

Objašnjiva umjetna inteligencija (XAI)

Skin Cancer MNIST: HAM10000

```
In [3]: import pandas as pd

import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
import numpy as np
import pandas as pd
import tensorflow as tf
import keras
import sklearn.metrics as metrics
from imblearn.over_sampling import RandomOverSampler
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, Flatten, Dense, MaxPool2D
```

Pregled skupa podataka

Baza podataka o srčanim bolestima

HAM10000 ("Human Against Machine with 10000 training images") je skup 10015 dermatoskopskih slika iz različitih populacija, snimljenih i pohranjenih različitim metodama.

Slučajevi uključuju reprezentativnu kolekciju svih važnih dijagnostičkih kategorija pigmentiranih lezija: aktiničke keratoze i intraepitelni karcinom / Bowenova bolest (akiec), bazocelularni karcinom (bcc), benigne keratoze (solarne lentigine / seboreične keratoze i keratoze slične lišaju planusu, bkl), dermatofibrom (df), melanom (mel), melanocitni nevusi (nv) i vaskularne lezije (angiomi, angioqueratomi, piogeni granulomi i hemoragije, vasc).

```
In [4]: dataset_images_RGB = pd.read_csv("data/hmnist_28_28_RGB.csv")
print(dataset_images_RGB.head(3))
print('Slike: ', dataset_images_RGB.shape)
```

| | pixel0000 | pixel0001 | pixel0002 | pixel0003 | pixel0004 | pixel0005 | \ |
|---|-----------|-----------|-----------|-----------|-----------|-----------|---|
| 0 | 192 | 153 | 193 | 195 | 155 | 192 | |
| 1 | 25 | 14 | 30 | 68 | 48 | 75 | |
| 2 | 192 | 138 | 153 | 200 | 145 | 163 | |

| | pixel0006 | pixel0007 | pixel0008 | pixel0009 | ... | pixel2343 | pixel2344 | \ |
|---|-----------|-----------|-----------|-----------|-----|-----------|-----------|---|
| 0 | 197 | 154 | 185 | 202 | ... | 173 | 124 | |
| 1 | 123 | 93 | 126 | 158 | ... | 60 | 39 | |
| 2 | 201 | 142 | 160 | 206 | ... | 167 | 129 | |

| | pixel2345 | pixel2346 | pixel2347 | pixel2348 | pixel2349 | pixel2350 | \ |
|---|-----------|-----------|-----------|-----------|-----------|-----------|---|
| 0 | 138 | 183 | 147 | 166 | 185 | 154 | |
| 1 | 55 | 25 | 14 | 28 | 25 | 14 | |
| 2 | 143 | 159 | 124 | 142 | 136 | 104 | |

| | pixel2351 | label |
|---|-----------|-------|
| 0 | 177 | 2 |
| 1 | 27 | 2 |
| 2 | 117 | 2 |

