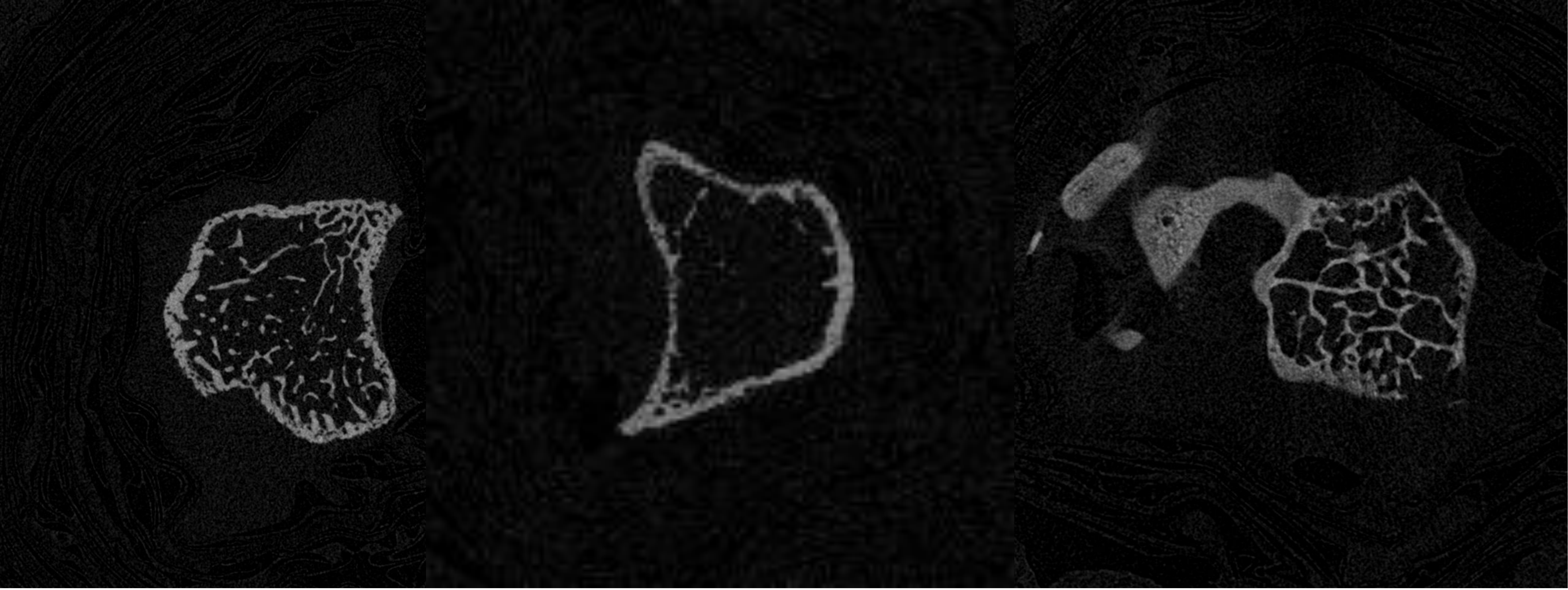


INTERNAL BONE RECONSTRUCTION USING MACHINE LEARNING

Moira Shooter
Lucien Hugueniot

OVERVIEW

- Predicting the **porosity factor** (amount of void space) of a porous object such as a bone to **3D reconstruct** the internal structure of the object with help of **machine learning**

- **Can** the Machine learning algorithm **learn** the porosity of objects?

Machine learning technical terms

Epoch: An epoch is one **complete presentation** of the data set **to be learned** by the machine learning algorithm

ReLU: Stands for Rectified Linear Unit and is a non-linear operation. It **replaces** all **negative pixel values** in feature map **with zero**.

