Análisis de Datos y Aprendizaje Máquina con Tensorflow 2.0: Redes neuronales convolucionales

2019/09/30

1 Redes Neuronales Convolucionales (CNN)

- Obetivo: Conocer el tipo de capas de las CNN.
- Las redes convolucionales no solo se aplican a imágenes, también se pueden aplicar a caracteres o datos en el tiempo.

1.1 Convolución

- La convolución es una operación matemática generalmente denotada como $*$, en la que una función se aplica otra función, dando como resultado la combinación de las dos funciones.

1.2 Clasificar ropa

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import backend as K
K.clear_session()

fashion_mnist = keras.datasets.fashion_mnist

(x_train, y_train), (x_test, y_test) = fashion_mnist.load_data()
```

In [2]:
```
class_names = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress',
               'Coat', 'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot']
```

In [3]:
```
for i in range(5):
    rand_image_idx = np.random.randint(0, y_train.shape[0])
    plt.subplot(1, 5, i+1)
    plt.xticks([])
    plt.yticks([])
    plt.grid('off')
    plt.imshow(x_train[rand_image_idx])
    plt.xlabel(class_names[y_train[rand_image_idx]])
plt.show()
```


```
In [4]: # escalar entre 0 y 1
        x_train = x_train.reshape(x_train.shape[0], 28, 28, 1).astype('float32') / 255
        x_test = x_test.reshape(x_test.shape[0], 28, 28, 1).astype('float32') / 255

        print(x_train.shape) # (60000, 28, 28, 1)
        print(x_test.shape)  # (10000, 28, 28, 1)
```

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

1.3 Obtener dimensiones

```
In [5]: # con 1: no se cuenta la primera dimensión
        x, y, channel = x_train.shape[1:]