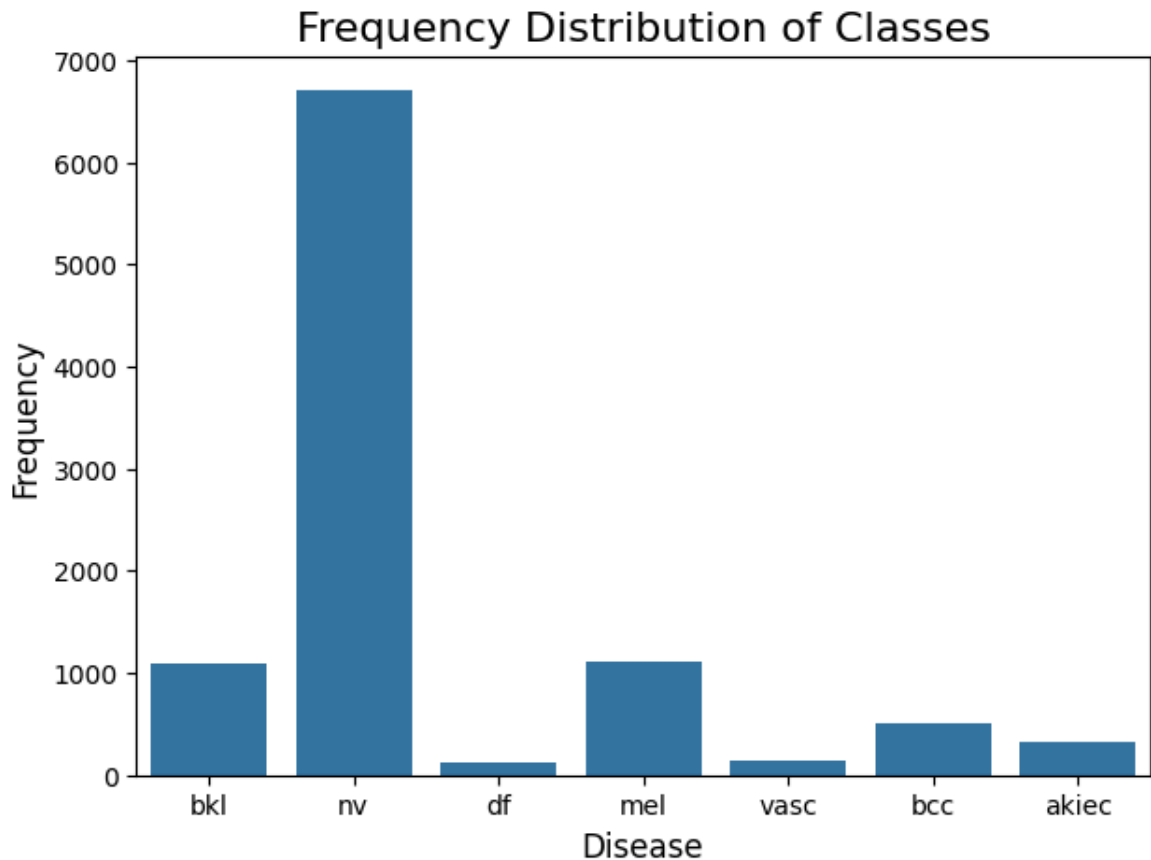
[3 rows x 2353 columns]
Slike: (10015, 2353)

```
In [ ]: dataset_meta = pd.read_csv("data/HAM10000_metadata.csv")
print(dataset_meta.head(3))
print('Metapodaci: ', dataset_meta.shape)
```

| | lesion_id | image_id | dx | dx_type | age | sex | localization |
|---|-------------|--------------|-----|---------|------|------|--------------|
| 0 | HAM_0000118 | ISIC_0027419 | bkl | histo | 80.0 | male | scalp |
| 1 | HAM_0000118 | ISIC_0025030 | bkl | histo | 80.0 | male | scalp |
| 2 | HAM_0002730 | ISIC_0026769 | bkl | histo | 80.0 | male | scalp |

Metapodaci: (10015, 7)

```
In [6]: bar, ax = plt.subplots(figsize=(7, 5))
sns.countplot(x = 'dx', data = dataset_meta)
plt.xlabel('Disease', size=12)
plt.ylabel('Frequency', size=12)
plt.title('Frequency Distribution of Classes', size=16)
plt.show()
```



```
In [7]: fig = px.histogram(data_frame=dataset_meta, x='age', color= 'sex')
fig.show()
```

