator = datagen.flow(
    x_train_normalized,
    y_train_re,
    batch_size=64,
    subset='validation',
)
```

In [50]:
```python
reduce_lr = tf.keras.callbacks.ReduceLROnPlateau(monitor='val_loss',
                                                 factor=0.1,
                                                 patience=5,
                                                 min_lr=0.000001,
                                                 verbose=1)

checkpoint = tf.keras.callbacks.ModelCheckpoint(filepath='model.hdf5',
                                                monitor='val_loss',
                                                save_best_only=True,
                                                save_weights_only=True,
                                                verbose=1)
```

In [51]:
```python
training_history = model.fit_generator(train_generator,
                              epochs=50,
                              validation_data=validation_generator,
                              callbacks=[reduce_lr,checkpoint],
                              verbose=1)
```

```
C:\Users\dubey\AppData\Local\Temp\ipykernel_9556\566919499.py:1: UserWarning: `Model.fit_generator` is deprecated and will be removed in a future version. Plea
se use `Model.fit`, which supports generators.
  training_history = model.fit_generator(train_generator,
Epoch 1/50
475/475 [==============================] - ETA: 0s - loss: 0.6368 - accuracy: 0.7944
Epoch 1: val_loss improved from inf to 0.24415, saving model to model.hdf5
475/475 [==============================] - 46s 95ms/step - loss: 0.6368 - accuracy: 0.7944 - val_loss: 0.2441 - val_accuracy: 0.9242 - lr: 0.0010
Epoch 2/50
475/475 [==============================] - ETA: 0s - loss: 0.2439 - accuracy: 0.9246
Epoch 2: val_loss improved from 0.24415 to 0.16803, saving model to model.hdf5
475/475 [==============================] - 47s 99ms/step - loss: 0.2439 - accuracy: 0.9246 - val_loss: 0.1680 - val_accuracy: 0.9475 - lr: 0.0010
Epoch 3/50
475/475 [==============================] - ETA: 0s - loss: 0.1862 - accuracy: 0.9427
Epoch 3: val_loss improved from 0.16803 to 0.14907, saving model to model.hdf5
475/475 [==============================] - 49s 103ms/step - loss: 0.1862 - accuracy: 0.9427 - val_loss: 0.1491 - val_accuracy: 0.9539 - lr: 0.0010
Epoch 4/50
475/475 [==============================] - ETA: 0s - loss: 0.1568 - accuracy: 0.9510
Epoch 4: val_loss improved from 0.14907 to 0.11459, saving model to model.hdf5
475/475 [==============================] - 52s 110ms/step - loss: 0.1568 - accuracy: 0.9510 - val_loss: 0.1146 - val_accuracy: 0.9642 - lr: 0.0010
Epoch 5/50
475/475 [==============================] - ETA: 0s - loss: 0.1375 - accuracy: 0.9572
Epoch 5: val_loss improved from 0.11459 to 0.10309, saving model to model.hdf5
475/475 [==============================] - 50s 106ms/step - loss: 0.1375 - accuracy: 0.9572 - val_loss: 0.1031 - val_accuracy: 0.9680 - lr: 0.0010
Epoch 6/50
475/475 [==============================] - ETA: 0s - loss: 0.1273 - accuracy: 0.9603
Epoch 6: val_loss improved from 0.10309 to 0.09047, saving model to model.hdf5
475/475 [==============================] - 47s 98ms/step - loss: 0.1273 - accuracy: 0.9603 - val_loss: 0.0905 - val_accuracy: 0.9725 - lr: 0.0010
Epoch 7/50
