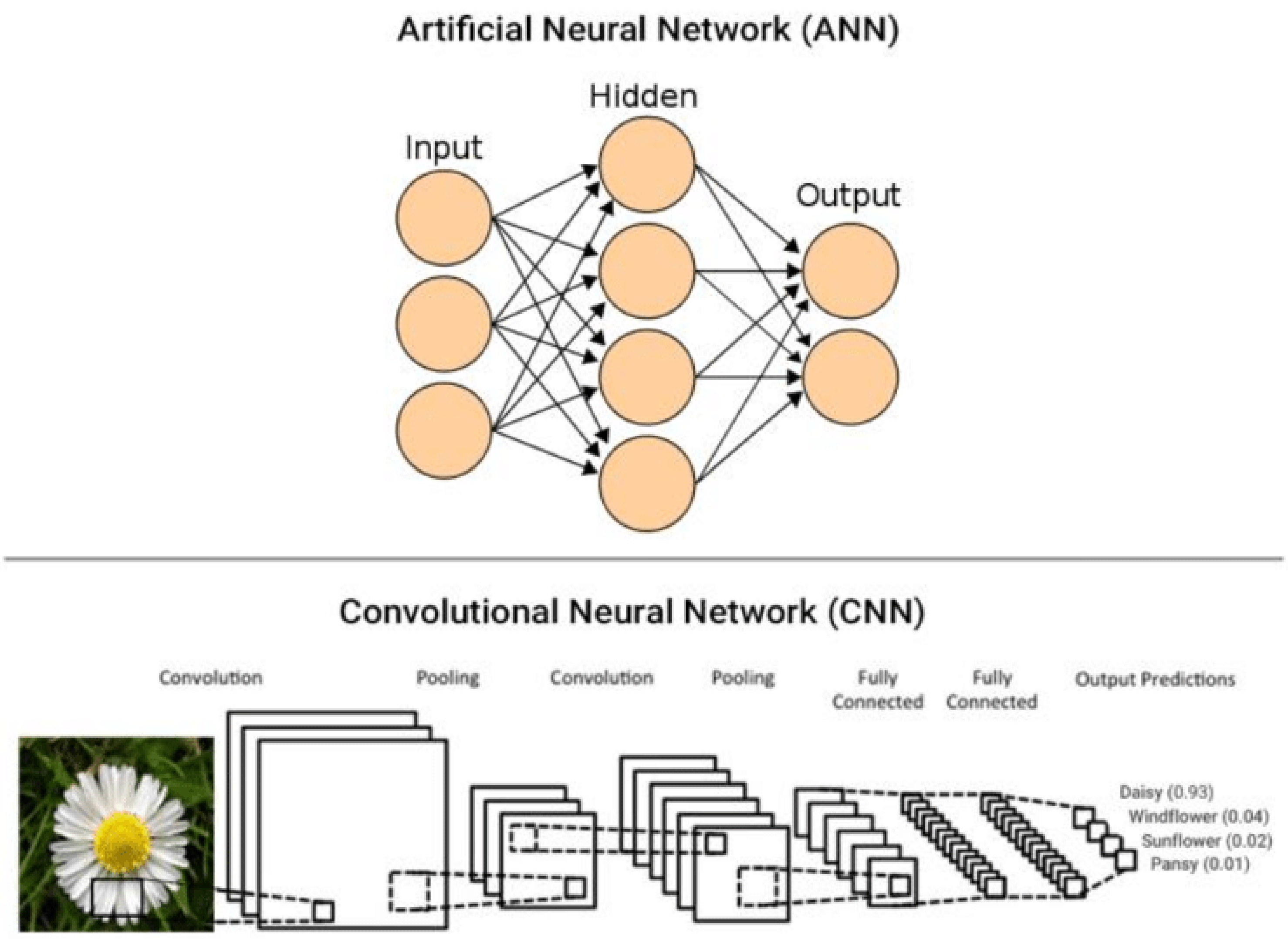
Artificial Neural Network (ANN) VS Convolutional Neural Network (CNN)

Using both **ANN** and **CNN** on **Digits Mnist dataset**

https://en.wikipedia.org/wiki/MNIST_database



Artificial Neural Network (ANN)

In [1]:
```
# !pip install tensorflow
```

In [47]:
```
# Importing required libraries
import warnings
warnings.filterwarnings("ignore")
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
import os
import seaborn as sns
import keras
from keras.models import Sequential
from keras.layers import Dense,Flatten,BatchNormalization,Dropout
from keras.layers import LeakyReLU,Conv2D,MaxPooling2D,AveragePooling2D
from keras import regularizers
import time
```

In [3]:
```
print(tf.__version__) # Tensorflow version
```

```
2.13.0
```

In [4]:
```
tf.config.list_physical_devices("GPU") # Finding GPU
```

Out[4]:
```
[]
```

In [5]:
```
tf.config.list_physical_devices("CPU") # Finding CPU
```

Out[5]:
```
[PhysicalDevice(name='/physical_device:CPU:0', device_type='CPU')]
```

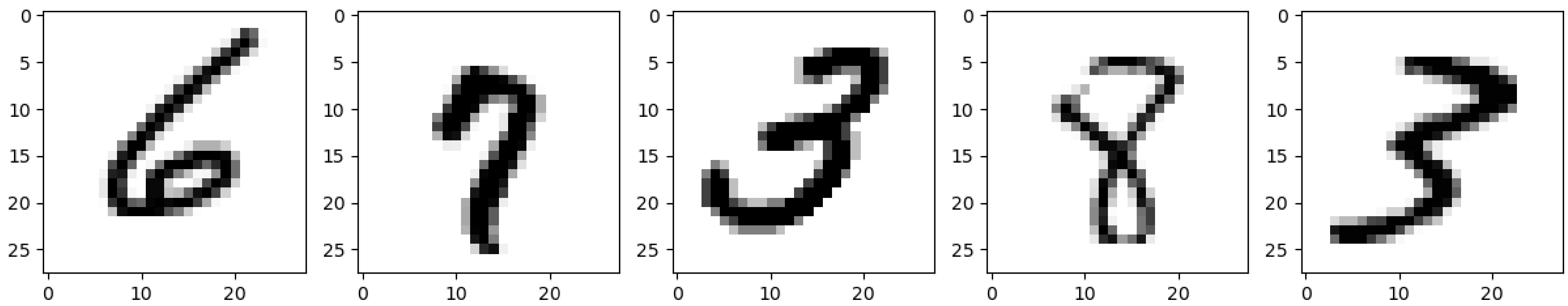
In [6]:
```
# Loading Mnist dataset from tensorflow
mnist = tf.keras.datasets.mnist
(x_train_full, y_train_full) , (x_test, y_test) = mnist.load_data()
```

In [7]:
```
# Shape of Mnist dataset
print(x_train_full.shape) # Training data shape
print(x_test.shape)       # Testing data shape
```

```
(60000, 28, 28)
(10000, 28, 28)
```

In [8]:
```
# There are 60000 image of handwritten digits and each image has resolution 28*28 which is equal to 784 pixels
```

In [9]:
```
# Here is some example
k = 5
plt.figure(figsize=(15,5))
for i in range(1,k+1):
    plt.subplot(1,k,i)
    idx = int(np.random.randint(0,60000,1))
    plt.imshow(x_train_full[idx], cmap="binary")
plt.show()
```



In [10]:
```
x_train_full[0] # Image at "0" index
```

```
Out[10]: 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,   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,   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,   3,
           18,  18,  18, 126, 136, 175,  26, 166, 255, 247, 127,   0,   0,
            0,   0],
          [  0,   0,   0,   0,   0,   0,   0,   0,  30,  36,  94, 154, 170,
          253, 253, 253, 253, 253, 225, 172, 253, 242, 195,  64,   0,   0,
            0,   0],
          [  0,   0,   0,   0,   0,   0,   0,  49, 238, 253, 253, 253, 253,
          253, 253, 253, 253, 251,  93,  82,  82,  56,  39,   0,   0,   0,
            0,   0],
          [  0,   0,   0,   0,   0,   0,   0,  18, 219, 253, 253, 253, 253,
          253, 198, 182, 247, 241,   0,   0,   0,   0,   0,   0,   0,   0,
            0,   0],
          [  0,   0,   0,   0,   0,   0,   0,   0,  80, 156, 107, 253, 253,
          205,  11,   0,  43, 154,   0,   0,   0,   0,   0,   0,   0,   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, 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,  11, 190,
          253,  70,   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,  35,
          241, 225, 160, 108,   1,   0,   0,   0,   0,   0,   0,   0,   0,
            0,   0],
          [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
           81, 240, 253, 253, 119,  25,   0,   0,   0,   0,   0,   0,   0,
            0,   0],
          [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
            0,  45, 186, 253, 253, 150,  27,   0,   0,   0,   0,   0,   0,
            0,   0],
          [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
            0,   0,  16,  93, 252, 253, 187,   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, 249, 253, 249,  64,   0,   0,   0,   0,   0,
            0,   0],
          [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
            0,  46, 130, 183, 253, 253, 207,   2,   0,   0,   0,   0,   0,
            0,   0],
          [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,  39,
          148, 229, 253, 253, 253, 250, 182,   0,   0,   0,   0,   0,   0,
            0,   0],
          [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,  24, 114, 221,
          253, 253, 253, 253, 201,  78,   0,   0,   0,   0,   0,   0,   0,
            0,   0],
          [  0,   0,   0,   0,   0,   0,   0,   0,  23,  66, 213, 253, 253,
          253, 253, 198,  81,   2,   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,  55, 172, 226, 253, 253, 253, 253, 244, 133,
           11,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
            0,   0],
          [  0,   0,   0,   0, 136, 253, 253, 253, 212, 135, 132,  16,   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,   0,   0,   0,   0,   0,   0,   0,
            0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
            0,   0]], dtype=uint8)
```

```
In [11]: y_train_full[0] # Number at "0" index
```

Out[11]: 5

In [12]:
```
# Converting the pixels value between 0 to 1
x_valid, x_train = x_train_full[:5000]/255, x_train_full[5000:]/255
y_valid, y_train = y_train_full[:5000], y_train_full[5000:]

x_test = x_test/255
```

First ANN Network

In [13]:
```
# Defining the layers
LAYERS = [
    tf.keras.layers.Flatten(input_shape=[28,28],name="inputLayer"),
    tf.keras.layers.Dense(300,activation="relu",name="hiddenLayer1"),
    tf.keras.layers.Dense(100,activation="relu",name="hiddenLayer2"),
    tf.keras.layers.Dense(10,activation="softmax",name="outputLayer")
]

model = tf.keras.models.Sequential(LAYERS)
```