CNN (Convolutional Neural Network)

```
In [8]: num_classes = 7
batch_size = 128
epochs = 10

img_rows = 28
img_cols = 28
```

```
In [9]: images = dataset_images_RGB.drop(['label'], axis=1)
labels = dataset_images_RGB['label']
```

```
In [10]: oversample = RandomOverSampler()
images, labels = oversample.fit_resample(images, labels)
```

```
In [11]: images = np.array(images)
images = images.reshape(-1, 28, 28, 3)
print('Shape of images: ', images.shape)

images = np.array(images)
images = images.reshape(-1, 28, 28, 3)
print('Shape of images: ', images.shape)
```

```
Shape of images: (46935, 28, 28, 3)
Shape of images: (46935, 28, 28, 3)
```

```
In [12]: x_train, x_test, y_train, y_test = train_test_split(images, labels,
random_state=1, test_size=0.20)
```

```
y_train = keras.utils.to_categorical(y_train, num_classes)
y_test = keras.utils.to_categorical(y_test, num_classes)
```

```
In [13]: model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu',
input_shape=(img_rows, img_cols, 3)))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.40))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))
model.summary()
```

Model: "sequential"

| Layer (type) | Output Shape | Param # |
|--------------------------------------|--------------------|---------|
| ===== | | |
| conv2d (Conv2D) | (None, 26, 26, 32) | 896 |
| max_pooling2d (MaxPooling2D) | (None, 13, 13, 32) | 0 |
| conv2d_1 (Conv2D) | (None, 11, 11, 64) | 18496 |
| max_pooling2d_1 (MaxPooling2D) | (None, 5, 5, 64) | 0 |
| dropout (Dropout) | (None, 5, 5, 64) | 0 |
| flatten (Flatten) | (None, 1600) | 0 |
| dense (Dense) | (None, 128) | 204928 |
| dropout_1 (Dropout) | (None, 128) | 0 |
| dense_1 (Dense) | (None, 7) | 903 |
| ===== | | |
| Layer (type) | Output Shape | Param # |
| ===== | | |
| conv2d (Conv2D) | (None, 26, 26, 32) | 896 |
| max_pooling2d (MaxPooling2D) | (None, 13, 13, 32) | 0 |
| conv2d_1 (Conv2D) | (None, 11, 11, 64) | 18496 |
| max_pooling2d_1 (MaxPooling2D) | (None, 5, 5, 64) | 0 |
| dropout (Dropout) | (None, 5, 5, 64) | 0 |
| flatten (Flatten) | (None, 1600) | 0 |
| dense (Dense) | (None, 128) | 204928 |
| dropout_1 (Dropout) | (None, 128) | 0 |
| dense_1 (Dense) | (None, 7) | 903 |
| ===== | | |
| Total params: 225223 (879.78 KB) | | |
| Trainable params: 225223 (879.78 KB) | | |
| Non-trainable params: 0 (0.00 Byte) | | |

```
In [14]: callback = tf.keras.callbacks.ModelCheckpoint(filepath='CNN/cnn-RGB.keras', monitor=model.compile(loss=keras.losses.categorical_crossentropy, optimizer='adam', metrics=['accuracy']))
```

```
In [15]: history = model.fit(x_train, y_train, batch_size=batch_size, epochs=epochs, validation_split=0.2, callbacks=[callback])
```