Convolutional layer : Extracts features such as edges **from the input image**, and creates feature maps, the more features extracted the better the network recognise images

Machine learning technical terms

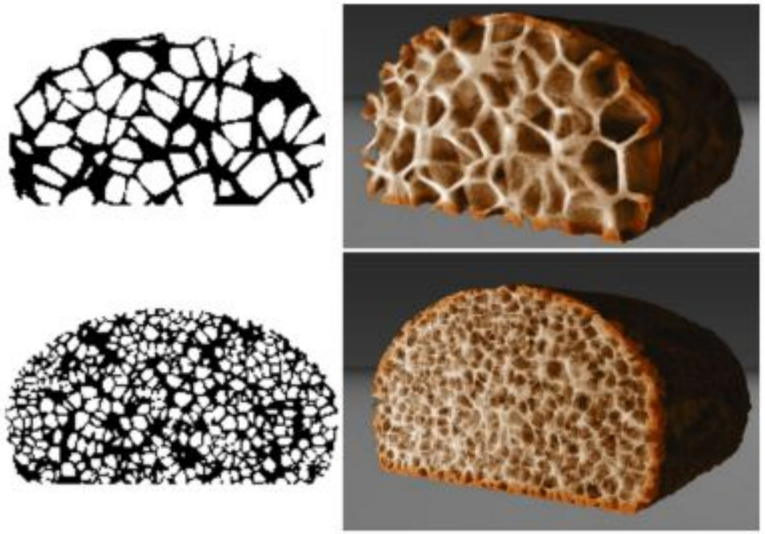
Pooling Layer: Reduces the dimensionality of each feature map but keeps the most important information

Dense Layer(Fully connected layer): all the neurons from the previous layer with the current layer

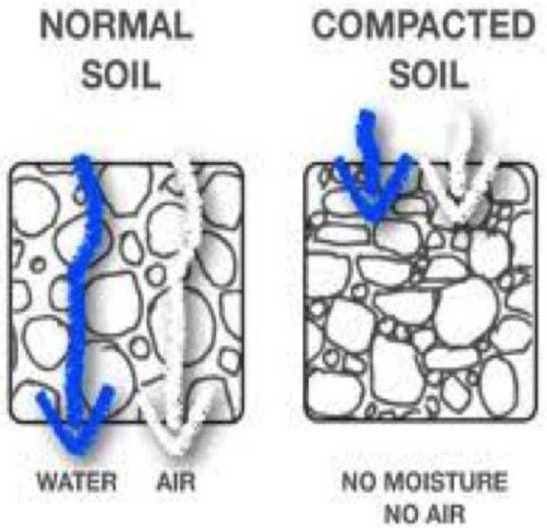
Drop out layer: The purpose of this layer is to **avoid overfitting**

Motivation

Simulations
Realistic modeling of porous materials [2]



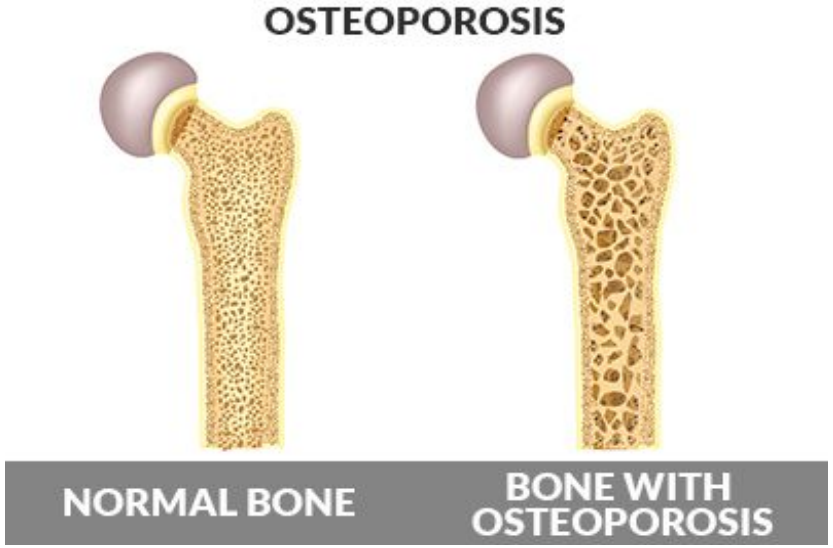
Engineering
Soil conditions and plant growth [3]