475/475 [==============================] - ETA: 0s - loss: 0.1163 - accuracy: 0.9641
Epoch 7: val_loss improved from 0.09047 to 0.08648, saving model to model.hdf5
475/475 [==============================] - 47s 98ms/step - loss: 0.1163 - accuracy: 0.9641 - val_loss: 0.0865 - val_accuracy: 0.9730 - lr: 0.0010
Epoch 8/50
475/475 [==============================] - ETA: 0s - loss: 0.1079 - accuracy: 0.9669
Epoch 8: val_loss improved from 0.08648 to 0.08328, saving model to model.hdf5
475/475 [==============================] - 48s 100ms/step - loss: 0.1079 - accuracy: 0.9669 - val_loss: 0.0833 - val_accuracy: 0.9730 - lr: 0.0010
Epoch 9/50
475/475 [==============================] - ETA: 0s - loss: 0.1029 - accuracy: 0.9680
Epoch 9: val_loss improved from 0.08328 to 0.07553, saving model to model.hdf5
475/475 [==============================] - 48s 100ms/step - loss: 0.1029 - accuracy: 0.9680 - val_loss: 0.0755 - val_accuracy: 0.9763 - lr: 0.0010
Epoch 10/50
475/475 [==============================] - ETA: 0s - loss: 0.1008 - accuracy: 0.9690
Epoch 10: val_loss did not improve from 0.07553
475/475 [==============================] - 46s 97ms/step - loss: 0.1008 - accuracy: 0.9690 - val_loss: 0.0784 - val_accuracy: 0.9753 - lr: 0.0010
Epoch 11/50
475/475 [==============================] - ETA: 0s - loss: 0.0941 - accuracy: 0.9707
Epoch 11: val_loss improved from 0.07553 to 0.07303, saving model to model.hdf5
475/475 [==============================] - 47s 99ms/step - loss: 0.0941 - accuracy: 0.9707 - val_loss: 0.0730 - val_accuracy: 0.9771 - lr: 0.0010
Epoch 12/50
475/475 [==============================] - ETA: 0s - loss: 0.0925 - accuracy: 0.9718
Epoch 12: val_loss improved from 0.07303 to 0.06358, saving model to model.hdf5
475/475 [==============================] - 48s 100ms/step - loss: 0.0925 - accuracy: 0.9718 - val_loss: 0.0636 - val_accuracy: 0.9801 - lr: 0.0010
Epoch 13/50
==========================] - ETA: 0s - loss: 0.0876 - accuracy: 0.9734
```

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```
Epoch 13: val_loss improved from 0.06358 to 0.06325, saving model to model.hdf5
475/475 [==============================] - 46s 97ms/step - loss: 0.0876 - accuracy: 0.9734 - val_loss: 0.0633 - val_accuracy: 0.9808 - lr: 0.0010
Epoch 14/50
475/475 [==============================] - ETA: 0s - loss: 0.0843 - accuracy: 0.9742
Epoch 14: val_loss improved from 0.06325 to 0.05794, saving model to model.hdf5
475/475 [==============================] - 47s 99ms/step - loss: 0.0843 - accuracy: 0.9742 - val_loss: 0.0579 - val_accuracy: 0.9824 - lr: 0.0010
Epoch 15/50
475/475 [==============================] - ETA: 0s - loss: 0.0827 - accuracy: 0.9739
Epoch 15: val_loss did not improve from 0.05794
475/475 [==============================] - 48s 100ms/step - loss: 0.0827 - accuracy: 0.9739 - val_loss: 0.0602 - val_accuracy: 0.9817 - lr: 0.0010
Epoch 16/50
475/475 [==============================] - ETA: 0s - loss: 0.0772 - accuracy: 0.9761
Epoch 16: val_loss improved from 0.05794 to 0.05783, saving model to model.hdf5
475/475 [==============================] - 48s 100ms/step - loss: 0.0772 - accuracy: 0.9761 - val_loss: 0.0578 - val_accuracy: 0.9819 - lr: 0.0010
Epoch 17/50
475/475 [==============================] - ETA: 0s - loss: 0.0792 - accuracy: 0.9761