Epoch 1/10
235/235 [=====] - ETA: 0s - loss: 2.7896 - accuracy: 0.3393
Epoch 1: saving model to CNN\cnn-RGB.keras
235/235 [=====] - 10s 40ms/step - loss: 2.7896 - accuracy: 0.3393 - val_loss: 1.4271 - val_accuracy: 0.4442
Epoch 2/10
235/235 [=====] - ETA: 0s - loss: 1.4210 - accuracy: 0.4320
Epoch 2: saving model to CNN\cnn-RGB.keras
235/235 [=====] - 9s 40ms/step - loss: 1.4210 - accuracy: 0.4320 - val_loss: 1.2047 - val_accuracy: 0.5352
Epoch 3/10
235/235 [=====] - ETA: 0s - loss: 1.2810 - accuracy: 0.4819
Epoch 3: saving model to CNN\cnn-RGB.keras
235/235 [=====] - 10s 41ms/step - loss: 1.2810 - accuracy: 0.4819 - val_loss: 1.1361 - val_accuracy: 0.5722
Epoch 4/10
235/235 [=====] - ETA: 0s - loss: 1.2138 - accuracy: 0.5134
Epoch 4: saving model to CNN\cnn-RGB.keras
235/235 [=====] - 10s 43ms/step - loss: 1.2138 - accuracy: 0.5134 - val_loss: 1.0285 - val_accuracy: 0.5883
Epoch 5/10
235/235 [=====] - ETA: 0s - loss: 1.1361 - accuracy: 0.5489
Epoch 5: saving model to CNN\cnn-RGB.keras
235/235 [=====] - 10s 41ms/step - loss: 1.1361 - accuracy: 0.5489 - val_loss: 0.9605 - val_accuracy: 0.6406
Epoch 6/10
235/235 [=====] - ETA: 0s - loss: 1.0383 - accuracy: 0.5948
Epoch 6: saving model to CNN\cnn-RGB.keras
235/235 [=====] - 10s 41ms/step - loss: 1.0383 - accuracy: 0.5948 - val_loss: 0.8683 - val_accuracy: 0.6933
Epoch 7/10
235/235 [=====] - ETA: 0s - loss: 0.9763 - accuracy: 0.6176
Epoch 7: saving model to CNN\cnn-RGB.keras
235/235 [=====] - 10s 41ms/step - loss: 0.9763 - accuracy: 0.6176 - val_loss: 0.7642 - val_accuracy: 0.7142
Epoch 8/10
235/235 [=====] - ETA: 0s - loss: 0.9349 - accuracy: 0.6405
Epoch 8: saving model to CNN\cnn-RGB.keras
235/235 [=====] - 9s 40ms/step - loss: 0.9349 - accuracy: 0.6405 - val_loss: 0.7199 - val_accuracy: 0.7628
Epoch 9/10
235/235 [=====] - ETA: 0s - loss: 0.8848 - accuracy: 0.6580
Epoch 9: saving model to CNN\cnn-RGB.keras
235/235 [=====] - 10s 43ms/step - loss: 0.8848 - accuracy: 0.6580 - val_loss: 0.6555 - val_accuracy: 0.7668
Epoch 10/10
235/235 [=====] - ETA: 0s - loss: 0.8086 - accuracy: 0.6900
Epoch 10: saving model to CNN\cnn-RGB.keras
235/235 [=====] - 10s 42ms/step - loss: 0.8086 - accuracy: 0.6900 - val_loss: 0.5675 - val_accuracy: 0.8025

Evaluacija

```
In [16]: score = model.evaluate(x_test, y_test, verbose=0)
print('Summary: Loss over the test dataset: %.2f, Accuracy: %.2f' %(score[0], sc
```

