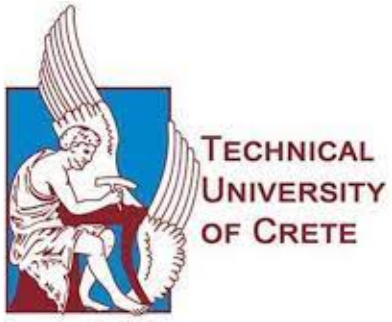

Autonomous Agents Report

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Project's topic

Agent Training to recognise Invasive Ductal Carcinoma (IDC), the most common subtype of all breast cancers, given breast histopathology images, with the use of Deep Learning

Contents

1 Introduction

Nowadays, medicine has made huge steps forward, there are still many health problems that are not completely solved. One of those and probably the most major one is the disease of cancer. This was the reason why I decided to make a project to predict breast cancer, a form of cancer that causes the death of 670,000 women annually.

So to solve the problem I decided to build a Convolutional Neural Network (CNN) in Python and train it properly on a database with histopathology images. The agent is used to process those images and then predict the state of the patients health, more specifically if they are positive or negative in the disease of breast cancer.

2 Data Management

2.1 Visualization

The first step to complete the project was to choose and understand the dataset that it needs to train the model. First of all, the dataset was fully labeled, which helps to train the model the right way and also to visualize the given data.

To visualize the data, it was split in 2 sets, the positive and the negative ones, and then with the use of Python modules there was created at first a data frame (pandas module) and then a histogram (plotly.express module), to see how the dataset is distributed, and a matrix of images and their labels (numpy, keras.preprocessing and matplotlib.pyplot modules).