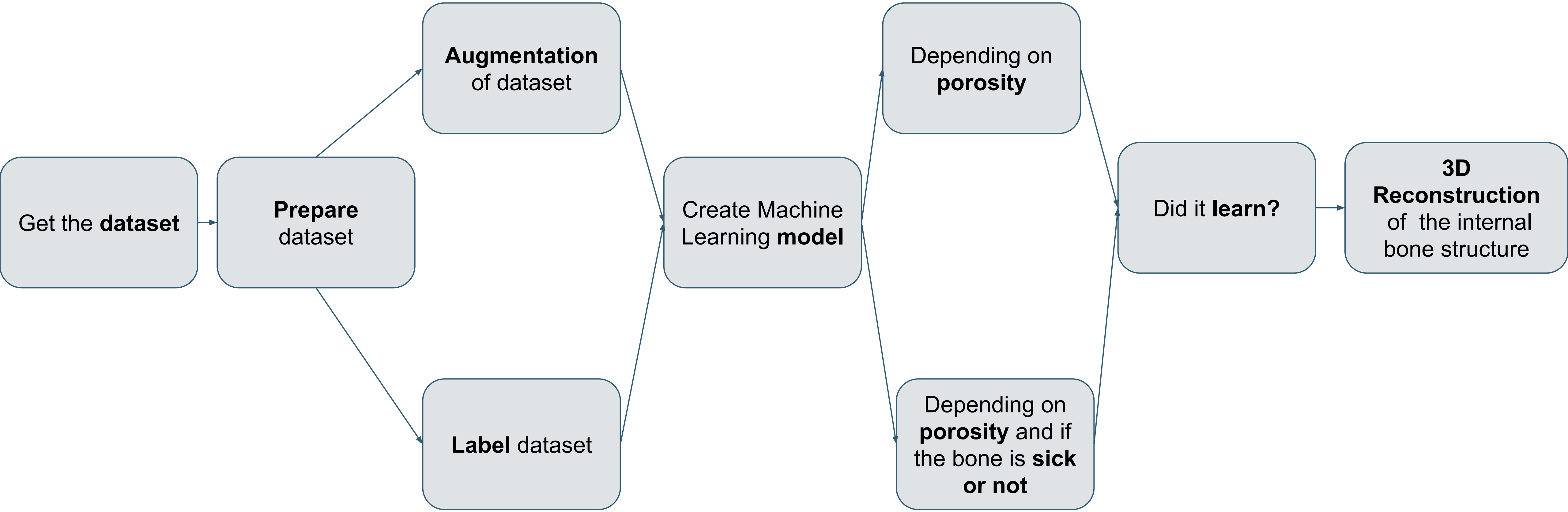
Motivation

Medical area
Prosthetics [5]

Medical area
Analysing bone sickness[6]



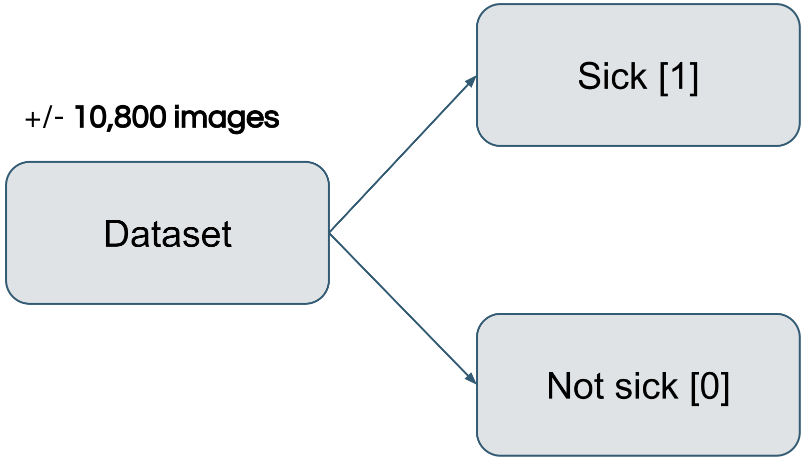
APPROACH


Get the dataset
Prepare dataset
Augmentation of dataset
Label dataset
Create Machine Learning model
Depending on porosity
Depending on porosity and if the bone is sick or not
Did it learn?
3D Reconstruction of the internal bone structure