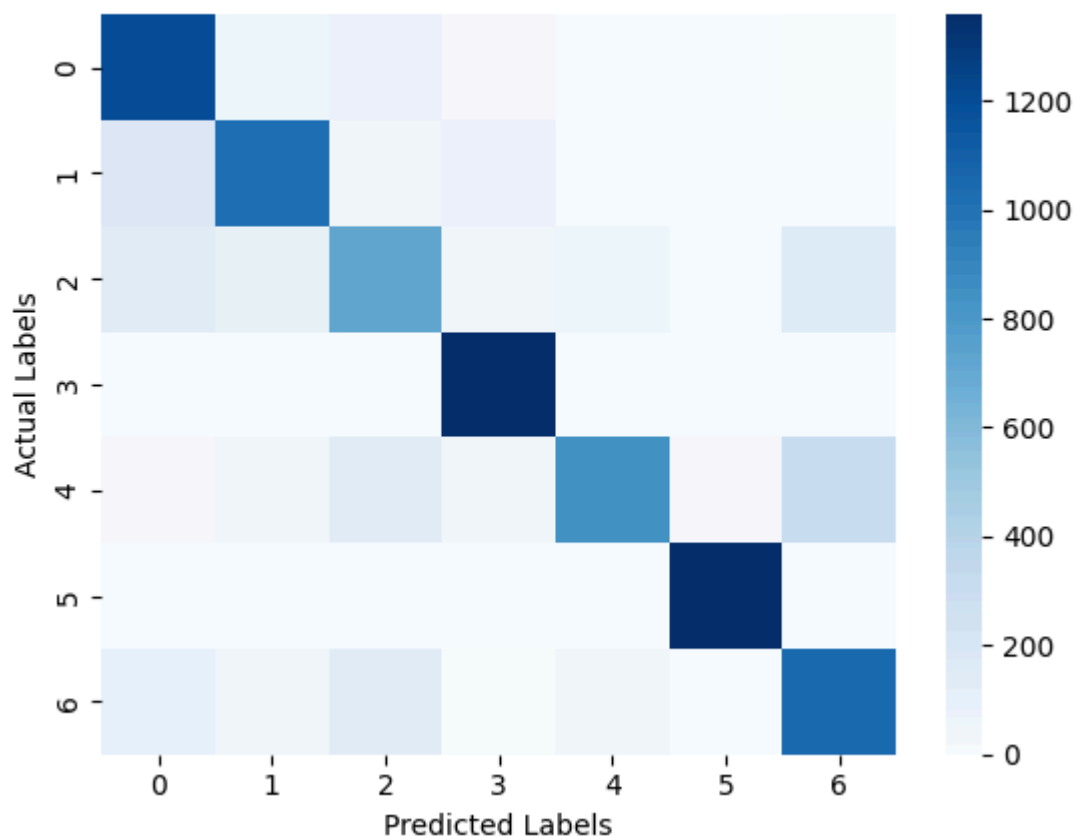
Summary: Loss over the test dataset: 0.58, Accuracy: 0.80

```
In [17]: y_pred = model.predict(x_test)
y_pred_classes = np.argmax(y_pred, axis=1)
y_true = np.argmax(y_test, axis =1)
confusion_matrix = metrics.confusion_matrix(y_true=y_true,
y_pred=y_pred_classes )

ax = sns.heatmap(confusion_matrix, fmt='', cmap='Blues')
ax.set_title('Confusion Matrix with labels\n');
ax.set_xlabel('Predicted Labels')
ax.set_ylabel('Actual Labels')
plt.show()
```

294/294 [=====] - 1s 4ms/step

Confusion Matrix with labels



Saliency maps (Pixel Attribution)

```
In [18]: from tensorflow.keras.preprocessing.image import load_img, img_to_array
from tensorflow.keras.preprocessing import image
from tensorflow.keras import backend as K
from tf_keras_vis.saliency import Saliency
from tf_keras_vis.utils import normalize
from vis.utils import utils
```

```
from tf_keras_vis.utils.scores import CategoricalScore

import random
```

```
In [19]: layer_idx = utils.find_layer_idx(model, model.layers[-1].name)
model.layers[-1].activation = tf.keras.activations.linear
model = utils.apply_modifications(model)
```

C:\Users\Antonia\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.8_qbz5n2kfra8p0\LocalCache\local-packages\Python38\site-packages\keras\src\engine\training.py:3000: UserWarning:

You are saving your model as an HDF5 file via `model.save()`. This file format is considered legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')`.

```
In [21]: def saliencyPlot(img_index = 0):
    x = x_test[img_index]
    x = x.reshape((1,) + x.shape)
    x = np.array(x, dtype=np.float32)

    prediction = model.predict(x)
    y_prediction = np.argmax(prediction)
    y_true = np.argmax([y_test[img_index]])
    print(f"Model output: {prediction}")
    print(f"Model prediction: {y_prediction}")
    print(f"True clasification: {y_true}")

    score = CategoricalScore([y_prediction])

    saliency = Saliency(model, clone=False)

    saliency_map = saliency(score, x, smooth_samples=20)
    saliency_map = normalize(saliency_map)

    subplot_args = {
        'nrows': 1,
        'ncols': 2,
        'figsize': (6, 3),
        'subplot_kw': {'xticks': [], 'yticks': []}
    }

    f, ax = plt.subplots(**subplot_args)
    ax[0].imshow(x_test[img_index])
    ax[1].imshow(saliency_map[0], cmap='Reds')
    plt.tight_layout()
    plt.show()

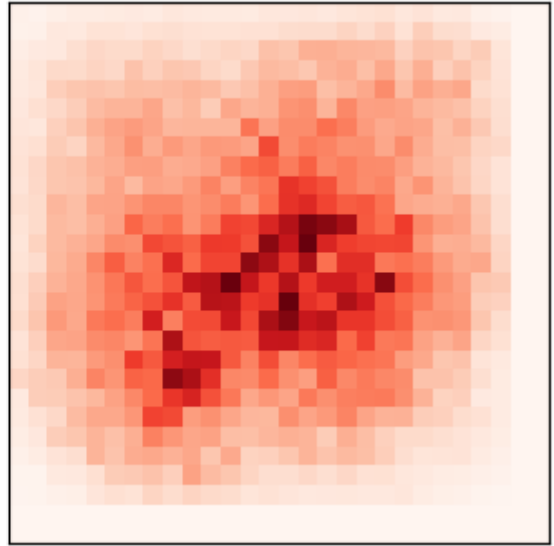
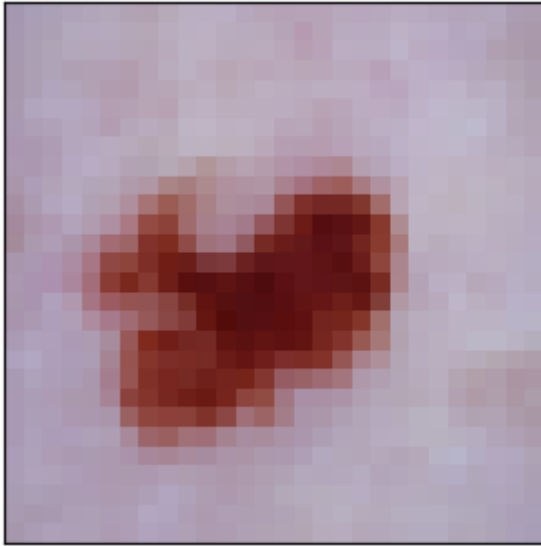
    for i in range(5):
        saliencyPlot(random.randrange(0, len(x_test)))
```

1/1 [=====] - 0s 16ms/step

Model output: [[-5.529092 -6.287302 13.48935 -20.948671 20.702822 -16.64197
22.525131]]

Model prediction: 6

True clasification: 6

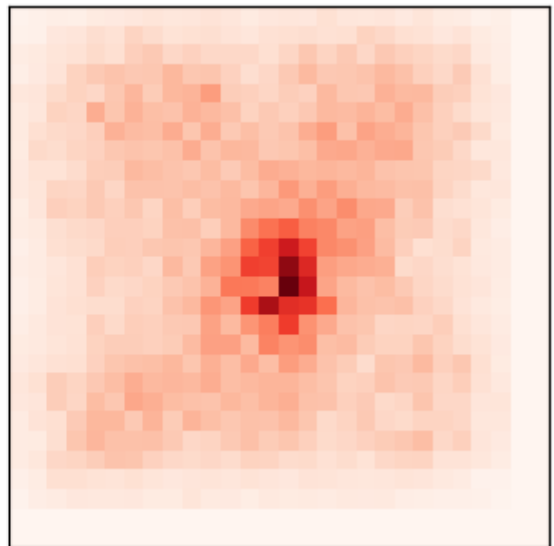
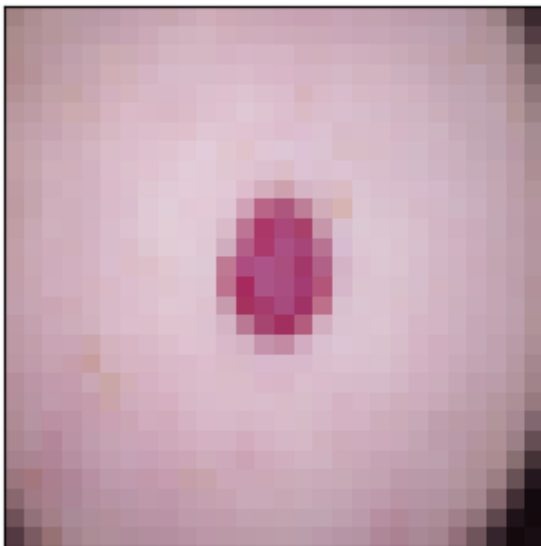