Epoch 17: val_loss did not improve from 0.05783
475/475 [==============================] - 51s 107ms/step - loss: 0.0792 - accuracy: 0.9761 - val_loss: 0.0603 - val_accuracy: 0.9807 - lr: 0.0010
Epoch 18/50
475/475 [==============================] - ETA: 0s - loss: 0.0755 - accuracy: 0.9768
Epoch 18: val_loss improved from 0.05783 to 0.05723, saving model to model.hdf5
475/475 [==============================] - 48s 102ms/step - loss: 0.0755 - accuracy: 0.9768 - val_loss: 0.0572 - val_accuracy: 0.9819 - lr: 0.0010
Epoch 19/50
475/475 [==============================] - ETA: 0s - loss: 0.0740 - accuracy: 0.9777
Epoch 19: val_loss improved from 0.05723 to 0.05714, saving model to model.hdf5
475/475 [==============================] - 47s 100ms/step - loss: 0.0740 - accuracy: 0.9777 - val_loss: 0.0571 - val_accuracy: 0.9821 - lr: 0.0010
Epoch 20/50
475/475 [==============================] - ETA: 0s - loss: 0.0731 - accuracy: 0.9775
Epoch 20: val_loss improved from 0.05714 to 0.05332, saving model to model.hdf5
475/475 [==============================] - 47s 100ms/step - loss: 0.0731 - accuracy: 0.9775 - val_loss: 0.0533 - val_accuracy: 0.9837 - lr: 0.0010
Epoch 21/50
475/475 [==============================] - ETA: 0s - loss: 0.0710 - accuracy: 0.9782
Epoch 21: val_loss improved from 0.05332 to 0.05146, saving model to model.hdf5
475/475 [==============================] - 46s 96ms/step - loss: 0.0710 - accuracy: 0.9782 - val_loss: 0.0515 - val_accuracy: 0.9845 - lr: 0.0010
Epoch 22/50
475/475 [==============================] - ETA: 0s - loss: 0.0699 - accuracy: 0.9786
Epoch 22: val_loss improved from 0.05146 to 0.05109, saving model to model.hdf5
475/475 [==============================] - 46s 97ms/step - loss: 0.0699 - accuracy: 0.9786 - val_loss: 0.0511 - val_accuracy: 0.9842 - lr: 0.0010
Epoch 23/50
475/475 [==============================] - ETA: 0s - loss: 0.0684 - accuracy: 0.9787
Epoch 23: val_loss improved from 0.05109 to 0.04893, saving model to model.hdf5
475/475 [==============================] - 46s 98ms/step - loss: 0.0684 - accuracy: 0.9787 - val_loss: 0.0489 - val_accuracy: 0.9846 - lr: 0.0010
Epoch 24/50
475/475 [==============================] - ETA: 0s - loss: 0.0681 - accuracy: 0.9796
Epoch 24: val_loss did not improve from 0.04893
475/475 [==============================] - 47s 98ms/step - loss: 0.0681 - accuracy: 0.9796 - val_loss: 0.0499 - val_accuracy: 0.9839 - lr: 0.0010
Epoch 25/50
475/475 [==============================] - ETA: 0s - loss: 0.0667 - accuracy: 0.9795
Epoch 25: val_loss did not improve from 0.04893
475/475 [==============================] - 49s 103ms/step - loss: 0.0667 - accuracy: 0.9795 - val_loss: 0.0496 - val_accuracy: 0.9839 - lr: 0.0010
Epoch 26/50
475/475 [==============================] - ETA: 0s - loss: 0.0644 - accuracy: 0.9800
Epoch 26: val_loss improved from 0.04893 to 0.04852, saving model to model.hdf5
475/475 [==============================] - 47s 99ms/step - loss: 0.0644 - accuracy: 0.9800 - val_loss: 0.0485 - val_accuracy: 0.9849 - lr: 0.0010
Epoch 27/50
475/475 [==============================] - ETA: 0s - loss: 0.0655 - accuracy: 0.9799
Epoch 27: val_loss did not improve from 0.04852
475/475 [==============================] - 49s 103ms/step - loss: 0.0655 - accuracy: 0.9799 - val_loss: 0.0487 - val_accuracy: 0.9851 - lr: 0.0010