PREPARE THE DATASET[1]

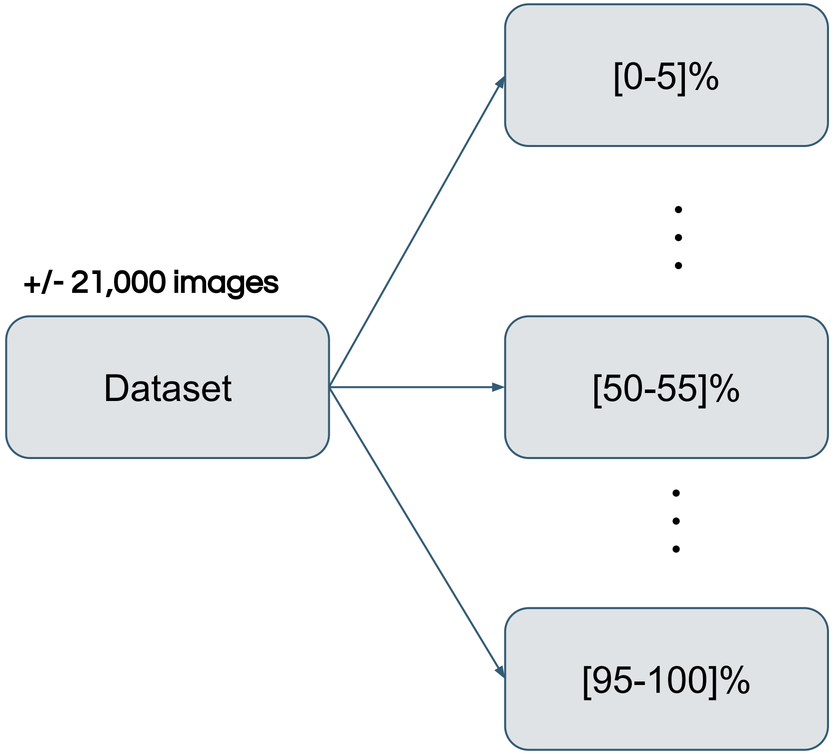
Depending on **healthiness factor** of the bone