In [14]:
```
model.summary() # Summary of the model
```

```
Model: "sequential"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 inputLayer (Flatten)        (None, 784)               0

 hiddenLayer1 (Dense)        (None, 300)               235500

 hiddenLayer2 (Dense)        (None, 100)               30100

 outputLayer (Dense)         (None, 10)                1010

=================================================================
Total params: 266610 (1.02 MB)
Trainable params: 266610 (1.02 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [15]:
```
input_layer = model.layers[0]
input_layer.get_weights()
```

Out[15]: []

In [16]:
```
# Input layer has no weights
```

In [17]:
```
hidden1 = model.layers[1]
hidden1.get_weights() # The weights of first hidden layer
```

Out[17]:
```
[array([[ 0.05054694,  0.05149697,  0.03309961, ...,  0.02394158,
         -0.05443621, -0.0246108 ],
        [-0.03562779,  0.052334  , -0.00815411, ..., -0.05099124,
         -0.03987789,  0.06253996],
        [-0.05267614, -0.00288451, -0.04274706, ..., -0.03713851,
         -0.006381  , -0.04133867],
        ...,
        [-0.00974952, -0.05030172,  0.00722869, ...,  0.04120136,
          0.05719981, -0.03929667],
        [ 0.05011772, -0.07320872,  0.03449158, ...,  0.06320289,
         -0.00371967, -0.04382963],
        [ 0.0317823 , -0.03270683, -0.00461791, ..., -0.02013218,
         -0.06971186,  0.01487658]], dtype=float32),
 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., 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., 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., 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.,
        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.], dtype=float32)]
```

In [18]:
```
# Defining Loss_function,Optimizer,Metrics and compiling the model
loss_function = "sparse_categorical_crossentropy"
```

```python
OPTIMIZER = tf.keras.optimizers.SGD(learning_rate=0.001)
METRICS = ["accuracy"]

model.compile(
    loss=loss_function,
    optimizer=OPTIMIZER,
    metrics=METRICS
)
```

In [19]:
```python
# Creating a function for saving the logs at proper folder
def get_log_path(log_dir="logs/fit"):
    filename = time.strftime("1_log_%y_%m_%d_%H_%M_%S")
    logs_path = os.path.join(log_dir,filename)
    print(f"Saving logs at {logs_path}")
    return logs_path
```

In [20]:
```python
# Creating logs callback
log_dirs = get_log_path()
tb_cb = tf.keras.callbacks.TensorBoard(log_dir=log_dirs)
```

```
Saving logs at logs/fit/1_log_23_09_26_19_48_02
```

In [21]:
```python
# Creating early stopping callback
early_stopping_cb = tf.keras.callbacks.EarlyStopping(patience=7, restore_best_weights=True)
```

In [22]:
```python
# Saving the model with callback
CKPT_path = os.path.join("Models","Model_ckpt_Digit_mnist_1.h5")
checkpoint_cb = tf.keras.callbacks.ModelCheckpoint(CKPT_path, save_best_only=True)
```

In [23]:
```python
EPOCHS = 50 # Number of Epochs
VALIDATION_SET = (x_valid,y_valid) # Validation data
history = model.fit(x_train,y_train,epochs=EPOCHS,validation_data=VALIDATION_SET,batch_size=64, # Training the model
                    callbacks=[tb_cb,early_stopping_cb,checkpoint_cb],use_multiprocessing=True)
```

```
Epoch 1/50
860/860 [==============================] - 4s 4ms/step - loss: 2.0446 - accuracy: 0.4097 - val_loss: 1.7333 - val_accuracy:
0.6436
Epoch 2/50
860/860 [==============================] - 3s 4ms/step - loss: 1.4550 - accuracy: 0.7157 - val_loss: 1.1851 - val_accuracy:
0.7628
Epoch 3/50
860/860 [==============================] - 4s 4ms/step - loss: 1.0196 - accuracy: 0.7898 - val_loss: 0.8604 - val_accuracy:
0.8108
Epoch 4/50
860/860 [==============================] - 3s 4ms/step - loss: 0.7823 - accuracy: 0.8234 - val_loss: 0.6892 - val_accuracy:
0.8376
Epoch 5/50
860/860 [==============================] - 3s 4ms/step - loss: 0.6523 - accuracy: 0.8436 - val_loss: 0.5889 - val_accuracy:
0.8564
Epoch 6/50
860/860 [==============================] - 3s 4ms/step - loss: 0.5727 - accuracy: 0.8573 - val_loss: 0.5238 - val_accuracy:
0.8694
Epoch 7/50
860/860 [==============================] - 3s 4ms/step - loss: 0.5191 - accuracy: 0.8671 - val_loss: 0.4781 - val_accuracy:
0.8798
Epoch 8/50
860/860 [==============================] - 3s 4ms/step - loss: 0.4806 - accuracy: 0.8746 - val_loss: 0.4446 - val_accuracy:
0.8860
Epoch 9/50
860/860 [==============================] - 4s 4ms/step - loss: 0.4515 - accuracy: 0.8803 - val_loss: 0.4181 - val_accuracy:
0.8916
Epoch 10/50
860/860 [==============================] - 3s 4ms/step - loss: 0.4287 - accuracy: 0.8844 - val_loss: 0.3975 - val_accuracy:
0.8954
Epoch 11/50
860/860 [==============================] - 3s 4ms/step - loss: 0.4102 - accuracy: 0.8883 - val_loss: 0.3804 - val_accuracy:
0.8988
Epoch 12/50
860/860 [==============================] - 3s 4ms/step - loss: 0.3947 - accuracy: 0.8915 - val_loss: 0.3666 - val_accuracy:
0.9014
Epoch 13/50
860/860 [==============================] - 3s 4ms/step - loss: 0.3817 - accuracy: 0.8940 - val_loss: 0.3545 - val_accuracy:
0.9036
Epoch 14/50
860/860 [==============================] - 3s 4ms/step - loss: 0.3705 - accuracy: 0.8967 - val_loss: 0.3441 - val_accuracy:
0.9052
Epoch 15/50
860/860 [==============================] - 3s 4ms/step - loss: 0.3607 - accuracy: 0.8986 - val_loss: 0.3350 - val_accuracy:
0.9072
Epoch 16/50
860/860 [==============================] - 3s 4ms/step - loss: 0.3520 - accuracy: 0.9012 - val_loss: 0.3265 - val_accuracy:
0.9082
Epoch 17/50
860/860 [==============================] - 3s 4ms/step - loss: 0.3441 - accuracy: 0.9027 - val_loss: 0.3193 - val_accuracy:
0.9094
Epoch 18/50
860/860 [==============================] - 3s 4ms/step - loss: 0.3369 - accuracy: 0.9049 - val_loss: 0.3126 - val_accuracy:
0.9116
Epoch 19/50
860/860 [==============================] - 3s 4ms/step - loss: 0.3304 - accuracy: 0.9063 - val_loss: 0.3067 - val_accuracy:
0.9148
Epoch 20/50
860/860 [==============================] - 3s 4ms/step - loss: 0.3243 - accuracy: 0.9083 - val_loss: 0.3010 - val_accuracy:
0.9158
Epoch 21/50
860/860 [==============================] - 3s 4ms/step - loss: 0.3187 - accuracy: 0.9096 - val_loss: 0.2957 - val_accuracy:
0.9168
Epoch 22/50
860/860 [==============================] - 3s 4ms/step - loss: 0.3135 - accuracy: 0.9110 - val_loss: 0.2911 - val_accuracy:
0.9182
Epoch 23/50
860/860 [==============================] - 3s 4ms/step - loss: 0.3087 - accuracy: 0.9122 - val_loss: 0.2862 - val_accuracy:
0.9202
Epoch 24/50
860/860 [==============================] - 3s 4ms/step - loss: 0.3039 - accuracy: 0.9135 - val_loss: 0.2823 - val_accuracy:
0.9210
Epoch 25/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2995 - accuracy: 0.9143 - val_loss: 0.2782 - val_accuracy:
0.9216
Epoch 26/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2954 - accuracy: 0.9157 - val_loss: 0.2742 - val_accuracy:
0.9234
Epoch 27/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2913 - accuracy: 0.9168 - val_loss: 0.2707 - val_accuracy:
0.9236
Epoch 28/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2875 - accuracy: 0.9180 - val_loss: 0.2670 - val_accuracy:
0.9246
Epoch 29/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2839 - accuracy: 0.9192 - val_loss: 0.2637 - val_accuracy:
0.9256
```

