Projet computer vision

SKIN CANCER DETECTION

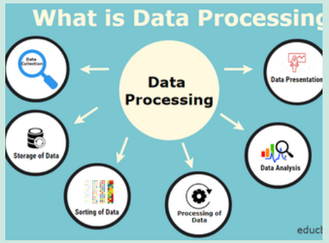
Réalisé par
Farah jbara & Ahlem Azizi

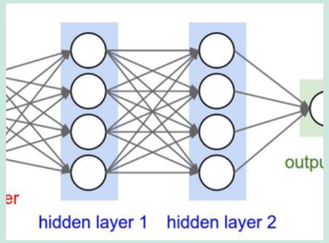
Introduction →

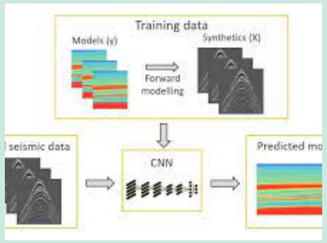
In recent days, skin cancer is seen as one of the most Hazardous form of Cancers found in Humans. Skin cancer is found in various types such as Melanoma, Basal and Squamous cell Carcinoma among which Melanoma is the most unpredictable. The detection of Melanoma cancer in the early stage can be helpful to cure it. Computer vision can play important role in Medical Image Diagnosis and it has been proved by many existing systems.

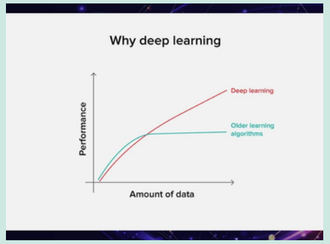
NEXT

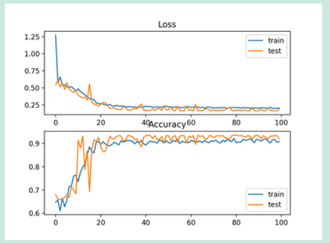
Steps











DATA PROCESSING

BUILD THE MODEL

TRAINING THE MODEL

CHECKING PERFORMANCE

TEST & RANDOM

Data augmentation

Data augmentation is a process of artificially increasing the amount of data by generating new data points from existing data

```
train_datagen = tf.keras.preprocessing.image.ImageDataGenerator(
      rescale = 1./255,
      rotation_range=40,
      horizontal_flip=True,
      width_shift_range=0.2,
      height_shift_range=0.2,
      shear_range=0.2,
      zoom_range=0.2,
      fill_mode='nearest',
      validation_split=0.4,
      brightness_range=[0.4,1.5])

train_generator = train_datagen.flow_from_directory(
    train_dir,
    subset="training",
    shuffle=True,
    seed=42,
    color_mode="rgb",
    class_mode="categorical",
    target_size=IMAGE_SIZE,
    batch_size=BATCH_SIZE)

validation_generator = train_datagen.flow_from_directory(
    train_dir,
    shuffle=False,
    seed=42,
    color_mode="rgb",
    class_mode="categorical",
    subset="validation",
    target_size=IMAGE_SIZE,
    batch_size=BATCH_SIZE)
```

```
Found 24 images belonging to 2 classes.
Found 16 images belonging to 2 classes.
```

Adding a Dropout

Le Dropout est une technique permettant de réduire l'overfitting lors de l'entraînement du modèle.

```
print("Building model with", MODULE_HANDLE)
model = tf.keras.Sequential([
    feature_extractor,
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(512, activation='relu'),
    tf.keras.layers.Dropout(rate=0.5),
    tf.keras.layers.Dense(train_generator.num_classes, activation='softmax',
                          kernel_regularizer=tf.keras.regularizers.l2(0.0001))
])
#model.build((None,)+IMAGE_SIZE+(3,))

model.summary()
```

```
Building model with https://tfhub.dev/google/tf2-preview/mobilenet_v2/feature_vector/2
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                 Output Shape              Param #
=================================================================
 keras_layer_1 (KerasLayer)  (None, 1280)              2257984

 flatten_7 (Flatten)         (None, 1280)              0

 dense_12 (Dense)            (None, 512)               655872

 dropout_7 (Dropout)         (None, 512)               0

 dense_13 (Dense)            (None, 2)                 1026

=================================================================
Total params: 2,914,882
Trainable params: 656,898
Non-trainable params: 2,257,984
_________________________________________________________________
```

Early stopping

Is designed to monitor the generalization error of one model and stop training when generalization error begins to degrade

```
from keras.callbacks import ReduceLROnPlateau, ModelCheckpoint, EarlyStopping
reduce_learning_rate = ReduceLROnPlateau(monitor = 'val_accuracy', patience = 3, verbose = 1, factor = 0.3, min_lr = 0.00001)
checkpoint = ModelCheckpoint('modelb.h5', monitor = 'val_accuracy', verbose = 1, save_best_only = True, mode = 'max')
early_stopping = EarlyStopping(monitor = 'val_loss', min_delta = 1e-10, patience = 10, verbose = 1, restore_best_weights = True)

callbacks = [reduce_learning_rate, checkpoint, early_stopping]
```

Pooling

involves sliding a two-dimensional filter over each channel of feature map and summarising the features lying within the region covered by the filter.

```
model = tf.keras.models.Sequential([
    tf.keras.layers.Conv2D(32,(3,3),strides=(1, 1),activation='relu',padding='same', input_shape=(224, 224, 3
    tf.keras.layers.MaxPooling2D(pool_size=(2,2)),

    tf.keras.layers.Conv2D(64,(3,3),strides=(1, 1) ,padding='same',activation='relu'),
    tf.keras.layers.MaxPooling2D(pool_size=(2,2)),

    tf.keras.layers.Conv2D(128,(3,3),strides=(1, 1),padding='same', activation='relu'),
    tf.keras.layers.MaxPooling2D(pool_size=(2,2)),

    tf.keras.layers.Conv2D(256,(3,3),strides=(1, 1),padding='same', activation='relu'),
    tf.keras.layers.MaxPooling2D(pool_size=(2,2)),


    tf.keras.layers.Flatten(),

    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid'),
])
```

```python
import numpy as np

acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

loss = history.history['loss']
val_loss = history.history['val_loss']

epochs_range = range(EPOCHS)

plt.figure(figsize=(10, 4))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')
plt.ylabel("Accuracy (training and validation)")
plt.xlabel("Training Steps")

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.ylabel("Loss (training and validation)")
plt.xlabel("Training Steps")
plt.show()
```