+/- **10,800 images**

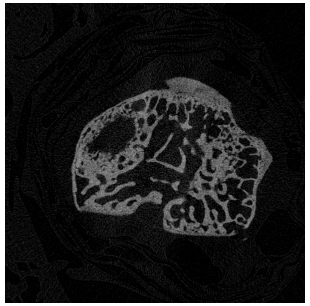


Depending on **porosity factor** of the bone

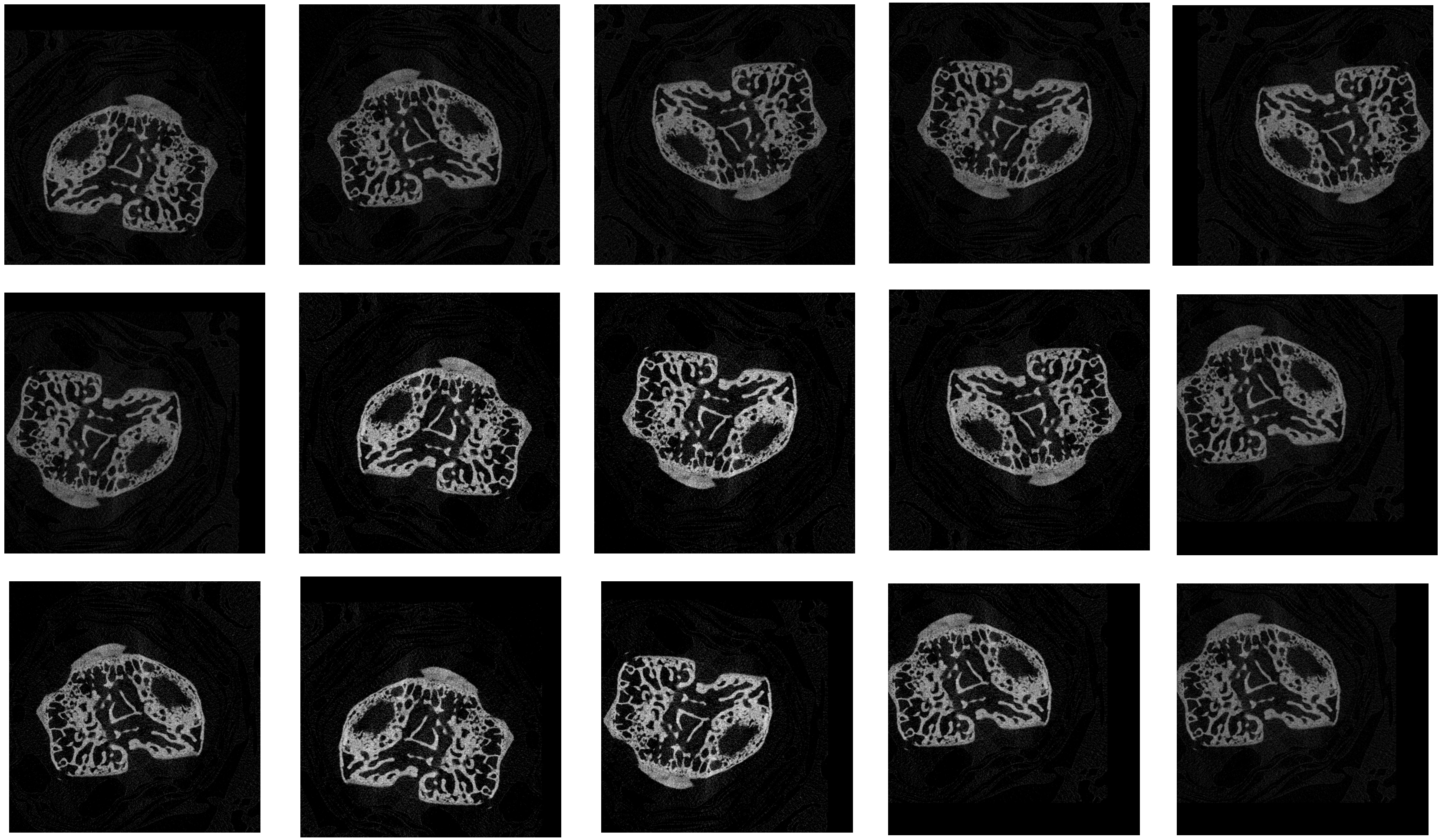
+/- 21,000 images



THE BIGGER THE BETTER



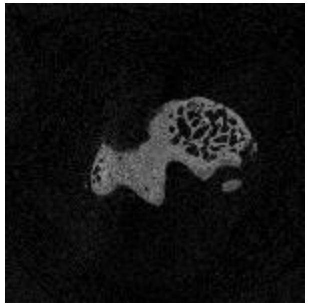