```
Epoch 30/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2804 - accuracy: 0.9205 - val_loss: 0.2607 - val_accuracy:
0.9256
Epoch 31/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2769 - accuracy: 0.9206 - val_loss: 0.2572 - val_accuracy:
0.9272
Epoch 32/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2737 - accuracy: 0.9216 - val_loss: 0.2545 - val_accuracy:
0.9270
Epoch 33/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2706 - accuracy: 0.9228 - val_loss: 0.2519 - val_accuracy:
0.9280
Epoch 34/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2675 - accuracy: 0.9241 - val_loss: 0.2489 - val_accuracy:
0.9286
Epoch 35/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2645 - accuracy: 0.9249 - val_loss: 0.2462 - val_accuracy:
0.9304
Epoch 36/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2617 - accuracy: 0.9256 - val_loss: 0.2433 - val_accuracy:
0.9312
Epoch 37/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2588 - accuracy: 0.9266 - val_loss: 0.2409 - val_accuracy:
0.9320
Epoch 38/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2561 - accuracy: 0.9271 - val_loss: 0.2385 - val_accuracy:
0.9328
Epoch 39/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2534 - accuracy: 0.9278 - val_loss: 0.2356 - val_accuracy:
0.9338
Epoch 40/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2509 - accuracy: 0.9284 - val_loss: 0.2337 - val_accuracy:
0.9336
Epoch 41/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2484 - accuracy: 0.9298 - val_loss: 0.2312 - val_accuracy:
0.9348
Epoch 42/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2459 - accuracy: 0.9301 - val_loss: 0.2291 - val_accuracy:
0.9364
Epoch 43/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2435 - accuracy: 0.9306 - val_loss: 0.2270 - val_accuracy:
0.9362
Epoch 44/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2412 - accuracy: 0.9315 - val_loss: 0.2247 - val_accuracy:
0.9372
Epoch 45/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2389 - accuracy: 0.9321 - val_loss: 0.2227 - val_accuracy:
0.9374
Epoch 46/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2367 - accuracy: 0.9326 - val_loss: 0.2211 - val_accuracy:
0.9382
Epoch 47/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2345 - accuracy: 0.9335 - val_loss: 0.2188 - val_accuracy:
0.9384
Epoch 48/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2323 - accuracy: 0.9338 - val_loss: 0.2169 - val_accuracy:
0.9384
Epoch 49/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2302 - accuracy: 0.9343 - val_loss: 0.2151 - val_accuracy:
0.9400
Epoch 50/50
860/860 [==============================] - 3s 4ms/step - loss: 0.2282 - accuracy: 0.9348 - val_loss: 0.2134 - val_accuracy:
0.9400
```

In [24]:
```
pd.DataFrame(history.history) # All the losses and accuracy in each epoch
```

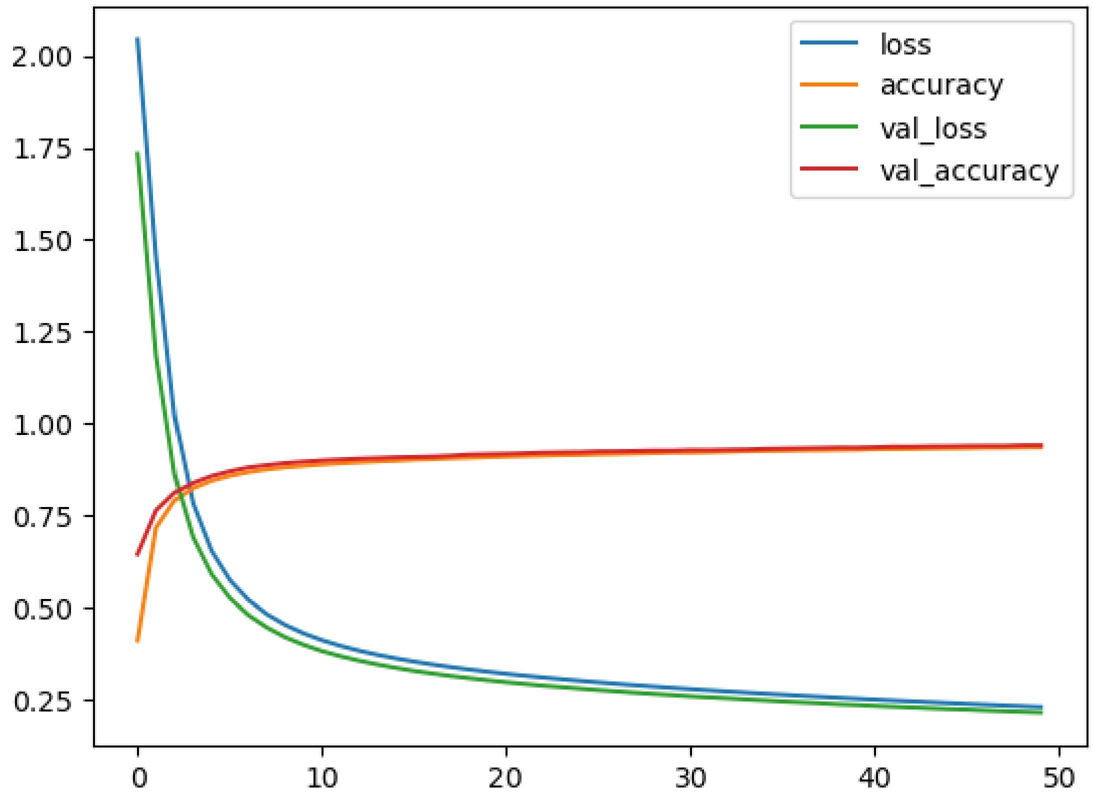
Out[24]:

	loss	accuracy	val_loss	val_accuracy
0	2.044599	0.409745	1.733334	0.6436
1	1.455023	0.715709	1.185071	0.7628
2	1.019633	0.789800	0.860445	0.8108
3	0.782261	0.823436	0.689154	0.8376
4	0.652308	0.843582	0.588874	0.8564
5	0.572710	0.857255	0.523771	0.8694
6	0.519132	0.867127	0.478128	0.8798
7	0.480602	0.874636	0.444642	0.8860
8	0.451508	0.880273	0.418126	0.8916
9	0.428673	0.884400	0.397529	0.8954
10	0.410156	0.888255	0.380364	0.8988
11	0.394743	0.891545	0.366589	0.9014
12	0.381738	0.894036	0.354540	0.9036
13	0.370523	0.896655	0.344144	0.9052
14	0.360709	0.898564	0.334979	0.9072
15	0.351955	0.901182	0.326504	0.9082
16	0.344110	0.902709	0.319325	0.9094
17	0.336940	0.904909	0.312572	0.9116
18	0.330399	0.906345	0.306733	0.9148
19	0.324309	0.908327	0.300988	0.9158
20	0.318691	0.909636	0.295740	0.9168
21	0.313513	0.911000	0.291094	0.9182
22	0.308652	0.912200	0.286233	0.9202
23	0.303929	0.913527	0.282320	0.9210
24	0.299470	0.914255	0.278207	0.9216
25	0.295367	0.915745	0.274233	0.9234
26	0.291341	0.916800	0.270697	0.9236
27	0.287510	0.917964	0.267022	0.9246
28	0.283905	0.919200	0.263742	0.9256
29	0.280367	0.920509	0.260654	0.9256
30	0.276936	0.920564	0.257197	0.9272
31	0.273685	0.921582	0.254464	0.9270
32	0.270556	0.922836	0.251917	0.9280
33	0.267517	0.924127	0.248867	0.9286
34	0.264475	0.924945	0.246232	0.9304
35	0.261701	0.925564	0.243337	0.9312
36	0.258824	0.926582	0.240950	0.9320
37	0.256124	0.927091	0.238550	0.9328
38	0.253415	0.927782	0.235629	0.9338
39	0.250865	0.928364	0.233744	0.9336
40	0.248369	0.929782	0.231237	0.9348
41	0.245898	0.930109	0.229094	0.9364
42	0.243542	0.930636	0.227009	0.9362
43	0.241214	0.931473	0.224715	0.9372
44	0.238904	0.932091	0.222734	0.9374
45	0.236651	0.932600	0.221052	0.9382
46	0.234489	0.933545	0.218850	0.9384
47	0.232283	0.933782	0.216922	0.9384
48	0.230208	0.934345	0.215123	0.9400
49	0.228181	0.934836	0.213441	0.9400

In [25]:

```
pd.DataFrame(history.history).plot() # Plotting all of the accuracy and losses
```

Out[25]: <AxesSubplot: >



In [26]:
```
ckpt_model = tf.keras.models.load_model(CKPT_path) # Loading model
ckpt_model.evaluate(x_test,y_test)                 # Evaluating the performance of the model on test data
```

```
313/313 [==============================] - 1s 2ms/step - loss: 0.2221 - accuracy: 0.9365
```

Out[26]: [0.2220998853445053, 0.9365000128746033]

The test accuracy of the first **ANN** model is **93.65 %**

In [27]:
```
# Predicting the probability of 5 samples randomly
print("Probability of each number for image of testing data:- \n")
for j in range(5):
    idx = np.random.randint(0,10000,1)[0]
    y_prob_lst = ckpt_model.predict(x_test[idx-1:idx]).round(3)[0]
    print("\nNumber : Probability")
    for i in range(10):
        print(i,"     :      ",y_prob_lst[i])
    y_predict = np.argmax(y_prob_lst,axis=-1)
    print("Predicted final output is: ",y_predict,"\n")
```

```
Probability of each number for image of testing data:-

1/1 [==============================] - 0s 105ms/step

Number : Probability
0      :      0.0
1      :      0.0
2      :      0.001
3      :      0.001
4      :      0.05
5      :      0.0
6      :      0.0
7      :      0.007
8      :      0.001
9      :      0.94
Predicted final output is:  9

1/1 [==============================] - 0s 26ms/step

Number : Probability
0      :      0.289
1      :      0.0
2      :      0.005
3      :      0.0
4      :      0.439
5      :      0.048
6      :      0.035
7      :      0.008
8      :      0.121
9      :      0.054
Predicted final output is:  4

1/1 [==============================] - 0s 25ms/step

Number : Probability
0      :      0.002
1      :      0.0
2      :      0.002
3      :      0.006
4      :      0.002
5      :      0.697
6      :      0.0
7      :      0.019
8      :      0.026
9      :      0.245
Predicted final output is:  5

1/1 [==============================] - 0s 26ms/step

Number : Probability
0      :      0.0
1      :      0.0
2      :      0.0
3      :      0.003
4      :      0.051
5      :      0.001
6      :      0.0
7      :      0.047
8      :      0.001
9      :      0.896
Predicted final output is:  9

1/1 [==============================] - 0s 26ms/step

Number : Probability
0      :      0.0
1      :      0.0
2      :      0.999
3      :      0.0
4      :      0.0
5      :      0.0
6      :      0.0
7      :      0.0
8      :      0.001
9      :      0.0
Predicted final output is:  2
```

In [28]:

```
del model
del ckpt_model
```

Second ANN Network

In [29]:

```
# Added kernel regularization,batch normalization,dropout and leakyrelu activation function
model = Sequential()
model.add(Flatten(input_shape=[28,28]))
```

```
model.add(Dense(units=256,kernel_regularizer=regularizers.L1L2(0.0001,0.0001)))
model.add(BatchNormalization())
model.add(LeakyReLU())
model.add(Dropout(0.1))
model.add(Dense(units=128,kernel_regularizer=regularizers.L1L2(0.0001,0.0001)))
model.add(BatchNormalization())
model.add(LeakyReLU())
model.add(Dropout(0.1))
model.add(Dense(units=64,kernel_regularizer=regularizers.L1L2(0.0001,0.0001)))
model.add(BatchNormalization())
model.add(LeakyReLU())
model.add(Dropout(0.1))
model.add(Dense(units=32,kernel_regularizer=regularizers.L1L2(0.0001,0.0001)))
model.add(BatchNormalization())
model.add(LeakyReLU())
model.add(Dropout(0.1))
model.add(Dense(units=16,kernel_regularizer=regularizers.L1L2(0.0001,0.0001)))
model.add(BatchNormalization())
model.add(LeakyReLU())
model.add(Dropout(0.1))
model.add(Dense(units=10,activation="softmax"))
```

In [30]:
```
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 flatten (Flatten)           (None, 784)               0

 dense (Dense)               (None, 256)               200960

 batch_normalization (Batch  (None, 256)               1024
 Normalization)

 leaky_re_lu (LeakyReLU)     (None, 256)               0

 dropout (Dropout)           (None, 256)               0

 dense_1 (Dense)             (None, 128)               32896

 batch_normalization_1 (Bat  (None, 128)               512
 chNormalization)

 leaky_re_lu_1 (LeakyReLU)   (None, 128)               0

 dropout_1 (Dropout)         (None, 128)               0

 dense_2 (Dense)             (None, 64)                8256

 batch_normalization_2 (Bat  (None, 64)                256
 chNormalization)

 leaky_re_lu_2 (LeakyReLU)   (None, 64)                0

 dropout_2 (Dropout)         (None, 64)                0

 dense_3 (Dense)             (None, 32)                2080

 batch_normalization_3 (Bat  (None, 32)                128
 chNormalization)

 leaky_re_lu_3 (LeakyReLU)   (None, 32)                0

 dropout_3 (Dropout)         (None, 32)                0

 dense_4 (Dense)             (None, 16)                528

 batch_normalization_4 (Bat  (None, 16)                64
 chNormalization)

 leaky_re_lu_4 (LeakyReLU)   (None, 16)                0

 dropout_4 (Dropout)         (None, 16)                0

 dense_5 (Dense)             (None, 10)                170

=================================================================
Total params: 246874 (964.35 KB)
Trainable params: 245882 (960.48 KB)
Non-trainable params: 992 (3.88 KB)
_________________________________________________________________
```

In [31]:
```
def get_log_path(log_dir="logs/fit"):
    filename = time.strftime("2_log_%y_%m_%d_%H_%M_%S")
    logs_path = os.path.join(log_dir, filename)
    print(f"Saving logs at {logs_path}")
```