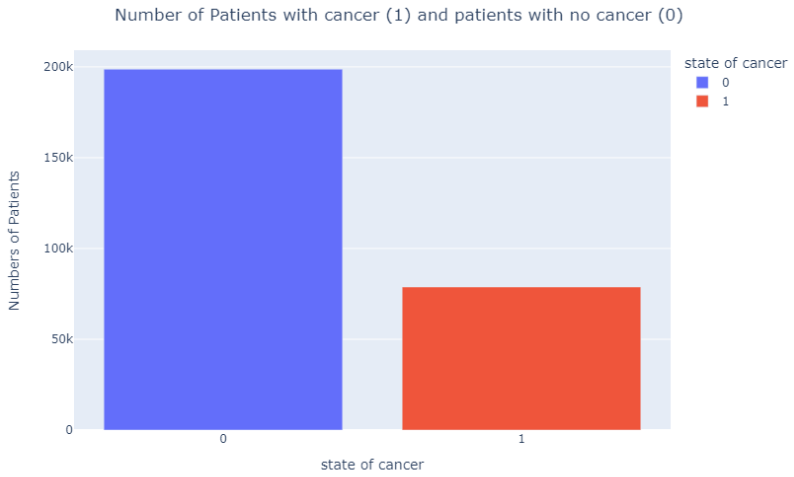


Figure 1: Data distribution

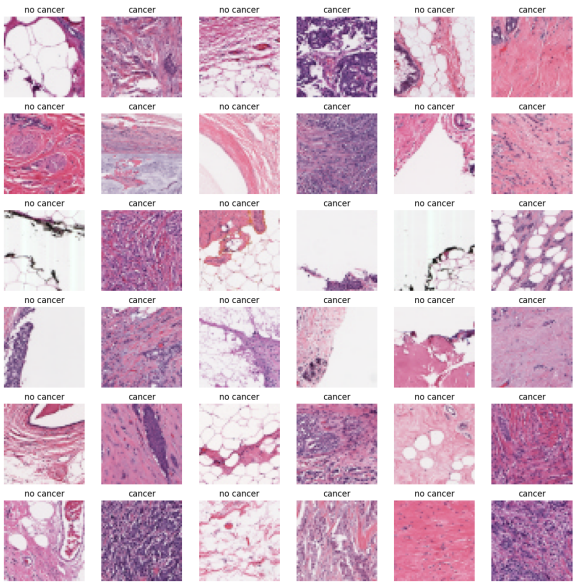


Figure 2: Data Visualization

2.2 Preprocessing

Before the training procedure the data that was split before on two sets, non cancer and cancer, are getting resized so the training is more reliable and then they are put to new lists with their labels. After that the two lists are concatenated and split back, with the criterion of being an image or label into two different arrays (X, Y). At the final step the data was encoded using the one-hot encoding, to represent categorical variables as numerical values that is quite beneficial in the current project. Finally, the parameters of the training are ready and the only thing left is to separate the labeled data in to training and testing set, used for validation and testing (validation was avoided because of the small dataset). The percentage of split was chosen after many trials and the most efficient was the following :

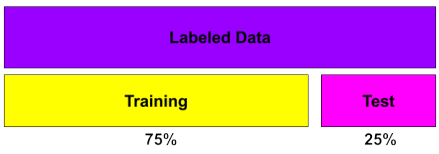


Figure 3: Data Split

3 Agent

3.1 Modules used

To build the network, the Keras API was used. Keras is a deep learning API written in Python, running on the TensorFlow machine learning platform.

The network model was based on data processing through the Deep Learning process. Algorithms are based on processing and collection data using multiple neurons, where each of them receives information, processes it and output a result. Specifically multiply each of their inputs with the corresponding synaptic weight and calculate the total sum of the products. This sum is fed as an argument to one activation function, where each node implements internally. The value that the function takes for the said argument is also the output of the neuron for the current inputs and weights.

In this implementation, the Sequential model, provided by Keras, is used and is nothing other than a linear stack of layers, where each layer consists of neurons. Neurons from different layers are connected to each other, and with appropriate weights, depending on the type of layer used.

For image processing, which is required to solve the problem, convolutional layers and computational layers (Dense Layers, Pooling Layers, Flatten Layers) are used. The particular neurons process the information at each level and pass it on to the next. More specifically:

- Convolutional layers in each unit, neuron takes an image as an input, apply a filter(or kernel) to it and output the results to neurons of the next layer. Overall, each layer apply a series of several filters where they map onto the image and extract details from it. Such details may be edge detection, bright and dark areas, information where they help the network learn and operate on patterns.

- Dense layers help to change the dimension of the input information, so that the model to be able to easily define the relationship between the data values on which it operates. These layers are usually used at the end of the model and take as an input, the output of Cl. Depending on the information, the output of each layer get the corresponding weights.

- Pooling layers are applied after the convolutional layer. The main purpose of pooling is to reduce the size of feature maps, which in turn make computation faster because the number of training parameters is reduced.

- Flatten layers are used to convert all the resultant 2-Dimensional arrays from pooled feature maps into a single long continuous linear vector. The flattened matrix is fed as an input to the fully connected layer to classify the image.

The following Python modules where used in order to implement the things mentioned before:

- from sklearn.model_selection import train_test_split
- from keras.utils import to_categorical
- import tensorflow

3.2 Optimizer

In order to train the models apart from their building blocks, it is necessary to define the process that the network is going to learn throughout the training. However, because of the large number of parameters, choosing the right weights for the model and in a relatively quick time can be a quite challenging task for the builder of the network.

For this reason, the use of an optimization algorithm (optimizer) was decided, so that it modifies the characteristics of the neural network, such as the weights and the learning rate, leading to an immediate reduction of total loss and improving accuracy. The optimizer used in this case is Adam with one relatively low learning rate, set as 0.001.

3.3 Model

For the creation of the model, a specific architecture was chosen. That came up after many trials in the model and constantly monitoring the results of the training and evaluation processes.