        input_shape = (x, y, channel)
```

1.4 Crear modelo

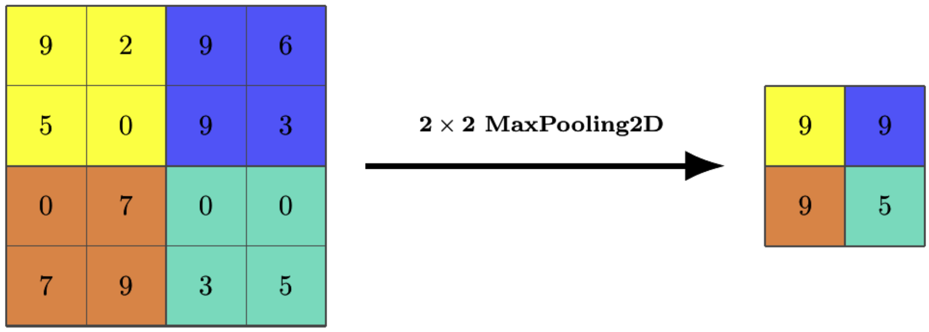
```
In [6]: from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import Dense, Activation, Flatten, Conv2D, MaxPooling2D
```

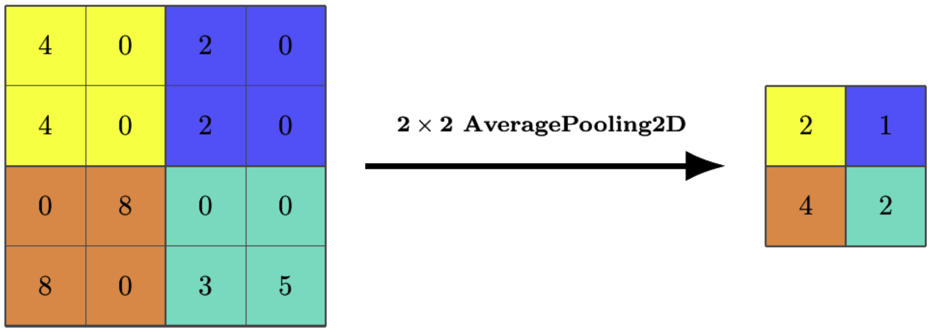
```
In [7]: epoch = 5
        verbose = 1
        batch = 50
```

1.5 Capa de convolución

$$\begin{pmatrix} 0 & 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 \end{pmatrix} * \begin{pmatrix} 1 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{pmatrix} = \begin{pmatrix} 0 & 4 & 2 & \boxed{5} \\ 1 & 2 & 4 & 3 \\ 1 & 2 & 3 & 4 \end{pmatrix}$$

- En general se utiliza la convolución 2D para el procesamiento de imagenes
- En tamaño del filtro es igual al ancho y largo de los campos receptivos
- Pooling reduce el número de parámetros





Imágenes generadas con https://github.com/MartinThoma/LaTeX-examples

In [8]:
```
num_filters = 20
filter_size = 3
pool_size = 3
```

- Diferente notación para crear modelo

In [9]:
```
model = Sequential([
  Conv2D(num_filters, filter_size, input_shape=input_shape),
  MaxPooling2D(pool_size=pool_size),
  Flatten(),
  Dense(10, activation='softmax'),
])
```

1.6 Compilar

In [10]:
```
model.compile('adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
```

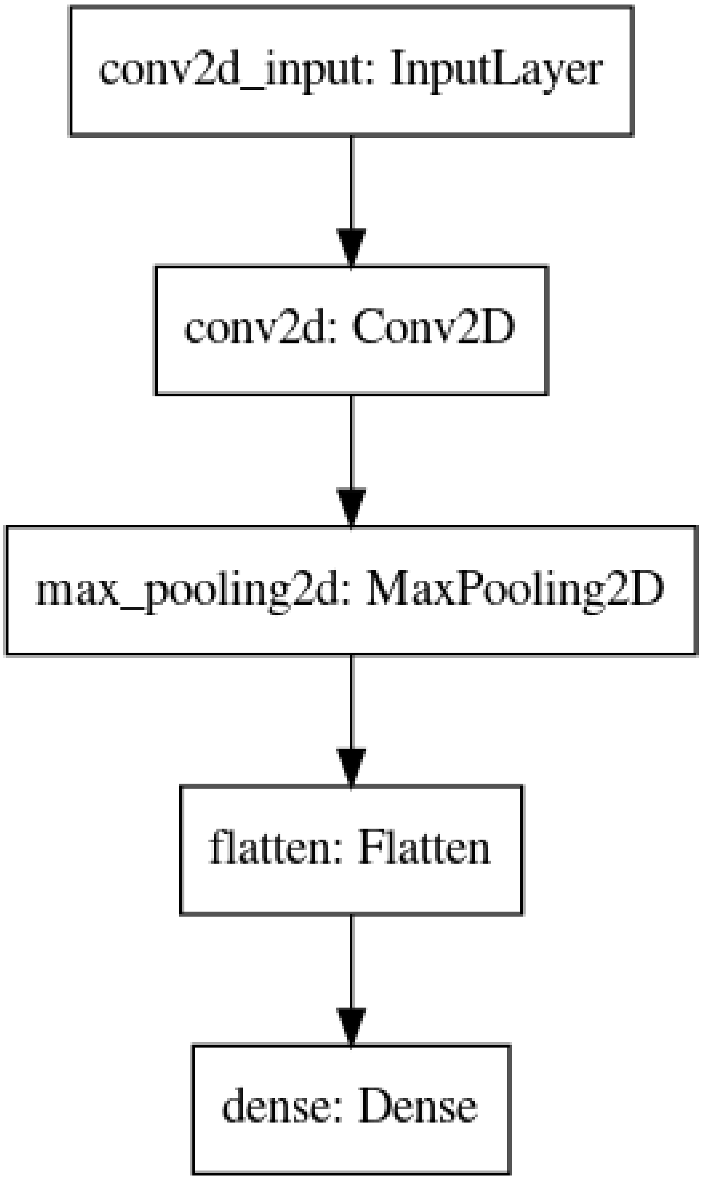
In [11]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 26, 26, 20)        200
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 8, 8, 20)          0
_________________________________________________________________
flatten (Flatten)            (None, 1280)              0
_________________________________________________________________
dense (Dense)                (None, 10)                12810
=================================================================
Total params: 13,010
Trainable params: 13,010
Non-trainable params: 0
_________________________________________________________________
```

```
In [12]: from tensorflow.keras.utils import plot_model
```

```
In [13]: plot_model(model)
```

```
Out[13]:
```