```
    return logs_path

log_dirs = get_log_path()
tb_cb = tf.keras.callbacks.TensorBoard(log_dir=log_dirs)

early_stopping_cb = tf.keras.callbacks.EarlyStopping(patience=7, restore_best_weights=True)

CKPT_path = os.path.join("Models","Model_ckpt_Digit_mnist_2.h5")
checkpoint_cb = tf.keras.callbacks.ModelCheckpoint(CKPT_path, save_best_only=True)

EPOCHS = 50
VALIDATION_SET = (x_valid, y_valid)

loss_function = "sparse_categorical_crossentropy"
OPTIMIZER = tf.keras.optimizers.Adam(learning_rate=0.001)
METRICS = ["accuracy"]

model.compile(
    loss=loss_function,
    optimizer=OPTIMIZER,
    metrics=METRICS
)

history = model.fit(x_train, y_train, epochs=EPOCHS, validation_data=VALIDATION_SET, batch_size=64,
                    callbacks=[tb_cb, early_stopping_cb, checkpoint_cb],use_multiprocessing=True)
```

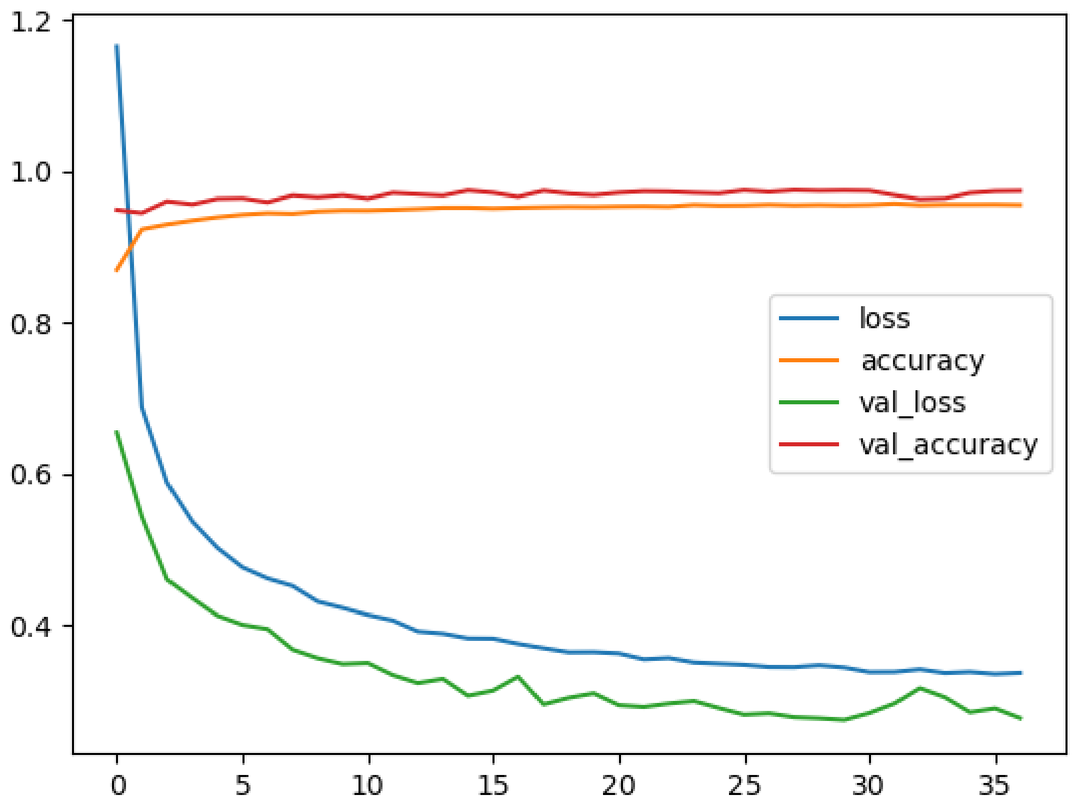
```
Saving logs at logs/fit/2_log_23_09_26_19_50_51
Epoch 1/50
860/860 [==============================] - 11s 9ms/step - loss: 1.1647 - accuracy: 0.8697 - val_loss: 0.6543 - val_accuracy:
0.9488
Epoch 2/50
860/860 [==============================] - 7s 8ms/step - loss: 0.6878 - accuracy: 0.9233 - val_loss: 0.5432 - val_accuracy:
0.9448
Epoch 3/50
860/860 [==============================] - 7s 8ms/step - loss: 0.5877 - accuracy: 0.9297 - val_loss: 0.4598 - val_accuracy:
0.9600
Epoch 4/50
860/860 [==============================] - 7s 8ms/step - loss: 0.5365 - accuracy: 0.9348 - val_loss: 0.4354 - val_accuracy:
0.9560
Epoch 5/50
860/860 [==============================] - 7s 8ms/step - loss: 0.5017 - accuracy: 0.9392 - val_loss: 0.4121 - val_accuracy:
0.9634
Epoch 6/50
860/860 [==============================] - 7s 8ms/step - loss: 0.4760 - accuracy: 0.9425 - val_loss: 0.4001 - val_accuracy:
0.9640
Epoch 7/50
860/860 [==============================] - 7s 8ms/step - loss: 0.4614 - accuracy: 0.9445 - val_loss: 0.3945 - val_accuracy:
0.9588
Epoch 8/50
860/860 [==============================] - 7s 8ms/step - loss: 0.4515 - accuracy: 0.9437 - val_loss: 0.3675 - val_accuracy:
0.9680
Epoch 9/50
860/860 [==============================] - 7s 8ms/step - loss: 0.4310 - accuracy: 0.9468 - val_loss: 0.3562 - val_accuracy:
0.9654
Epoch 10/50
860/860 [==============================] - 7s 8ms/step - loss: 0.4226 - accuracy: 0.9480 - val_loss: 0.3484 - val_accuracy:
0.9682
Epoch 11/50
860/860 [==============================] - 7s 8ms/step - loss: 0.4131 - accuracy: 0.9479 - val_loss: 0.3498 - val_accuracy:
0.9636
Epoch 12/50
860/860 [==============================] - 7s 8ms/step - loss: 0.4058 - accuracy: 0.9489 - val_loss: 0.3338 - val_accuracy:
0.9714
Epoch 13/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3914 - accuracy: 0.9501 - val_loss: 0.3233 - val_accuracy:
0.9696
Epoch 14/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3885 - accuracy: 0.9516 - val_loss: 0.3288 - val_accuracy:
0.9678
Epoch 15/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3823 - accuracy: 0.9516 - val_loss: 0.3065 - val_accuracy:
0.9746
Epoch 16/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3820 - accuracy: 0.9507 - val_loss: 0.3134 - val_accuracy:
0.9716
Epoch 17/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3751 - accuracy: 0.9516 - val_loss: 0.3318 - val_accuracy:
0.9662
Epoch 18/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3694 - accuracy: 0.9523 - val_loss: 0.2952 - val_accuracy:
0.9742
Epoch 19/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3640 - accuracy: 0.9528 - val_loss: 0.3038 - val_accuracy:
0.9704
Epoch 20/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3642 - accuracy: 0.9527 - val_loss: 0.3097 - val_accuracy:
0.9684
Epoch 21/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3625 - accuracy: 0.9533 - val_loss: 0.2941 - val_accuracy:
0.9716
Epoch 22/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3547 - accuracy: 0.9535 - val_loss: 0.2917 - val_accuracy:
0.9734
Epoch 23/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3564 - accuracy: 0.9531 - val_loss: 0.2963 - val_accuracy:
0.9730
Epoch 24/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3505 - accuracy: 0.9555 - val_loss: 0.2995 - val_accuracy:
0.9716
Epoch 25/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3490 - accuracy: 0.9545 - val_loss: 0.2903 - val_accuracy:
0.9706
Epoch 26/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3475 - accuracy: 0.9547 - val_loss: 0.2815 - val_accuracy:
0.9748
Epoch 27/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3446 - accuracy: 0.9557 - val_loss: 0.2833 - val_accuracy:
0.9726
Epoch 28/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3444 - accuracy: 0.9548 - val_loss: 0.2782 - val_accuracy:
0.9750
Epoch 29/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3469 - accuracy: 0.9554 - val_loss: 0.2768 - val_accuracy:
```

```
0.9742
Epoch 30/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3439 - accuracy: 0.9548 - val_loss: 0.2746 - val_accuracy: 0.9746
Epoch 31/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3379 - accuracy: 0.9554 - val_loss: 0.2837 - val_accuracy: 0.9742
Epoch 32/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3380 - accuracy: 0.9570 - val_loss: 0.2963 - val_accuracy: 0.9684
Epoch 33/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3415 - accuracy: 0.9551 - val_loss: 0.3166 - val_accuracy: 0.9628
Epoch 34/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3366 - accuracy: 0.9558 - val_loss: 0.3045 - val_accuracy: 0.9638
Epoch 35/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3380 - accuracy: 0.9558 - val_loss: 0.2847 - val_accuracy: 0.9712
Epoch 36/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3353 - accuracy: 0.9559 - val_loss: 0.2898 - val_accuracy: 0.9736
Epoch 37/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3368 - accuracy: 0.9554 - val_loss: 0.2770 - val_accuracy: 0.9740
```

In [32]:

```
pd.DataFrame(history.history).plot()
```

Out[32]: <AxesSubplot: >



In [33]:

```
ckpt_model = tf.keras.models.load_model(CKPT_path)
ckpt_model.evaluate(x_test,y_test)
```

```
313/313 [==============================] - 1s 2ms/step - loss: 0.2719 - accuracy: 0.9740
```

Out[33]: [0.27185875177383423, 0.9739999771118164]

The accuracy of the second **ANN** model is **97.40 %**

In [34]:

```
del model
del ckpt_model
```

Third **ANN** Network

In [35]:

```
# Added kernel regularization,batch normalization,dropout,kernel initializer and Leakyrelu activation function
model = Sequential()
model.add(Flatten(input_shape=[28,28]))
model.add(Dense(units=256,kernel_regularizer=regularizers.L1L2(0.0001,0.0001),kernel_initializer=tf.keras.initializers.HeNorma
model.add(BatchNormalization())
model.add(LeakyReLU())
model.add(Dropout(0.1))
model.add(Dense(units=128,kernel_regularizer=regularizers.L1L2(0.0001,0.0001),kernel_initializer=tf.keras.initializers.HeNorma
model.add(BatchNormalization())
model.add(LeakyReLU())
model.add(Dropout(0.1))
model.add(Dense(units=64,kernel_regularizer=regularizers.L1L2(0.0001,0.0001),kernel_initializer=tf.keras.initializers.HeNormal
model.add(BatchNormalization())
model.add(LeakyReLU())
model.add(Dropout(0.1))
model.add(Dense(units=32,kernel_regularizer=regularizers.L1L2(0.0001,0.0001),kernel_initializer=tf.keras.initializers.HeNormal
```

```python
model.add(BatchNormalization())
model.add(LeakyReLU())
model.add(Dropout(0.1))
model.add(Dense(units=16,kernel_regularizer=regularizers.L1L2(0.0001,0.0001),kernel_initializer=tf.keras.initializers.HeNormal
model.add(BatchNormalization())
model.add(LeakyReLU())
model.add(Dropout(0.1))
model.add(Dense(units=10,activation="softmax"))
```

In [36]:
```python
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 flatten_1 (Flatten)         (None, 784)               0         
                                                                 
 dense_6 (Dense)             (None, 256)               200960    
                                                                 
 batch_normalization_5 (Bat  (None, 256)               1024      
 chNormalization)                                                
                                                                 
 leaky_re_lu_5 (LeakyReLU)   (None, 256)               0         
                                                                 
 dropout_5 (Dropout)         (None, 256)               0         
                                                                 
 dense_7 (Dense)             (None, 128)               32896     
                                                                 
 batch_normalization_6 (Bat  (None, 128)               512       
 chNormalization)                                                
                                                                 
 leaky_re_lu_6 (LeakyReLU)   (None, 128)               0         
                                                                 
 dropout_6 (Dropout)         (None, 128)               0         
                                                                 
 dense_8 (Dense)             (None, 64)                8256      
                                                                 
 batch_normalization_7 (Bat  (None, 64)                256       
 chNormalization)                                                
                                                                 
 leaky_re_lu_7 (LeakyReLU)   (None, 64)                0         
                                                                 
 dropout_7 (Dropout)         (None, 64)                0         
                                                                 
 dense_9 (Dense)             (None, 32)                2080      
                                                                 
 batch_normalization_8 (Bat  (None, 32)                128       
 chNormalization)                                                
                                                                 
 leaky_re_lu_8 (LeakyReLU)   (None, 32)                0         
                                                                 
 dropout_8 (Dropout)         (None, 32)                0         
                                                                 
 dense_10 (Dense)            (None, 16)                528       
                                                                 
 batch_normalization_9 (Bat  (None, 16)                64        
 chNormalization)                                                
                                                                 
 leaky_re_lu_9 (LeakyReLU)   (None, 16)                0         
                                                                 
 dropout_9 (Dropout)         (None, 16)                0         
                                                                 
 dense_11 (Dense)            (None, 10)                170       
                                                                 
=================================================================
Total params: 246874 (964.35 KB)
Trainable params: 245882 (960.48 KB)
Non-trainable params: 992 (3.88 KB)
_________________________________________________________________
```

In [37]:
```python
def get_log_path(log_dir="logs/fit"):
    filename = time.strftime("3_log_%y_%m_%d_%H_%M_%S")
    logs_path = os.path.join(log_dir, filename)
    print(f"Saving logs at {logs_path}")
    return logs_path

log_dirs = get_log_path()
tb_cb = tf.keras.callbacks.TensorBoard(log_dir=log_dirs)

early_stopping_cb = tf.keras.callbacks.EarlyStopping(patience=7, restore_best_weights=True)

CKPT_path = os.path.join("Models","Model_ckpt_Digit_mnist_3.h5")
checkpoint_cb = tf.keras.callbacks.ModelCheckpoint(CKPT_path, save_best_only=True)

EPOCHS = 50
VALIDATION_SET = (x_valid, y_valid)
```

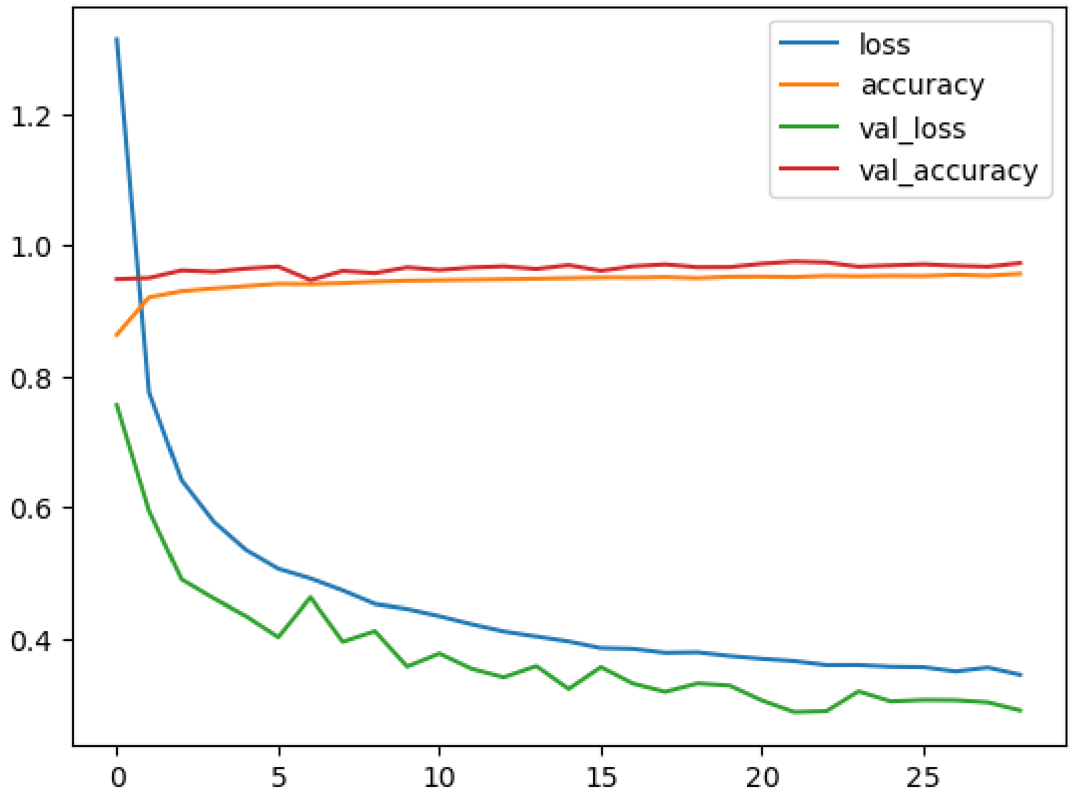
```python
loss_function = "sparse_categorical_crossentropy"
OPTIMIZER = tf.keras.optimizers.Adam(learning_rate=0.001,weight_decay=1e-4) # Weight decay is used here
METRICS = ["accuracy"]

model.compile(
    loss=loss_function,
    optimizer=OPTIMIZER,
    metrics=METRICS
)

history = model.fit(x_train, y_train, epochs=EPOCHS, validation_data=VALIDATION_SET, batch_size=64,
                    callbacks=[tb_cb, early_stopping_cb, checkpoint_cb], use_multiprocessing=True)
```

```
Saving logs at logs/fit/3_log_23_09_26_19_55_20
Epoch 1/50
860/860 [==============================] - 11s 9ms/step - loss: 1.3140 - accuracy: 0.8640 - val_loss: 0.7566 - val_accuracy:
0.9488
Epoch 2/50
860/860 [==============================] - 7s 8ms/step - loss: 0.7761 - accuracy: 0.9210 - val_loss: 0.5952 - val_accuracy:
0.9506
Epoch 3/50
860/860 [==============================] - 7s 8ms/step - loss: 0.6420 - accuracy: 0.9304 - val_loss: 0.4907 - val_accuracy:
0.9622
Epoch 4/50
860/860 [==============================] - 7s 8ms/step - loss: 0.5784 - accuracy: 0.9347 - val_loss: 0.4616 - val_accuracy:
0.9600
Epoch 5/50
860/860 [==============================] - 7s 8ms/step - loss: 0.5354 - accuracy: 0.9382 - val_loss: 0.4349 - val_accuracy:
0.9650
Epoch 6/50
860/860 [==============================] - 7s 8ms/step - loss: 0.5069 - accuracy: 0.9418 - val_loss: 0.4030 - val_accuracy:
0.9680
Epoch 7/50
860/860 [==============================] - 7s 8ms/step - loss: 0.4922 - accuracy: 0.9414 - val_loss: 0.4635 - val_accuracy:
0.9474
Epoch 8/50
860/860 [==============================] - 7s 8ms/step - loss: 0.4738 - accuracy: 0.9428 - val_loss: 0.3959 - val_accuracy:
0.9614
Epoch 9/50
860/860 [==============================] - 7s 8ms/step - loss: 0.4534 - accuracy: 0.9450 - val_loss: 0.4122 - val_accuracy:
0.9580
Epoch 10/50
860/860 [==============================] - 7s 8ms/step - loss: 0.4458 - accuracy: 0.9465 - val_loss: 0.3582 - val_accuracy:
0.9668
Epoch 11/50
860/860 [==============================] - 7s 8ms/step - loss: 0.4350 - accuracy: 0.9471 - val_loss: 0.3781 - val_accuracy:
0.9628
Epoch 12/50
860/860 [==============================] - 7s 9ms/step - loss: 0.4228 - accuracy: 0.9479 - val_loss: 0.3549 - val_accuracy:
0.9666
Epoch 13/50
860/860 [==============================] - 7s 8ms/step - loss: 0.4117 - accuracy: 0.9487 - val_loss: 0.3418 - val_accuracy:
0.9684
Epoch 14/50
860/860 [==============================] - 7s 8ms/step - loss: 0.4042 - accuracy: 0.9495 - val_loss: 0.3588 - val_accuracy:
0.9644
Epoch 15/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3965 - accuracy: 0.9505 - val_loss: 0.3241 - val_accuracy:
0.9702
Epoch 16/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3865 - accuracy: 0.9513 - val_loss: 0.3574 - val_accuracy:
0.9616
Epoch 17/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3853 - accuracy: 0.9512 - val_loss: 0.3323 - val_accuracy:
0.9684
Epoch 18/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3793 - accuracy: 0.9520 - val_loss: 0.3197 - val_accuracy:
0.9714
Epoch 19/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3799 - accuracy: 0.9504 - val_loss: 0.3325 - val_accuracy:
0.9670
Epoch 20/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3744 - accuracy: 0.9526 - val_loss: 0.3292 - val_accuracy:
0.9672
Epoch 21/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3701 - accuracy: 0.9527 - val_loss: 0.3064 - val_accuracy:
0.9724
Epoch 22/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3666 - accuracy: 0.9521 - val_loss: 0.2888 - val_accuracy:
0.9758
Epoch 23/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3605 - accuracy: 0.9539 - val_loss: 0.2902 - val_accuracy:
0.9744
Epoch 24/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3606 - accuracy: 0.9533 - val_loss: 0.3204 - val_accuracy:
0.9678
Epoch 25/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3580 - accuracy: 0.9539 - val_loss: 0.3051 - val_accuracy:
0.9698
Epoch 26/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3573 - accuracy: 0.9537 - val_loss: 0.3073 - val_accuracy:
0.9716
Epoch 27/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3508 - accuracy: 0.9555 - val_loss: 0.3069 - val_accuracy:
0.9692
Epoch 28/50
860/860 [==============================] - 7s 8ms/step - loss: 0.3568 - accuracy: 0.9541 - val_loss: 0.3036 - val_accuracy:
0.9678
Epoch 29/50
```