The previously mentioned architecture consists :

- At first, a Convolutional Layer is being put into the architecture that has the size of the input (50,50) with 32 filters. After that the data was passed to a max_pooling layer, so the size can be reduced (25,25) and their characteristics get more obvious.
- After that we repeat the previous step for 3 more times. Firstly, the input shape is (25,25) but with 64 filters, with the same procedure as before using max_pooling and reducing the size to (12,12). The second time the input shape is (12,12), the filters are 128 and max_pooling reduces the size once more on to (5,5). The final time the input shape of the Convolutional Layer is (5,5) and reduced to a (2,2) after max_pooling, keeping the filters the same as before.
- In the end, we add a Flatten Layer to transform the 2-dimensional array we receive after the previous layers to a vector so we can simplify the classification process. After having converted the data into a one-dimensional sequence, in order to reduce the effect of overfitting on the data with which the model is trained (not to learn specific patterns). The last stage of the network consists of two Dense Layers. The first sized

128 to reduce the data and the second, sized 2, to output the two probabilities of the objects it was trained on.

Additionally, each Convolutional Layer and the first Dense use the Rectified Linear Unit (ReLU) activation function, to activate the corresponding nodes and calculate the corresponding weights. Function's type is ReLU(x) = max(0,x), with x being the inputs and is returned when it is positive, otherwise 0 is returned. The last Dense Layer uses softmax as activitation function in order to output a probability distribution over the two possible classes and allow the CNN to make more accurate predictions.

Furthermore, each layer has its strides set to 2. As a result the filter will move two pixels to the right at each step instead of one. This means the filter would be applied fewer times, and the resulting output (often referred to as a feature map) would be smaller. Also, same padding is used to keep the output size equal to the input size after convolution.

The model analytically and graphicly:

Layer (type)	Output Shape	Param #
conv2d_36 (Conv2D)	(None, 50, 50, 32)	896
max_pooling2d_36 (MaxPooling2D)	(None, 25, 25, 32)	0
conv2d_37 (Conv2D)	(None, 25, 25, 64)	18,496
max_pooling2d_37 (MaxPooling2D)	(None, 12, 12, 64)	0
conv2d_38 (Conv2D)	(None, 12, 12, 128)	73,856
max_pooling2d_38 (MaxPooling2D)	(None, 5, 5, 128)	0
conv2d_39 (Conv2D)	(None, 5, 5, 128)	147,584
max_pooling2d_39 (MaxPooling2D)	(None, 2, 2, 128)	0
flatten_9 (Flatten)	(None, 512)	0
dense_18 (Dense)	(None, 128)	65,664
dense_19 (Dense)	(None, 2)	258

Total params: 306,754 (1.17 MB)
Trainable params: 306,754 (1.17 MB)
Non-trainable params: 0 (0.00 B)