Original Image



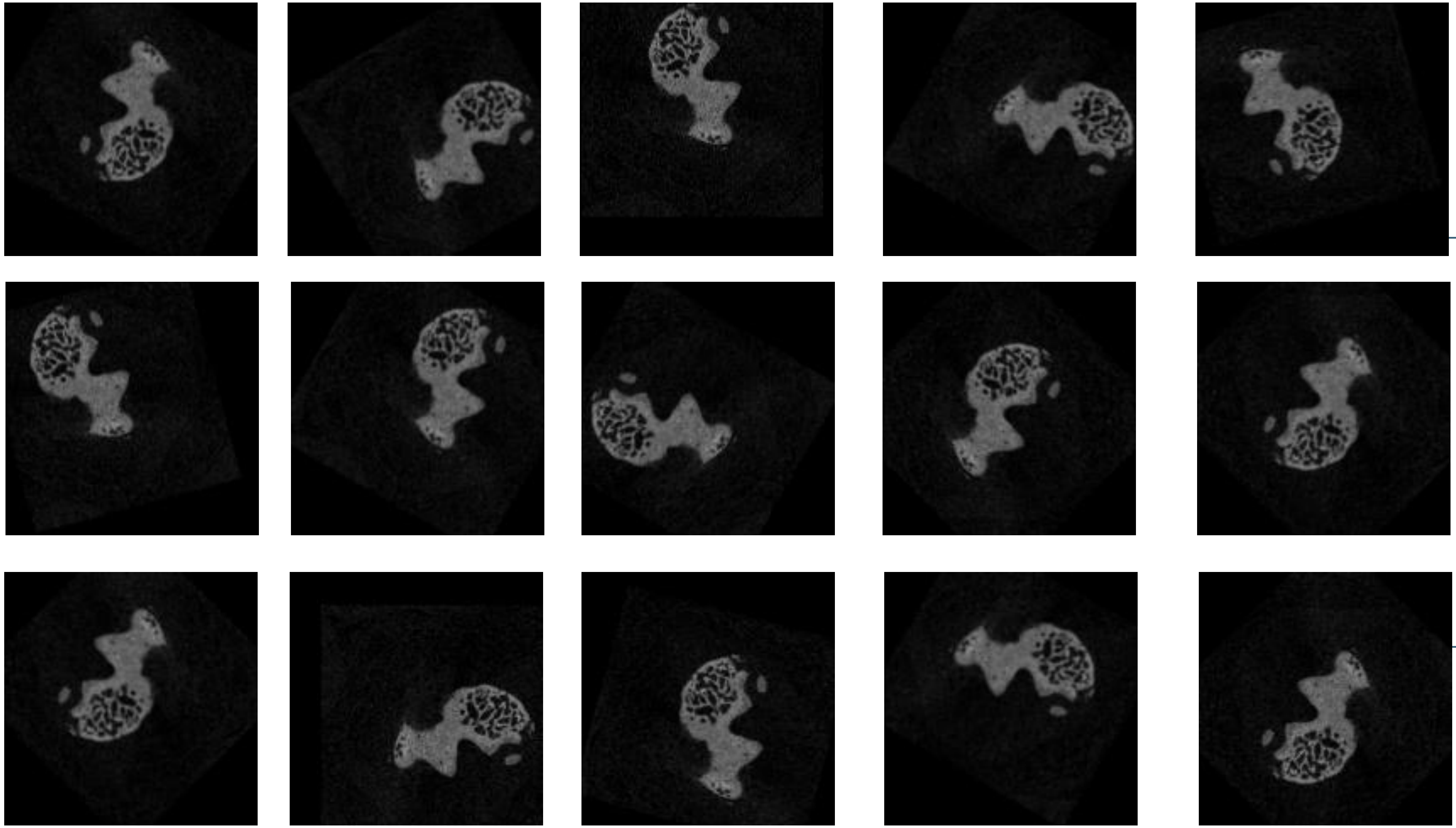
= 190,219 images

Iterations:
Flip vertically,
horizontally,
both,
Translate,
Brightness

THE BIGGER THE BETTER

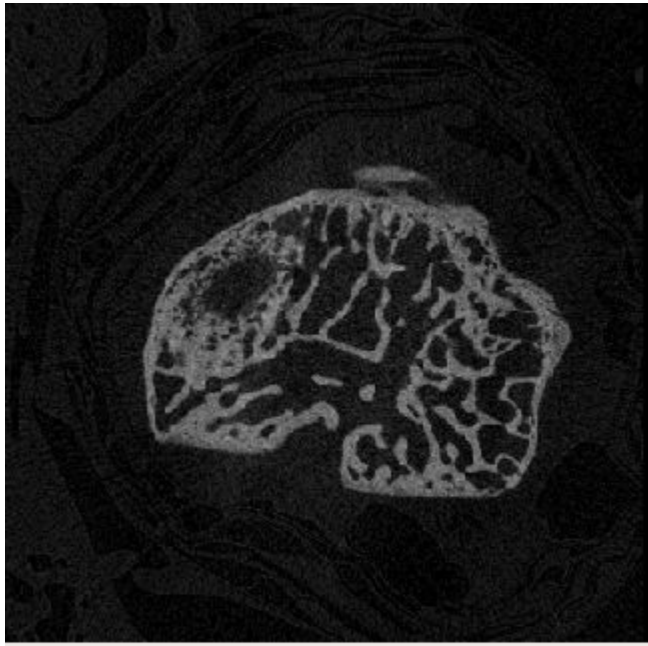