Epoch 28/50
475/475 [==============================] - ETA: 0s - loss: 0.0637 - accuracy: 0.9804
Epoch 28: val_loss improved from 0.04852 to 0.04546, saving model to model.hdf5
475/475 [==============================] - 50s 106ms/step - loss: 0.0637 - accuracy: 0.9804 - val_loss: 0.0455 - val_accuracy: 0.9857 - lr: 0.0010
Epoch 29/50
475/475 [==============================] - ETA: 0s - loss: 0.0616 - accuracy: 0.9810
Epoch 29: val_loss improved from 0.04546 to 0.04491, saving model to model.hdf5
475/475 [==============================] - 46s 97ms/step - loss: 0.0616 - accuracy: 0.9810 - val_loss: 0.0449 - val_accuracy: 0.9859 - lr: 0.0010
Epoch 30/50
475/475 [==============================] - ETA: 0s - loss: 0.0615 - accuracy: 0.9810
Epoch 30: val_loss did not improve from 0.04491
475/475 [==============================] - 46s 96ms/step - loss: 0.0615 - accuracy: 0.9810 - val_loss: 0.0467 - val_accuracy: 0.9854 - lr: 0.0010
Epoch 31/50
475/475 [==============================] - ETA: 0s - loss: 0.0598 - accuracy: 0.9813
Epoch 31: val_loss did not improve from 0.04491
475/475 [==============================] - 46s 97ms/step - loss: 0.0598 - accuracy: 0.9813 - val_loss: 0.0484 - val_accuracy: 0.9856 - lr: 0.0010
Epoch 32/50
475/475 [==============================] - ETA: 0s - loss: 0.0606 - accuracy: 0.9815
Epoch 32: val_loss did not improve from 0.04491
475/475 [==============================] - 46s 96ms/step - loss: 0.0606 - accuracy: 0.9815 - val_loss: 0.0455 - val_accuracy: 0.9859 - lr: 0.0010
Epoch 33/50
475/475 [==============================] - ETA: 0s - loss: 0.0595 - accuracy: 0.9820
Epoch 33: val_loss did not improve from 0.04491
475/475 [==============================] - 46s 97ms/step - loss: 0.0595 - accuracy: 0.9820 - val_loss: 0.0449 - val_accuracy: 0.9859 - lr: 0.0010
Epoch 34/50
475/475 [==============================] - ETA: 0s - loss: 0.0594 - accuracy: 0.9817
Epoch 34: val_loss improved from 0.04491 to 0.04402, saving model to model.hdf5
475/475 [==============================] - 47s 98ms/step - loss: 0.0594 - accuracy: 0.9817 - val_loss: 0.0440 - val_accuracy: 0.9859 - lr: 0.0010
Epoch 35/50
475/475 [==============================] - ETA: 0s - loss: 0.0567 - accuracy: 0.9820
Epoch 35: val_loss improved from 0.04402 to 0.04170, saving model to model.hdf5
475/475 [==============================] - 48s 101ms/step - loss: 0.0567 - accuracy: 0.9820 - val_loss: 0.0417 - val_accuracy: 0.9877 - lr: 0.0010
Epoch 36/50
475/475 [==============================] - ETA: 0s - loss: 0.0579 - accuracy: 0.9826
Epoch 36: val_loss improved from 0.04170 to 0.03999, saving model to model.hdf5
475/475 [==============================] - 47s 99ms/step - loss: 0.0579 - accuracy: 0.9826 - val_loss: 0.0400 - val_accuracy: 0.9872 - lr: 0.0010
Epoch 37/50
475/475 [==============================] - ETA: 0s - loss: 0.0575 - accuracy: 0.9824
Epoch 37: val_loss did not improve from 0.03999
475/475 [==============================] - 48s 100ms/step - loss: 0.0575 - accuracy: 0.9824 - val_loss: 0.0456 - val_accuracy: 0.9860 - lr: 0.0010
Epoch 38/50
475/475 [==============================] - ETA: 0s - loss: 0.0565 - accuracy: 0.9826
Epoch 38: val_loss improved from 0.03999 to 0.03931, saving model to model.hdf5