1.7 Entrenamiento

```
In [14]: history = model.fit(x_train, y_train,
             batch_size = batch,
             validation_split=0.3,
             epochs=epoch, verbose = verbose)
```

```
Epoch 1/5
840/840 [==============================] - 2s 3ms/step - loss: 0.6160 - accuracy: 0.7857 - val_lo
```

```
Epoch 2/5
840/840 [==============================] - 2s 2ms/step - loss: 0.4422 - accuracy: 0.8459 - val_lo
Epoch 3/5
840/840 [==============================] - 2s 2ms/step - loss: 0.4054 - accuracy: 0.8584 - val_lo
Epoch 4/5
840/840 [==============================] - 2s 2ms/step - loss: 0.3828 - accuracy: 0.8678 - val_lo
Epoch 5/5
840/840 [==============================] - 2s 3ms/step - loss: 0.3634 - accuracy: 0.8725 - val_lo
```

In [15]:
```
test_loss, test_acc = model.evaluate(x_test, y_test, verbose = 0)

print('\nTest acccuracy:', test_acc)
```

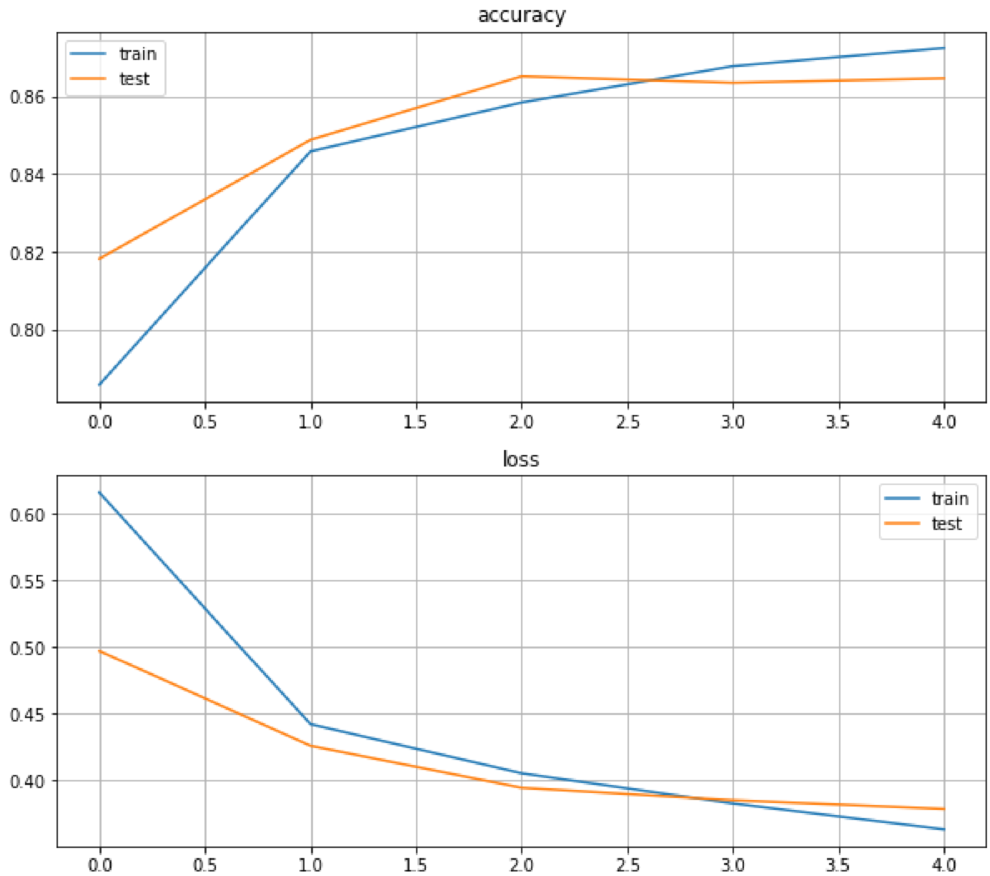
```
Test acccuracy: 0.8626999855041504
```