Figure 4: CNN model matrix

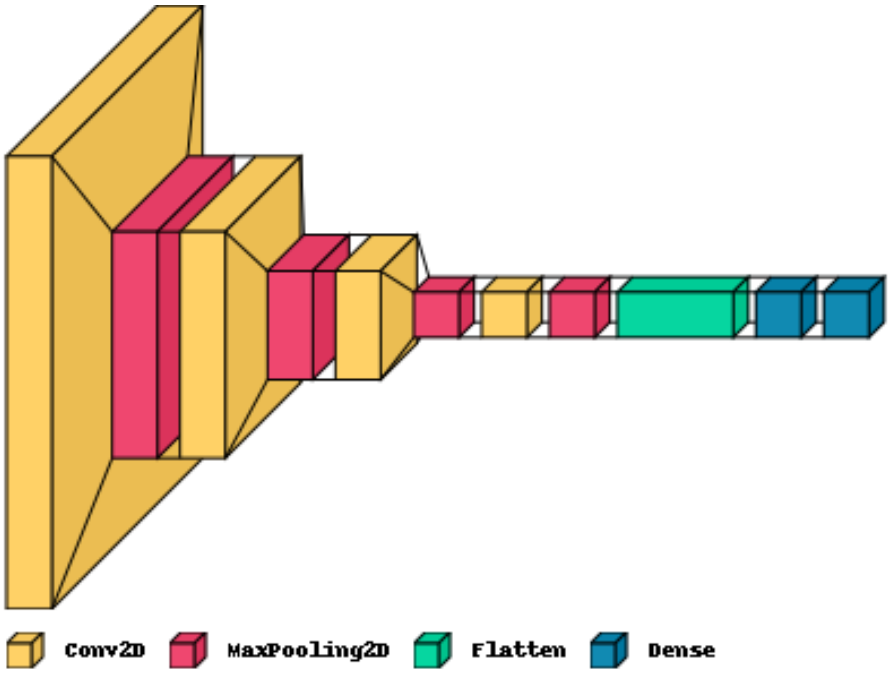


Figure 5: CNN model 3D Visualization

4 Agent Training

4.1 Training process

The training process was highly demanding concerning the computational resources and the size of the dataset (277,524 images) so it was decided to execute the procedure using cloud resources, specifically in a Kaggle notebook so the dataset can be accessed with ease. In order for the network to be trained properly the arrays X and Y where "fed" to the neurons in batches and for a specific number of times to complete many cycles of training and get more reliable weight values therefore better training results.

More specifically the batch size was set to 75 as long as there where available resources to use and reduce the mistakes. The number of training cycles, which are called epochs, was set to 25 because while monitoring the results they where stabilized to certain values. Also, a part of the dataset was used to validate the dataset and continuously adjust the weights to achieve better and more accurate results, by preventing overfitting.

Console's output in each epoch :

```
Epoch 1/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 22s 7ms/step - accuracy: 0.8073 - loss: 0.7728 - val_accuracy: 0.8425 - val_loss: 0.3652
Epoch 2/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8388 - loss: 0.3739 - val_accuracy: 0.8483 - val_loss: 0.3461
Epoch 3/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8466 - loss: 0.3550 - val_accuracy: 0.8463 - val_loss: 0.3514
Epoch 4/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8497 - loss: 0.3474 - val_accuracy: 0.8477 - val_loss: 0.3416
Epoch 5/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8535 - loss: 0.3409 - val_accuracy: 0.8567 - val_loss: 0.3283
Epoch 6/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8539 - loss: 0.3380 - val_accuracy: 0.8555 - val_loss: 0.3322
Epoch 7/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8559 - loss: 0.3351 - val_accuracy: 0.8549 - val_loss: 0.3395
Epoch 8/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8574 - loss: 0.3316 - val_accuracy: 0.8449 - val_loss: 0.3519
Epoch 9/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8585 - loss: 0.3309 - val_accuracy: 0.8561 - val_loss: 0.3340
Epoch 10/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8592 - loss: 0.3309 - val_accuracy: 0.8592 - val_loss: 0.3290
Epoch 11/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8607 - loss: 0.3253 - val_accuracy: 0.8577 - val_loss: 0.3306
Epoch 12/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8604 - loss: 0.3270 - val_accuracy: 0.8578 - val_loss: 0.3369
Epoch 13/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8615 - loss: 0.3237 - val_accuracy: 0.8605 - val_loss: 0.3272
```