475/475 [==============================] - 47s 99ms/step - loss: 0.0565 - accuracy: 0.9826 - val_loss: 0.0393 - val_accuracy: 0.9875 - lr: 0.0010
Epoch 39/50
475/475 [==============================] - ETA: 0s - loss: 0.0566 - accuracy: 0.9827
Epoch 39: val_loss did not improve from 0.03931
475/475 [==============================] - 47s 99ms/step - loss: 0.0566 - accuracy: 0.9827 - val_loss: 0.0446 - val_accuracy: 0.9867 - lr: 0.0010
Epoch 40/50
475/475 [==============================] - ETA: 0s - loss: 0.0576 - accuracy: 0.9823
Epoch 40: val_loss did not improve from 0.03931
475/475 [==============================] - 47s 100ms/step - loss: 0.0576 - accuracy: 0.9823 - val_loss: 0.0406 - val_accuracy: 0.9872 - lr: 0.0010
```

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```
475/475 [==============================] - ETA: 0s - loss: 0.0548 - accuracy: 0.9827
Epoch 41: val_loss did not improve from 0.03931
475/475 [==============================] - 49s 102ms/step - loss: 0.0548 - accuracy: 0.9827 - val_loss: 0.0418 - val_accuracy: 0.9868 - lr: 0.0010
Epoch 42/50
475/475 [==============================] - ETA: 0s - loss: 0.0551 - accuracy: 0.9832
Epoch 42: val_loss did not improve from 0.03931
475/475 [==============================] - 50s 104ms/step - loss: 0.0551 - accuracy: 0.9832 - val_loss: 0.0413 - val_accuracy: 0.9876 - lr: 0.0010
Epoch 43/50
475/475 [==============================] - ETA: 0s - loss: 0.0544 - accuracy: 0.9831
Epoch 43: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.

Epoch 43: val_loss did not improve from 0.03931
475/475 [==============================] - 46s 97ms/step - loss: 0.0544 - accuracy: 0.9831 - val_loss: 0.0419 - val_accuracy: 0.9868 - lr: 0.0010
Epoch 44/50
475/475 [==============================] - ETA: 0s - loss: 0.0492 - accuracy: 0.9849
Epoch 44: val_loss improved from 0.03931 to 0.03580, saving model to model.hdf5
475/475 [==============================] - 46s 97ms/step - loss: 0.0492 - accuracy: 0.9849 - val_loss: 0.0358 - val_accuracy: 0.9888 - lr: 1.0000e-04
Epoch 45/50
475/475 [==============================] - ETA: 0s - loss: 0.0477 - accuracy: 0.9853
Epoch 45: val_loss did not improve from 0.03580
475/475 [==============================] - 46s 97ms/step - loss: 0.0477 - accuracy: 0.9853 - val_loss: 0.0366 - val_accuracy: 0.9888 - lr: 1.0000e-04
Epoch 46/50
475/475 [==============================] - ETA: 0s - loss: 0.0447 - accuracy: 0.9859
Epoch 46: val_loss did not improve from 0.03580
475/475 [==============================] - 46s 97ms/step - loss: 0.0447 - accuracy: 0.9859 - val_loss: 0.0365 - val_accuracy: 0.9887 - lr: 1.0000e-04
Epoch 47/50
475/475 [==============================] - ETA: 0s - loss: 0.0461 - accuracy: 0.9860
Epoch 47: val_loss did not improve from 0.03580
475/475 [==============================] - 47s 99ms/step - loss: 0.0461 - accuracy: 0.9860 - val_loss: 0.0360 - val_accuracy: 0.9887 - lr: 1.0000e-04
Epoch 48/50
475/475 [==============================] - ETA: 0s - loss: 0.0444 - accuracy: 0.9862
Epoch 48: val_loss improved from 0.03580 to 0.03403, saving model to model.hdf5
475/475 [==============================] - 49s 104ms/step - loss: 0.0444 - accuracy: 0.9862 - val_loss: 0.0340 - val_accuracy: 0.9895 - lr: 1.0000e-04
Epoch 49/50