```
860/860 [==============================] - 7s 8ms/step - loss: 0.3457 - accuracy: 0.9571 - val_loss: 0.2913 - val_accuracy: 0.9734
```

In [38]:
```
pd.DataFrame(history.history).plot()
```

Out[38]:
```
<AxesSubplot: >
```



In [39]:
```
ckpt_model = tf.keras.models.load_model(CKPT_path)
ckpt_model.evaluate(x_test, y_test)
```

```
313/313 [==============================] - 1s 2ms/step - loss: 0.3027 - accuracy: 0.9693
```

Out[39]:
```
[0.30268532037734985, 0.9692999720573425]
```

The accuracy of the third **ANN** model is **96.93 %**

In [40]:
```
del model
del ckpt_model
```

LeNet5 CNN Architecture

Basic Introduction

LeNet-5, from the paper Gradient-Based Learning Applied to Document Recognition, is a very efficient convolutional neural network for handwritten character recognition.

Structure of the LeNet network

LeNet5 is a small network, it contains the basic modules of deep learning: convolutional layer, pooling layer, and full link layer. It is the basis of other deep learning models. Here we analyze LeNet5 in depth. At the same time, through example analysis, deepen the understanding of the convolutional layer and pooling layer.

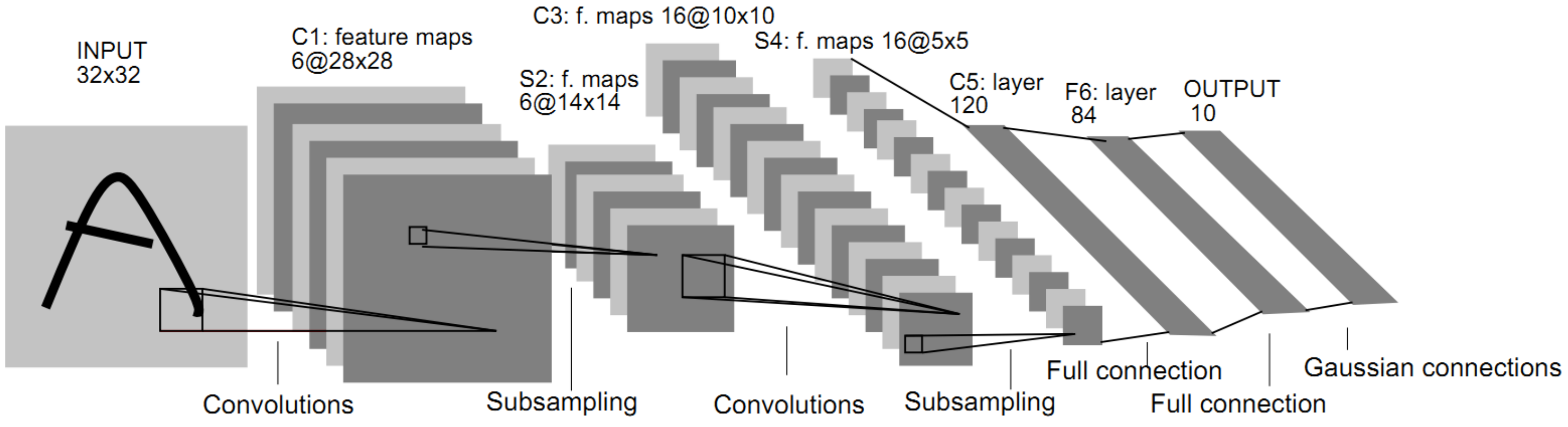


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

LeNet-5 Total seven layer , does not comprise an input, each containing a trainable parameters; each layer has a plurality of the Map the Feature , a characteristic of each of the input FeatureMap extracted by means of a convolution filter, and then each FeatureMap There are multiple neurons.

Layer		Feature Map	Size	Kernel Size	Stride	Activation
Input	Image	1	32x32	-	-	-
1	Convolution	6	28x28	5x5	1	tanh
2	Average Pooling	6	14x14	2x2	2	tanh
3	Convolution	16	10x10	5x5	1	tanh
4	Average Pooling	16	5x5	2x2	2	tanh
5	Convolution	120	1x1	5x5	1	tanh
6	FC	-	84	-	-	tanh
Output	FC	-	10	-	-	softmax

Detailed explanation of each layer parameter:

INPUT Layer

The first is the data INPUT layer. The size of the input image is uniformly normalized to 32 * 32.

> Note: This layer does not count as the network structure of LeNet-5. Traditionally, the input layer is not considered as one of the network hierarchy.

C1 layer-convolutional layer

> **Input picture**: 32 * 32

> **Convolution kernel size**: 5 * 5

> **Convolution kernel types**: 6

> **Output featuremap size**: 28 * 28 (32-5 + 1) = 28

> **Number of neurons**: 28 * 28 * 6

> **Trainable parameters**: (5 * 5 + 1) * 6 (5 * 5 = 25 unit parameters and one bias parameter per filter, a total of 6 filters)

> **Number of connections**: (5 * 5 + 1) * 6 * 28 * 28 = 122304

Detailed description:

1. The first convolution operation is performed on the input image (using 6 convolution kernels of size 5 * 5) to obtain 6 C1 feature maps (6 feature maps of size 28 * 28, 32-5 + 1 = 28).
2. Let's take a look at how many parameters are needed. The size of the convolution kernel is 5 * 5, and there are 6 * (5 * 5 + 1) = 156 parameters in total, where +1 indicates that a kernel has a bias.
3. For the convolutional layer C1, each pixel in C1 is connected to 5 * 5 pixels and 1 bias in the input image, so there are 156 * 28 * 28 = 122304 connections in total. There are 122,304 connections, but we only need to learn 156 parameters, mainly through weight sharing.

S2 layer-pooling layer (downsampling layer)

> **Input**: 28 * 28

> **Sampling area**: 2 * 2

> **Sampling method**: 4 inputs are added, multiplied by a trainable parameter, plus a trainable offset. Results via sigmoid

> **Sampling type**: 6

> **Output featureMap size**: 14 * 14 (28/2)

> **Number of neurons**: 14 * 14 * 6

> **Trainable parameters**: 2 * 6 (the weight of the sum + the offset)

> **Number of connections**: (2 * 2 + 1) * 6 * 14 * 14

> The size of each feature map in S2 is 1/4 of the size of the feature map in C1.

Detailed description:

The pooling operation is followed immediately after the first convolution. Pooling is performed using 2 * 2 kernels, and S2, 6 feature maps of 14 * 14 (28/2 = 14) are obtained.

The pooling layer of S2 is the sum of the pixels in the 2 * 2 area in C1 multiplied by a weight coefficient plus an offset, and then the result is mapped again.

So each pooling core has two training parameters, so there are 2x6 = 12 training parameters, but there are 5x14x14x6 = 5880 connections.

C3 layer-convolutional layer

> **Input**: all 6 or several feature map combinations in S2

> **Convolution kernel size**: 5 * 5

> **Convolution kernel type**: 16

> **Output featureMap size**: 10 * 10 (14-5 + 1) = 10

> Each feature map in C3 is connected to all 6 or several feature maps in S2, indicating that the feature map of this layer is a different combination of the feature maps extracted from the previous layer.

> One way is that the first 6 feature maps of C3 take 3 adjacent feature map subsets in S2 as input. The next 6 feature maps take 4 subsets of neighboring feature maps in S2 as input. The next three take the non-adjacent 4 feature map subsets as input. The last one takes all the feature maps in S2 as input.

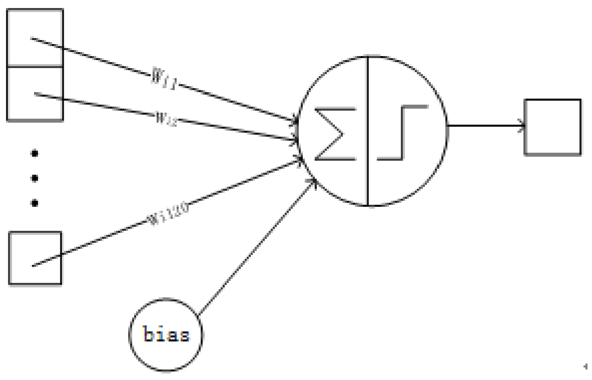
> **The trainable parameters are**: 6 * (3 * 5 * 5 + 1) + 6 * (4 * 5 * 5 + 1) + 3 * (4 * 5 * 5 + 1) + 1 * (6 * 5 * 5 +1) = 1516