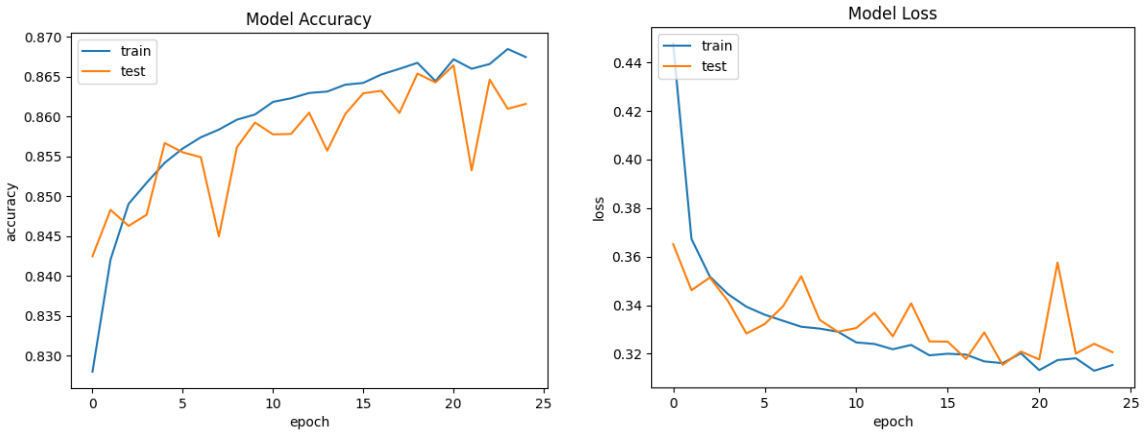
(a)

```
Epoch 14/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8619 - loss: 0.3240 - val_accuracy: 0.8557 - val_loss: 0.3408
Epoch 15/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8626 - loss: 0.3216 - val_accuracy: 0.8603 - val_loss: 0.3251
Epoch 16/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8634 - loss: 0.3212 - val_accuracy: 0.8629 - val_loss: 0.3250
Epoch 17/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8631 - loss: 0.3227 - val_accuracy: 0.8632 - val_loss: 0.3179
Epoch 18/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8646 - loss: 0.3184 - val_accuracy: 0.8604 - val_loss: 0.3288
Epoch 19/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8664 - loss: 0.3158 - val_accuracy: 0.8654 - val_loss: 0.3154
Epoch 20/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8636 - loss: 0.3219 - val_accuracy: 0.8643 - val_loss: 0.3209
Epoch 21/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8659 - loss: 0.3138 - val_accuracy: 0.8664 - val_loss: 0.3176
Epoch 22/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8660 - loss: 0.3137 - val_accuracy: 0.8532 - val_loss: 0.3575
Epoch 23/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8630 - loss: 0.3264 - val_accuracy: 0.8646 - val_loss: 0.3201
Epoch 24/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8670 - loss: 0.3152 - val_accuracy: 0.8610 - val_loss: 0.3241
Epoch 25/25
2776/2776 ━━━━━━━━━━━━━━━━━━━━ 16s 6ms/step - accuracy: 0.8665 - loss: 0.3159 - val_accuracy: 0.8616 - val_loss: 0.3207
```

(b)

Figure 6: Training Process

The model's result for it's accuracy and loss in the training process:



(a) Accuracy Plot

(b) Loss Plot

Figure 7: Training Overview

As it seems the average values of the validation and training are pretty close and in a satisfactory level, when taking into account that we deal with image recognition and in order to achieve better results it is needed a more analytic dataset and further training time.

5 Agent Testing

In order to test the created agent the data that where splitted for training are used and to present the result a Confusion Matrix was created. In that way it can be seen how many of the true lables the model was able to predict after the training and the results are the following :