In [16]:
```
#plot
plt.figure(figsize=(10,9))

plt.subplot(211)
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('accuracy')
plt.legend(['train', 'test'])
plt.grid()
plt.subplot(212)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('loss')
plt.legend(['train', 'test'])
plt.grid()




plt.show()
```



1.8 Diferente número de filtros

- Observar el número de parámetros y el efecto de los filtros y pooling en 'test accuracy'

In [17]:
```
num_filters = 30
filter_size = 3
pool_size = 3

model = Sequential([
  Conv2D(num_filters, filter_size, input_shape=input_shape),
  MaxPooling2D(pool_size=pool_size),
  Flatten(),
  Dense(10, activation='softmax'),
])

model.compile('adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])

model.summary()
```

```
history = model.fit(x_train, y_train,
  batch_size = batch,
  validation_split=0.3,
  epochs=epoch, verbose = verbose)
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 26, 26, 30)        300
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 8, 8, 30)          0
_________________________________________________________________
flatten_1 (Flatten)          (None, 1920)              0
_________________________________________________________________
dense_1 (Dense)              (None, 10)                19210
=================================================================
Total params: 19,510
Trainable params: 19,510
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
840/840 [==============================] - 2s 3ms/step - loss: 0.5705 - accuracy: 0.8058 - val_lo
Epoch 2/5
840/840 [==============================] - 2s 3ms/step - loss: 0.4097 - accuracy: 0.8581 - val_lo
Epoch 3/5
840/840 [==============================] - 2s 3ms/step - loss: 0.3766 - accuracy: 0.8692 - val_lo
Epoch 4/5
840/840 [==============================] - 2s 3ms/step - loss: 0.3554 - accuracy: 0.8757 - val_lo
Epoch 5/5
840/840 [==============================] - 2s 3ms/step - loss: 0.3412 - accuracy: 0.8812 - val_lo
```

In [18]:
```
test_loss, test_acc = model.evaluate(x_test, y_test, verbose = 0)

print('\nTest acccuracy:', test_acc)
```