> **Number of connections**: 10 * 10 * 1516 = 151600

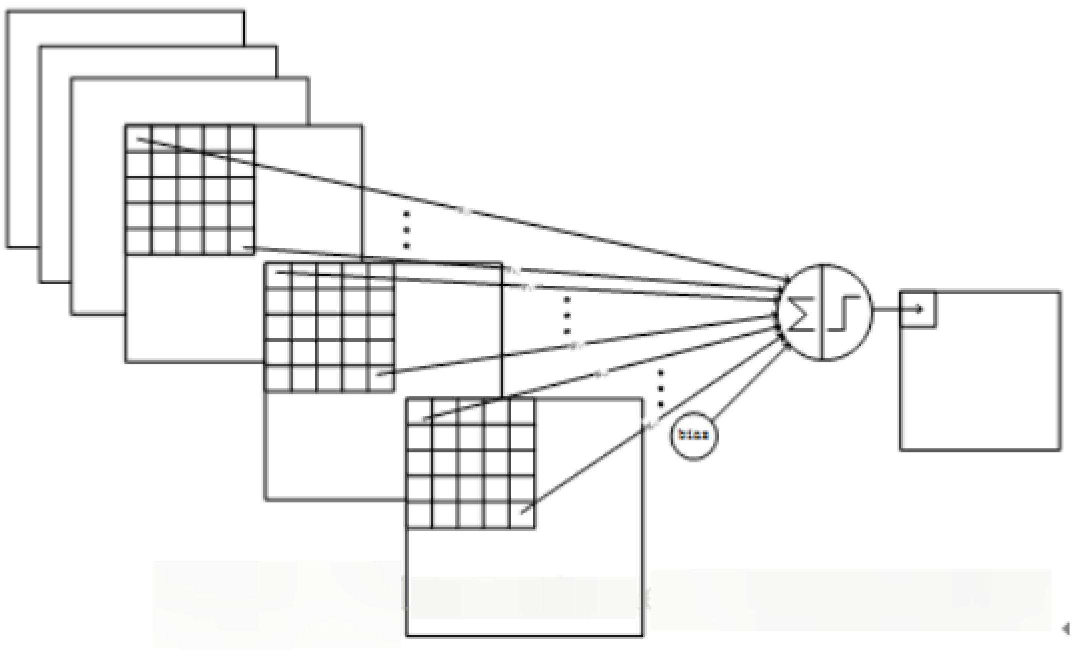
Detailed description:

After the first pooling, the second convolution, the output of the second convolution is C3, 16 10x10 feature maps, and the size of the convolution kernel is 5 * 5. We know that S2 has 6 14 * 14 feature maps, how to get 16 feature maps from 6 feature maps? Here are the 16 feature maps calculated by the special combination of the feature maps of S2. details as follows:

The first 6 feature maps of C3 (corresponding to the 6th column of the first red box in the figure above) are connected to the 3 feature maps connected to the S2 layer (the first red box in the above figure), and the next 6 feature maps are connected to the S2 layer The 4 feature maps are connected (the second red box in the figure above), the next 3 feature maps are connected with the 4 feature maps that are not connected at the S2 layer, and the last is connected with all the feature maps at the S2 layer. The convolution kernel size is still 5 * 5, so there are 6 * (3 * 5 * 5 + 1) + 6 * (4 * 5 * 5 + 1) + 3 * (4 * 5 * 5 + 1) +1 * (6 * 5 * 5 + 1) = 1516 parameters. The image size is 10 * 10, so there are 151600 connections.



The convolution structure of C3 and the first 3 graphs in S2 is shown below:



S4 layer-pooling layer (downsampling layer)

> **Input**: 10 * 10

> **Sampling area**: 2 * 2

> **Sampling method**: 4 inputs are added, multiplied by a trainable parameter, plus a trainable offset. Results via sigmoid

> **Sampling type**: 16

> **Output featureMap size**: 5 * 5 (10/2)

> **Number of neurons**: 5 * 5 * 16 = 400

> **Trainable parameters**: 2 * 16 = 32 (the weight of the sum + the offset)

> **Number of connections**: 16 * (2 * 2 + 1) * 5 * 5 = 2000

> The size of each feature map in S4 is 1/4 of the size of the feature map in C3

Detailed description:

S4 is the pooling layer, the window size is still 2 * 2, a total of 16 feature maps, and the 16 10x10 maps of the C3 layer are pooled in units of 2x2 to obtain 16 5x5 feature maps. This layer has a total of 32 training parameters of 2x16, 5x5x5x16 = 2000 connections.

The connection is similar to the S2 layer.

C5 layer-convolution layer

> **Input**: All 16 unit feature maps of the S4 layer (all connected to s4)

> **Convolution kernel size**: 5 * 5

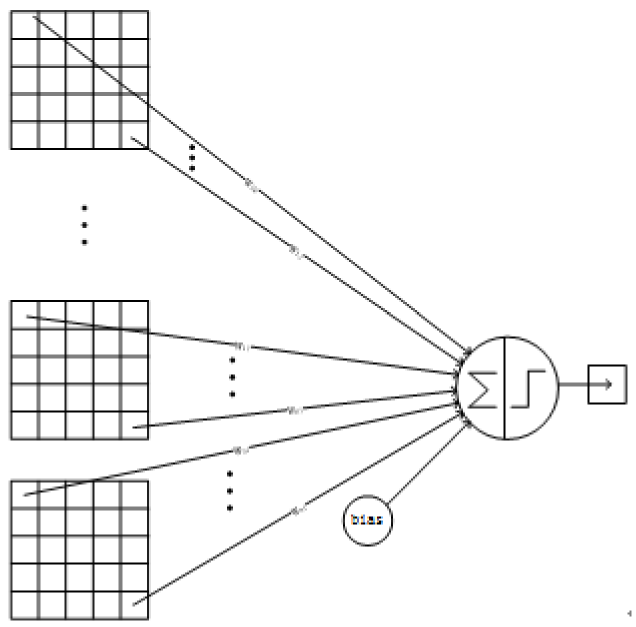
> **Convolution kernel type**: 120

> **Output featureMap size**: 1 * 1 (5-5 + 1)

> **Trainable parameters / connection**: 120 * (16 * 5 * 5 + 1) = 48120

Detailed description:

The C5 layer is a convolutional layer. Since the size of the 16 images of the S4 layer is 5x5, which is the same as the size of the convolution kernel, the size of the image formed after convolution is 1x1. This results in 120 convolution results. Each is connected to the 16 maps on the previous level. So there are (5x5x16 + 1) x120 = 48120 parameters, and there are also 48120 connections. The network structure of the C5 layer is as follows:



F6 layer-fully connected layer

> **Input**: c5 120-dimensional vector

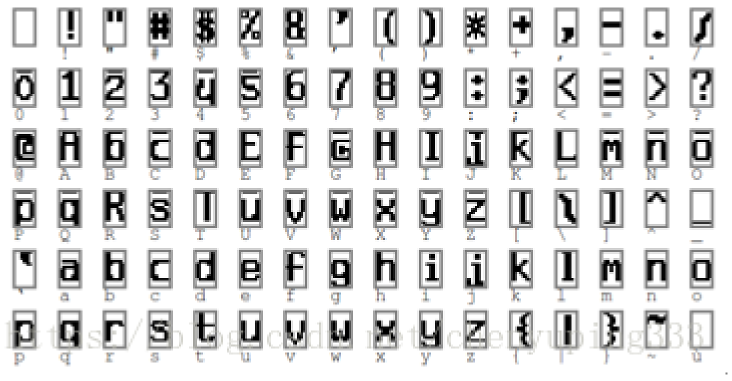
> **Calculation method**: calculate the dot product between the input vector and the weight vector, plus an offset, and the result is output through the sigmoid function.

> **Trainable parameters**: 84 * (120 + 1) = 10164

Detailed description:

Layer 6 is a fully connected layer. The F6 layer has 84 nodes, corresponding to a 7x12 bitmap, -1 means white, 1 means black, so the black and white of the bitmap of each symbol corresponds to a code. The training parameters and number of connections for this layer are (120 + 1) x84 = 10164. The ASCII encoding diagram is as follows:

The connection method of the F6 layer is as follows:

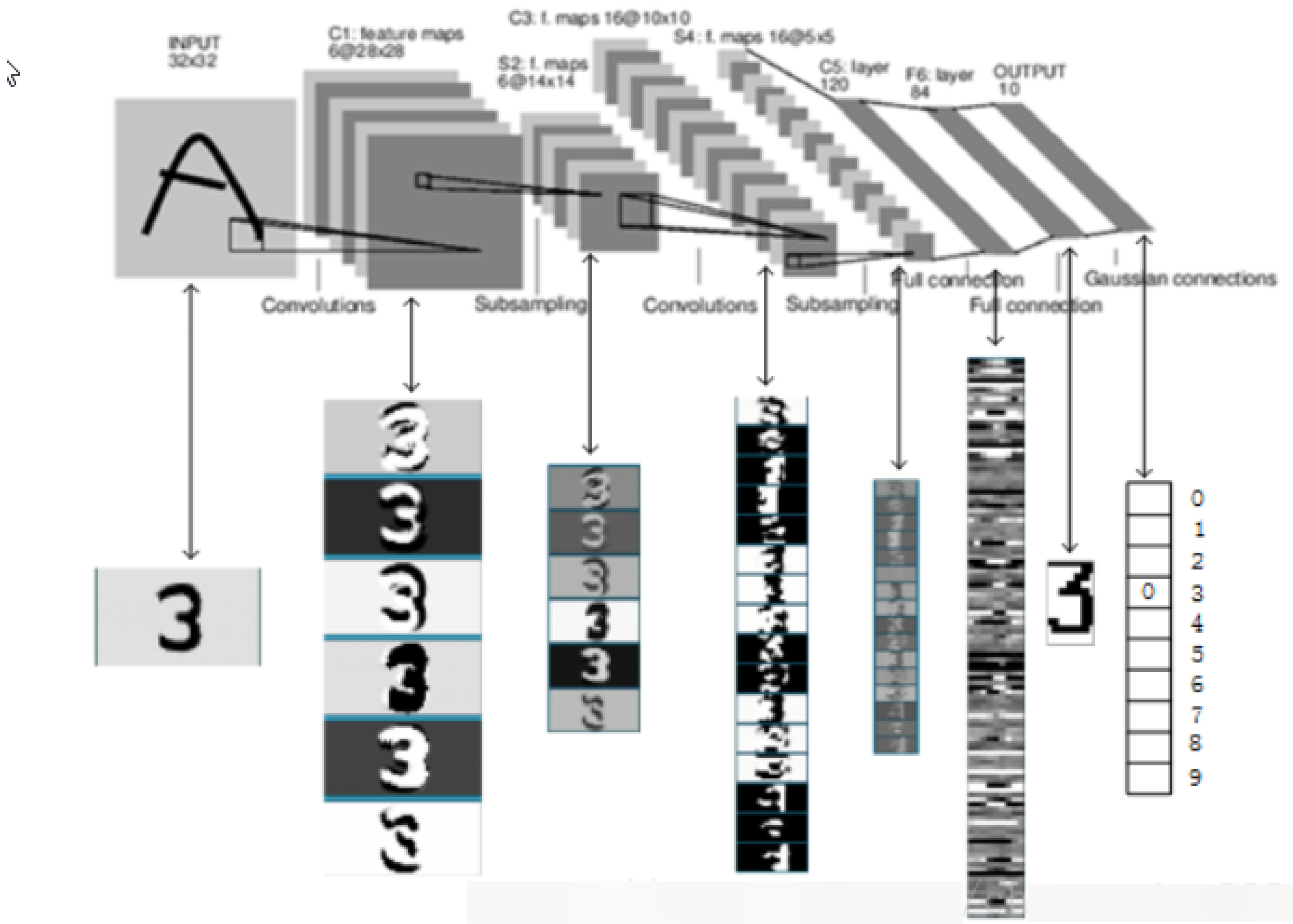


Output layer-fully connected layer

The output layer is also a fully connected layer, with a total of 10 nodes, which respectively represent the numbers 0 to 9, and if the value of node i is 0, the result of network recognition is the number i. A radial basis function (RBF) network connection is used. Assuming x is the input of the previous layer and y is the output of the RBF, the calculation of the RBF output is:

$$y_i = \sum_j (x_j - w_{ij})^2.$$

The value of the above formula w_ij is determined by the bitmap encoding of i, where i ranges from 0 to 9, and j ranges from 0 to 7 * 12-1. The closer the value of the RBF output is to 0, the closer it is to i, that is, the closer to the ASCII encoding figure of i, it means that the recognition result input by the current network is the character i. This layer has 84x10 = 840 parameters and connections.



Summary

- LeNet-5 is a very efficient convolutional neural network for handwritten character recognition.
- Convolutional neural networks can make good use of the structural information of images.
- The convolutional layer has fewer parameters, which is also determined by the main characteristics of the convolutional layer, that is, local connection and shared weights.

In [41]:
```
# Reshaping the data so that it is compatable with the architecture
x_train.reshape(x_train.shape[0],x_train.shape[1],x_train.shape[2],1)
x_test.reshape(x_test.shape[0],x_test.shape[1],x_test.shape[2],1)
```