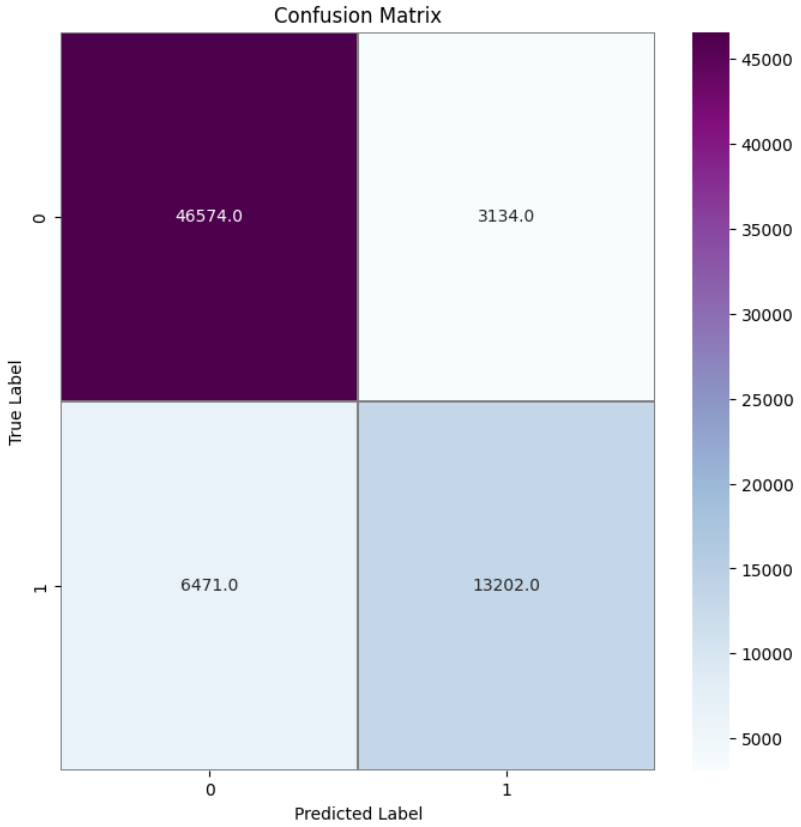


Figure 8: Data Split

In that way it is observed that works pretty well in general terms since the accuracy of the prediction was at the 84,9%, a percentage near to the one that was achieved in training. However, even thought in the negative cases the model predicts succesfully the 93.7% of the cases as negative, in the positive cases it performs significantly lower at 67.1%, but that is probably due to the unbalanced dataset, that as we can see in Figure 1 it has much more negative cases than positive (198,738 IDC negative and 78,786 IDC positive).

6 Breast Cancer Detection

6.1 App

To solve the initial problem it was created a small app that takes an image from the test dataset and print its label. After that the model predicts the value of the particular image and prints the comparison between the true label and the predicted one. This app can easily be expanded further in a next stage of development to take as input new histopathology images. The test image:

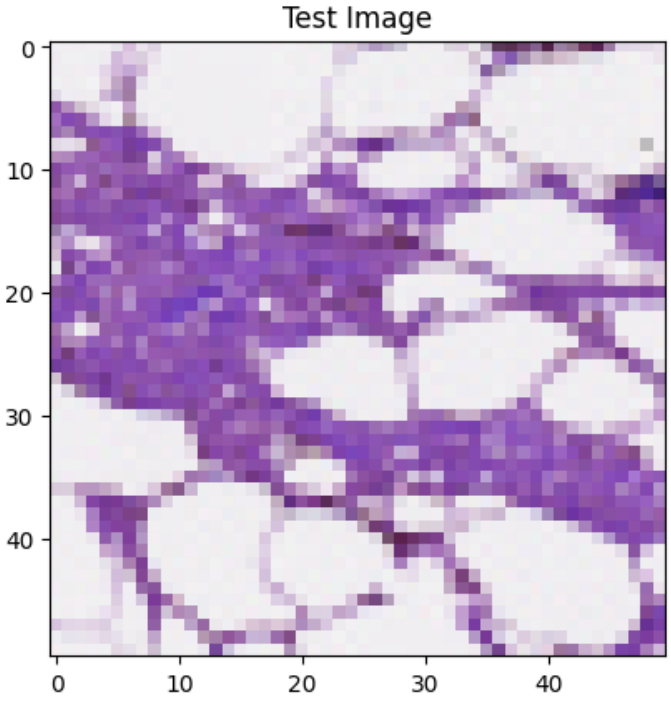


Figure 9: Test Image

The particular results for the image above:

```
Predicted Value using  cnn model 0
True Value 0
```

Figure 10: Results

6.2 Problems faced

The main problem that I faced during the creation of the project was the lack of computer resources that was solved with the help of cloud services. An other problem was that the dataset was not fully appropriate because of the inequality of the samples in our cases and its small size for this kind of use.

6.3 Conclusion

In conclusion, creating the project we managed to recognise Invasive Ductal Carcinoma, the most common subtype of all breast cancers, taking as input breast histopathology images. The agent can predict the result with 84.9% accuracy and even thought it is not in a satisfactory level of accuracy, when thinking about the ethical part of creating a tool that can have appliance in medicine, it was a great way to become familiar with the concept of deep learning and the use of neural networks.

7 References

- Dataset : Images
- Cource's book : Artificial Intelligence : One modern approach, 4th American version
- Deep Learning Fundamentals : Course
- Ideas for the implementation : Link
- Knowledge for Keras API : Link