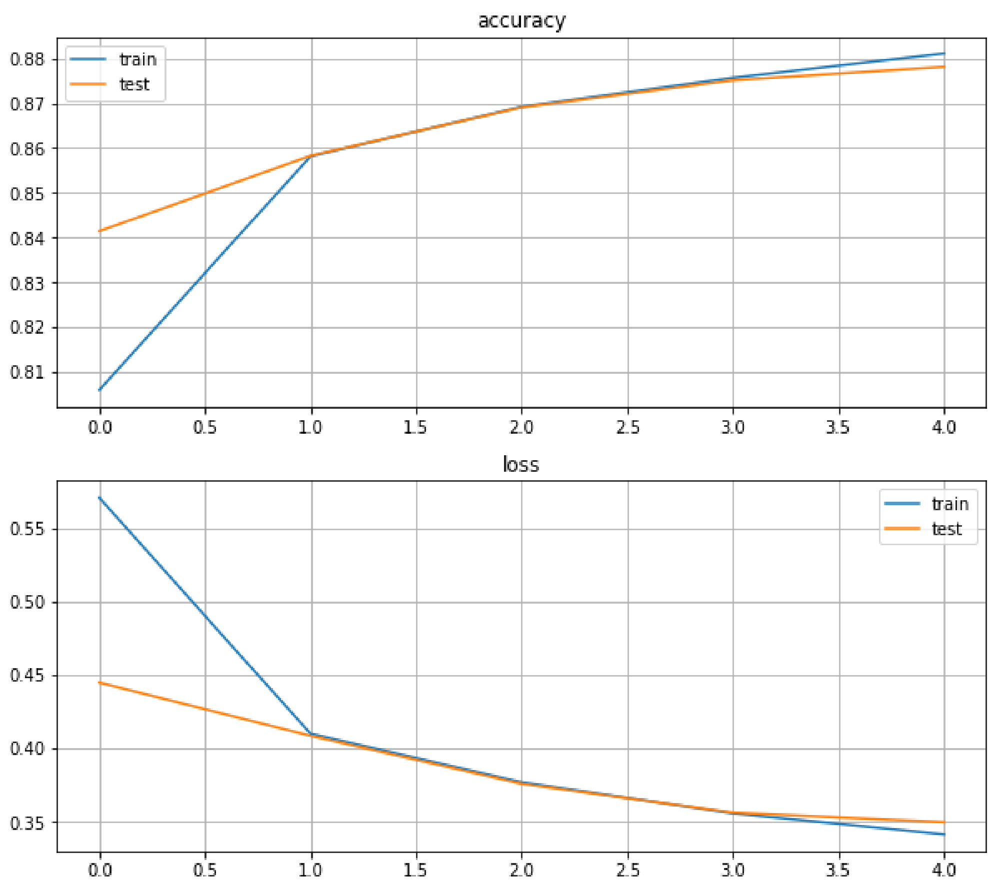
```
Test acccuracy: 0.871399998664856
```

In [19]:
```
#plot
plt.figure(figsize=(10,9))

plt.subplot(211)
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('accuracy')
plt.legend(['train', 'test'])
```

```
plt.grid()
plt.subplot(212)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('loss')
plt.legend(['train', 'test'])
plt.grid()
```

```
plt.show()
```



1.9 Strides y pooling

- Strides indica la unidad de desplazamiento del filtro. Si el valor es mayor a uno, los mapas de salida cuentan con un menor número de parámetros.

In [21]:
```
num_filters = 30
filter_size = 3


model = Sequential([
  Conv2D(num_filters, filter_size, input_shape=input_shape, strides=2),
  Flatten(),
  Dense(10, activation='softmax'),
])

model.compile('adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])

model.summary()

history = model.fit(
  x_train, y_train,
  batch_size = batch,
  validation_split=0.3,
  epochs=epoch, verbose = verbose)
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_2 (Conv2D)            (None, 13, 13, 30)        300
_________________________________________________________________
flatten_2 (Flatten)          (None, 5070)              0
_________________________________________________________________
dense_2 (Dense)              (None, 10)                50710
=================================================================
Total params: 51,010
Trainable params: 51,010
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
840/840 [==============================] - 2s 2ms/step - loss: 0.5653 - accuracy: 0.8016 - val_lo
Epoch 2/5
840/840 [==============================] - 2s 2ms/step - loss: 0.4540 - accuracy: 0.8423 - val_lo
Epoch 3/5
840/840 [==============================] - 2s 2ms/step - loss: 0.4332 - accuracy: 0.8490 - val_lo
Epoch 4/5
840/840 [==============================] - 2s 2ms/step - loss: 0.4227 - accuracy: 0.8535 - val_lo
Epoch 5/5
840/840 [==============================] - 2s 2ms/step - loss: 0.4123 - accuracy: 0.8555 - val_lo
```

In [22]:
```
test_loss, test_acc = model.evaluate(x_test, y_test, verbose = 0)

print('\nTest acccuracy:', test_acc)
```

```
Test acccuracy: 0.8367000222206116
```