```python
# Building the Model Architecture
model = Sequential()

model.add(Conv2D(6, kernel_size = (5,5), padding = 'valid', activation='tanh', input_shape = (28,28,1)))
model.add(AveragePooling2D(pool_size= (2,2), strides = 2, padding = 'valid'))

model.add(Conv2D(16, kernel_size = (5,5), padding = 'valid', activation='tanh'))
model.add(AveragePooling2D(pool_size= (2,2), strides = 2, padding = 'valid'))

model.add(Flatten())

model.add(Dense(120, activation='tanh'))
model.add(Dense(84, activation='tanh'))
model.add(Dense(10, activation='softmax'))
```

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

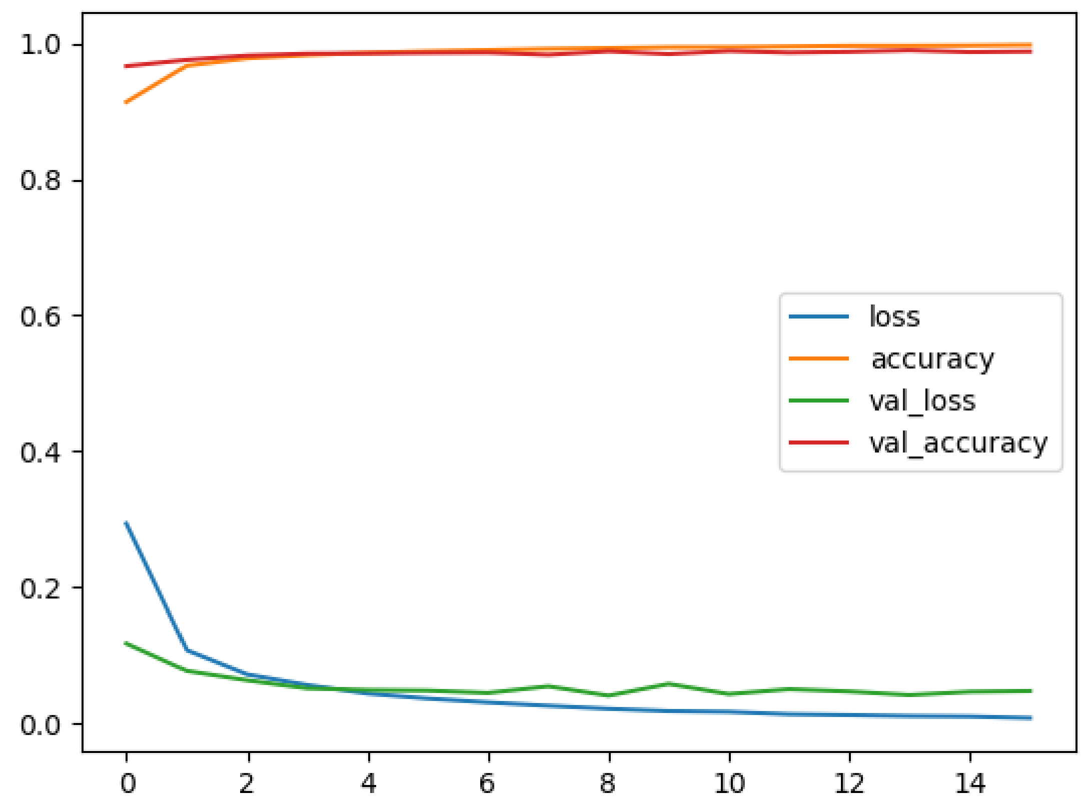
```
Model: "sequential_3"

_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d (Conv2D)             (None, 24, 24, 6)         156       
                                                                 
 average_pooling2d (Average  (None, 12, 12, 6)         0         
 Pooling2D)                                                      
                                                                 
 conv2d_1 (Conv2D)           (None, 8, 8, 16)          2416      
                                                                 
 average_pooling2d_1 (Avera  (None, 4, 4, 16)          0         
 gePooling2D)                                                    
                                                                 
 flatten_2 (Flatten)         (None, 256)               0         
                                                                 
 dense_12 (Dense)            (None, 120)               30840     
                                                                 
 dense_13 (Dense)            (None, 84)                10164     
                                                                 
 dense_14 (Dense)            (None, 10)                850       
                                                                 
=================================================================
Total params: 44426 (173.54 KB)
Trainable params: 44426 (173.54 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [43]:
```python
def get_log_path(log_dir="logs/fit"):
    filename = time.strftime("4_log_%y_%m_%d_%H_%M_%S")
    logs_path = os.path.join(log_dir, filename)
    print(f"Saving logs at {logs_path}")
    return logs_path

log_dirs = get_log_path()
tb_cb = tf.keras.callbacks.TensorBoard(log_dir=log_dirs)

early_stopping_cb = tf.keras.callbacks.EarlyStopping(patience=7, restore_best_weights=True)

CKPT_path = os.path.join("Models","Model_ckpt_Digit_mnist_4.h5")
checkpoint_cb = tf.keras.callbacks.ModelCheckpoint(CKPT_path, save_best_only=True)

EPOCHS = 50
VALIDATION_SET = (x_valid, y_valid)

loss_function = "sparse_categorical_crossentropy"
OPTIMIZER = tf.keras.optimizers.Adam(learning_rate=0.001)
METRICS = ["accuracy"]

model.compile(
    loss=loss_function,
    optimizer=OPTIMIZER,
    metrics=METRICS
)

history = model.fit(x_train, y_train, epochs=EPOCHS, validation_data=VALIDATION_SET, batch_size=64,verbose=1,
                          callbacks=[tb_cb, early_stopping_cb, checkpoint_cb], use_multiprocessing=True)
```

```
Saving logs at logs/fit/4_log_23_09_26_19_58_56
Epoch 1/50
860/860 [==============================] - 8s 8ms/step - loss: 0.2934 - accuracy: 0.9136 - val_loss: 0.1174 - val_accuracy:
0.9664
Epoch 2/50
860/860 [==============================] - 7s 8ms/step - loss: 0.1076 - accuracy: 0.9671 - val_loss: 0.0772 - val_accuracy:
0.9756
Epoch 3/50
860/860 [==============================] - 7s 8ms/step - loss: 0.0720 - accuracy: 0.9780 - val_loss: 0.0634 - val_accuracy:
0.9820
Epoch 4/50
860/860 [==============================] - 7s 8ms/step - loss: 0.0563 - accuracy: 0.9827 - val_loss: 0.0515 - val_accuracy:
0.9848
Epoch 5/50
860/860 [==============================] - 7s 8ms/step - loss: 0.0439 - accuracy: 0.9861 - val_loss: 0.0490 - val_accuracy:
0.9852
Epoch 6/50
860/860 [==============================] - 7s 8ms/step - loss: 0.0365 - accuracy: 0.9883 - val_loss: 0.0482 - val_accuracy:
0.9860
Epoch 7/50
860/860 [==============================] - 7s 8ms/step - loss: 0.0309 - accuracy: 0.9901 - val_loss: 0.0447 - val_accuracy:
0.9864
Epoch 8/50
860/860 [==============================] - 7s 8ms/step - loss: 0.0258 - accuracy: 0.9919 - val_loss: 0.0545 - val_accuracy:
0.9832
Epoch 9/50
860/860 [==============================] - 7s 8ms/step - loss: 0.0214 - accuracy: 0.9930 - val_loss: 0.0407 - val_accuracy:
0.9884
Epoch 10/50
860/860 [==============================] - 7s 8ms/step - loss: 0.0180 - accuracy: 0.9943 - val_loss: 0.0580 - val_accuracy:
0.9842
Epoch 11/50
860/860 [==============================] - 7s 8ms/step - loss: 0.0169 - accuracy: 0.9945 - val_loss: 0.0430 - val_accuracy:
0.9888
Epoch 12/50
860/860 [==============================] - 7s 8ms/step - loss: 0.0133 - accuracy: 0.9954 - val_loss: 0.0503 - val_accuracy:
0.9864
Epoch 13/50
860/860 [==============================] - 7s 8ms/step - loss: 0.0122 - accuracy: 0.9964 - val_loss: 0.0469 - val_accuracy:
0.9876
Epoch 14/50
860/860 [==============================] - 7s 8ms/step - loss: 0.0107 - accuracy: 0.9964 - val_loss: 0.0416 - val_accuracy:
0.9898
Epoch 15/50
860/860 [==============================] - 7s 8ms/step - loss: 0.0100 - accuracy: 0.9968 - val_loss: 0.0464 - val_accuracy:
0.9872
Epoch 16/50
860/860 [==============================] - 7s 8ms/step - loss: 0.0078 - accuracy: 0.9976 - val_loss: 0.0475 - val_accuracy:
0.9880
```

In [44]:
```
pd.DataFrame(history.history).plot()
```

Out[44]: <AxesSubplot: >



In [45]:
```
ckpt_model = tf.keras.models.load_model(CKPT_path)
ckpt_model.evaluate(x_test, y_test)
```

```
313/313 [==============================] - 1s 3ms/step - loss: 0.0432 - accuracy: 0.9861
```

Out[45]: [0.04321447014808655, 0.9861000180244446]

The accuracy of the **CNN** model is **98.61 %**

In [46]:

```
# %load_ext tensorboard
# %tensorboard --logdir logs/fit
```

Thank You