475/475 [==============================] - ETA: 0s - loss: 0.0427 - accuracy: 0.9870
Epoch 49: val_loss did not improve from 0.03403
475/475 [==============================] - 59s 124ms/step - loss: 0.0427 - accuracy: 0.9870 - val_loss: 0.0356 - val_accuracy: 0.9883 - lr: 1.0000e-04
Epoch 50/50
475/475 [==============================] - ETA: 0s - loss: 0.0439 - accuracy: 0.9864
Epoch 50: val_loss improved from 0.03403 to 0.03369, saving model to model.hdf5
475/475 [==============================] - 54s 114ms/step - loss: 0.0439 - accuracy: 0.9864 - val_loss: 0.0337 - val_accuracy: 0.9892 - lr: 1.0000e-04
```

6. Model evaluation

6.1 Loss plot curve for training and validation

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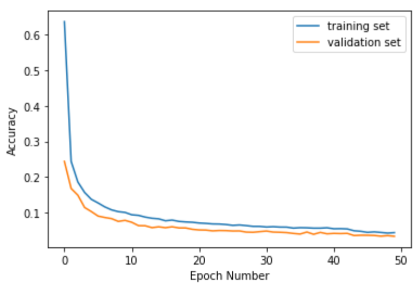
Let's see how the loss function was changing during the training. We expect it to get smaller and smaller on every next epoch.

In [52]:
```
plt.xlabel('Epoch Number')
plt.ylabel('Accuracy')
plt.plot(training_history.history['loss'], label='training set')
plt.plot(training_history.history['val_loss'], label='validation set')
plt.legend()
```

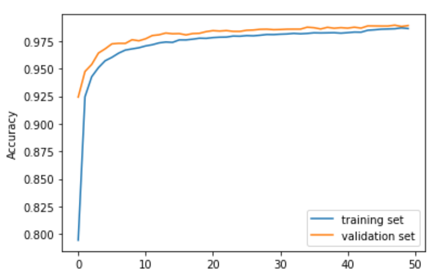
Out[52]:
```
<matplotlib.legend.Legend at 0x1d940fb8370>
```



6.2. Accuracy plot curve for training and validation

In [53]:
```
plt.xlabel('Epoch Number')
plt.ylabel('Accuracy')
plt.plot(training_history.history['accuracy'], label='training set')
plt.plot(training_history.history['val_accuracy'], label='validation set')
plt.legend()
```

Out[53]:
```
<matplotlib.legend.Legend at 0x1d94110cc10>
```



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6.3. Evaluation of the model accuracy

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We need to compare the accuracy of our model on training set and on valiation set. We expect our model to perform similarly on both sets. If the performance on a validation set will be poor comparing to a training set it would be an indicator for us that the model is overfitted and we have a "high variance" issue.

6.3.1 Performance of training dataset

In [55]:
```
%%capture
train_loss, train_accuracy = model.evaluate(x_train_normalized, y_train_re)
```

In [56]:
```
print('Train loss: ', train_loss)
print('Train accuracy: ', train_accuracy)
```

```
Train loss:  0.018946522846817 97
Train accuracy:  0.9940246939659119
```

6.3.2. Load the model

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We will save the entire model to a HDF5 file. The .h5 extension of the file indicates that the model shuold be saved in Keras format as HDF5 file. To use this model on the front-end we will convert it (later in this notebook) to Javascript understandable format.

In [57]:
```
# model_name = 'digits_recognition_cnn.h5'
# model.save(model_name, save_format='h5')
#loaded_model = tf.keras.models.load_model(model_name)
model.load_weights('model.hdf5')
```

7. Model prediction on unseen dataset (test data)

In [58]:
```
predictions_one_hot = model.predict([x_test_normalized])
print('predictions_one_hot:', predictions_one_hot.shape)
```

```
875/875 [==============================] - 3s 3ms/step
predictions_one_hot: (28000, 10)
```

Each prediction has ten probabilities (one for each number from 0 to 9). We need to choose the digit with the highest probability.