1.10 DIferente tamaño de pooling

- Se obtiene el mismo número de parámetros con strides=2 y sin capa pooling

```
In [23]: num_filters = 30
         filter_size = 3
         pool_size = 2

         model = Sequential([
           Conv2D(num_filters, filter_size, input_shape=input_shape),
           MaxPooling2D(pool_size=pool_size),
           Flatten(),
           Dense(10, activation='softmax'),
         ])

         model.compile('adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])

         model.summary()

         history = model.fit(
           x_train, y_train,
           batch_size = batch,
           validation_split=0.3,
           epochs=epoch, verbose = verbose)
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_3 (Conv2D)            (None, 26, 26, 30)        300
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 13, 13, 30)        0
_________________________________________________________________
flatten_3 (Flatten)          (None, 5070)              0
_________________________________________________________________
dense_3 (Dense)              (None, 10)                50710
=================================================================
Total params: 51,010
Trainable params: 51,010
Non-trainable params: 0
_________________________________________________________________
Epoch 1/5
840/840 [==============================] - 3s 3ms/step - loss: 0.5130 - accuracy: 0.8250 - val_lo
Epoch 2/5
840/840 [==============================] - 2s 3ms/step - loss: 0.3769 - accuracy: 0.8702 - val_lo
Epoch 3/5
840/840 [==============================] - 3s 3ms/step - loss: 0.3396 - accuracy: 0.8828 - val_lo
```

```
Epoch 4/5
840/840 [==============================] - 2s 3ms/step - loss: 0.3147 - accuracy: 0.8902 - val_lo
Epoch 5/5
840/840 [==============================] - 2s 3ms/step - loss: 0.2952 - accuracy: 0.8976 - val_lo
```

```
In [24]: test_loss, test_acc = model.evaluate(x_test, y_test, verbose = 0)

         print('\nTest acccuracy:', test_acc)
```

```
Test acccuracy: 0.8824999928474426
```

2 Probar predicciones del modelo

- 'argmax' retorna el elemento de mayor valor

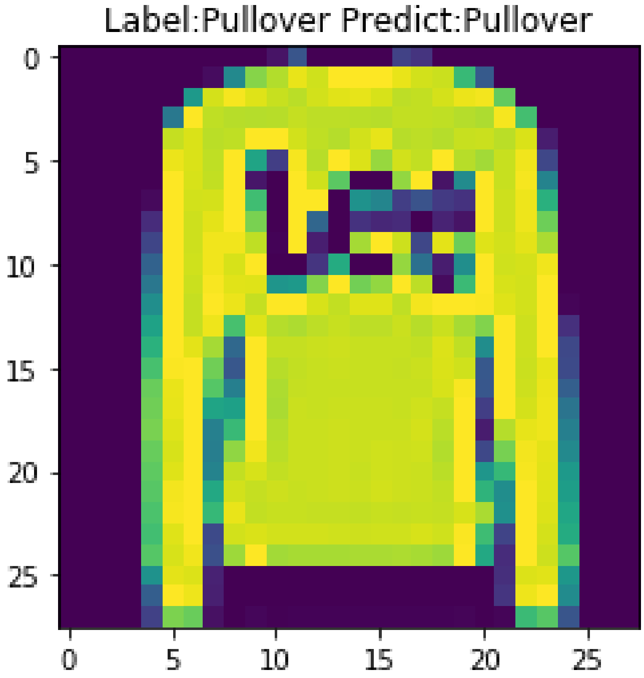
```
In [25]: # Primeras 5 imagenes de test
         predictions = model.predict(x_test[:5])

         print(np.argmax(predictions, axis=1))
         p = np.argmax(predictions, axis=1)

         print(y_test[:5])
```

```
[9 2 1 1 6]
[9 2 1 1 6]
```

```
In [26]: plt.imshow(np.squeeze(x_test[1]))
         plt.title('Label:' + class_names[int(y_test[1])]
                   + ' Predict:'+  class_names[int(p[1])])
         plt.show()
```



- Mejorar la arquitectura
- Probar con otro dataset