1/1 [=====] - 0s 17ms/step

Model output: [[-14.7710285 2.7037752 -3.7271929 -6.8785734 1.9419974 13.436104
-2.2827864]]

Model prediction: 5

True clasification: 5

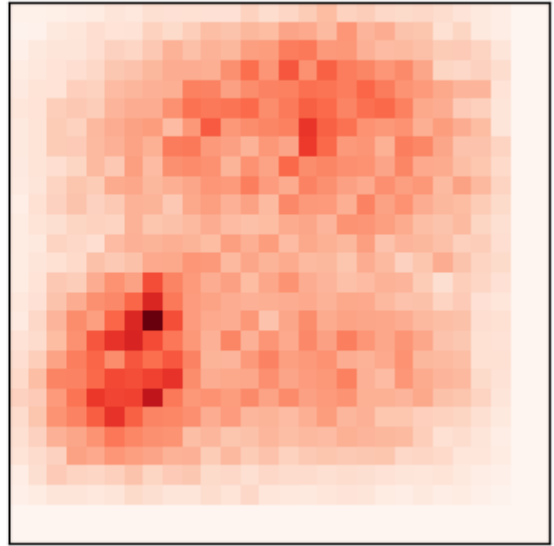


1/1 [=====] - 0s 15ms/step

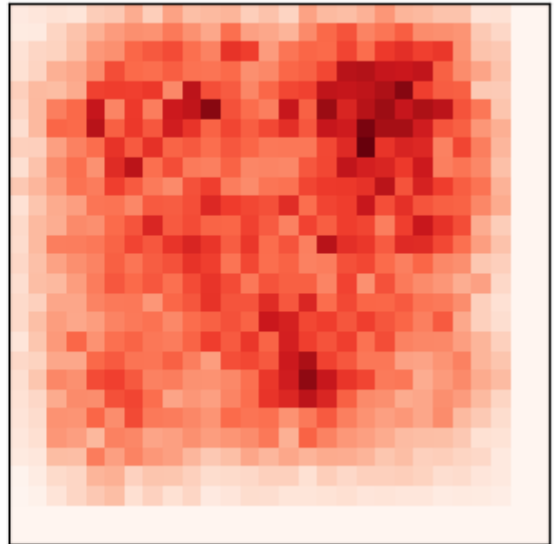
Model output: [[2.5476182 2.0607042 0.9720427 -1.2882347 -1.3925024 -2.9985223
0.1737361]]

Model prediction: 0

True clasification: 0



```
1/1 [=====] - 0s 16ms/step
Model output: [[ 2.343579  1.5000801  0.9288622  1.1681467 -1.5176104 -4.371785
 -1.5361764]]
Model prediction: 0
True clasification: 0
```



```
1/1 [=====] - 0s 17ms/step
Model output: [[ 2.1948698  0.42213526  3.3318202 -3.0356596 -0.38792053 -4.22
 6078
 1.4361802 ]]
Model prediction: 2
True clasification: 2
```