Predicted probabilities of all digits.

In [61]:
```
pd.DataFrame(predictions_one_hot)
```

Out[61]:

	0	1	2	3	4	5	6	7	8	9
0	1.781171e-12	1.442291e-11	9.999989e-01	2.989957e-07	8.458501e-09	9.151321e-08	4.563856e-12	6.654272e-07	9.626757e-11	4.231548e-09
1	9.999995e-01	2.505558e-12	1.321511e-08	2.180716e-11	4.247059e-09	1.036556e-07	1.765668e-07	2.628981e-11	6.667927e-09	1.353229e-07
2	3.163892e-10	3.170540e-12	6.300222e-06	8.214946e-08	4.385194e-07	4.779413e-08	9.421623e-09	4.572646e-08	9.760632e-05	9.998955e-01
3	8.439262e-01	2.731243e-06	4.284543e-02	2.331229e-02	1.112707e-03	1.645338e-03	5.197275e-03	7.870293e-05	5.270755e-02	2.917184e-02
4	1.468043e-22	1.551448e-14	4.842058e-10	1.000000e+00	1.767710e-19	4.717468e-10	2.184462e-20	6.716866e-14	4.835097e-11	7.986035e-14
...	...	...	...	...	...	...	...	...	...	...
27995	2.029743e-14	1.619046e-17	3.017429e-10	4.252064e-12	6.000774e-09	7.299546e-11	2.192801e-14	5.231710e-10	4.807209e-10	1.000000e+00
27996	5.196819e-09	2.165186e-06	9.053892e-05	1.365667e-05	1.239415e-06	3.663089e-07	3.026167e-11	9.998845e-01	2.342146e-07	7.319047e-06
27997	5.802587e-24	8.816616e-14	6.442450e-12	1.000000e+00	8.935451e-20	7.184616e-09	5.426159e-21	1.054883e-13	2.215899e-11	1.463649e-14
27998	2.275881e-11	1.425552e-12	8.731581e-08	5.421106e-08	2.616366e-06	6.535109e-09	9.417002e-13	8.534664e-07	1.076356e-09	9.999964e-01
27999	4.559195e-17	1.594835e-15	1.000000e+00	3.347225e-08	3.305892e-13	7.929736e-11	3.248144e-14	1.582618e-10	7.844302e-12	1.914855e-13

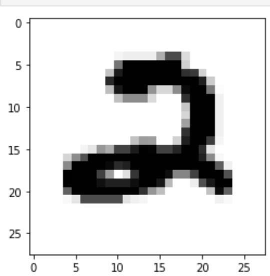
28000 rows × 10 columns

7.1 Visualise test predicted data how the digits were written¶ Back to Table of Contents

Predicted digits with highest probabilites

Actual first digit from the test data

In [62]:
```
plt.imshow(x_test_normalized[0].reshape((IMAGE_WIDTH, IMAGE_HEIGHT)), cmap=plt.cm.binary)
plt.show()
```



So our model is predicting that the first example from the test data is 2 and actual was also 2.

8. Submission

Loading [MathJax]/extensions/Safe.js

In [63]:
```
test_pred = pd.DataFrame( model.predict([x_test_normalized]))
test_pred = pd.DataFrame(test_pred.idxmax(axis = 1))
test_pred.index.name = 'ImageId'
test_pred = test_pred.rename(columns = {0: 'Label'}).reset_index()
test_pred['ImageId'] = test_pred['ImageId'] + 1

test_pred.head()
```

```
875/875 [==============================] - 2s 3ms/step
```

Out[63]:

	ImageId	Label
0	1	2
1	2	0
2	3	9
3	4	0
4	5	3

In [64]:
```
test_pred.to_csv('submission.csv', index = False)
```

In [ ]:

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