Original Image



Iterations: Rotation of image to the left

CALCULATING THE POROSITY



Original Image

Alpha Image Created

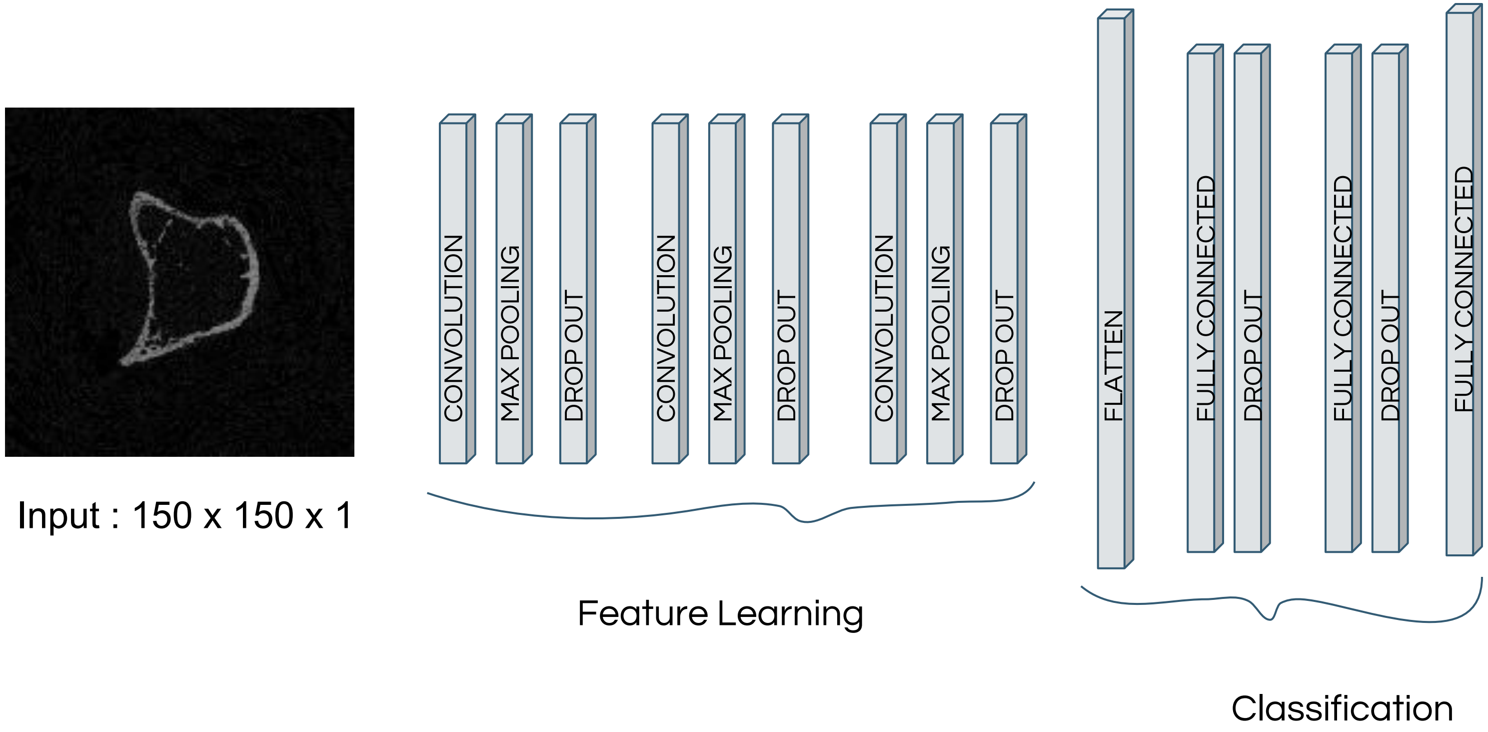
blur - threshold - contour - morph(closing)

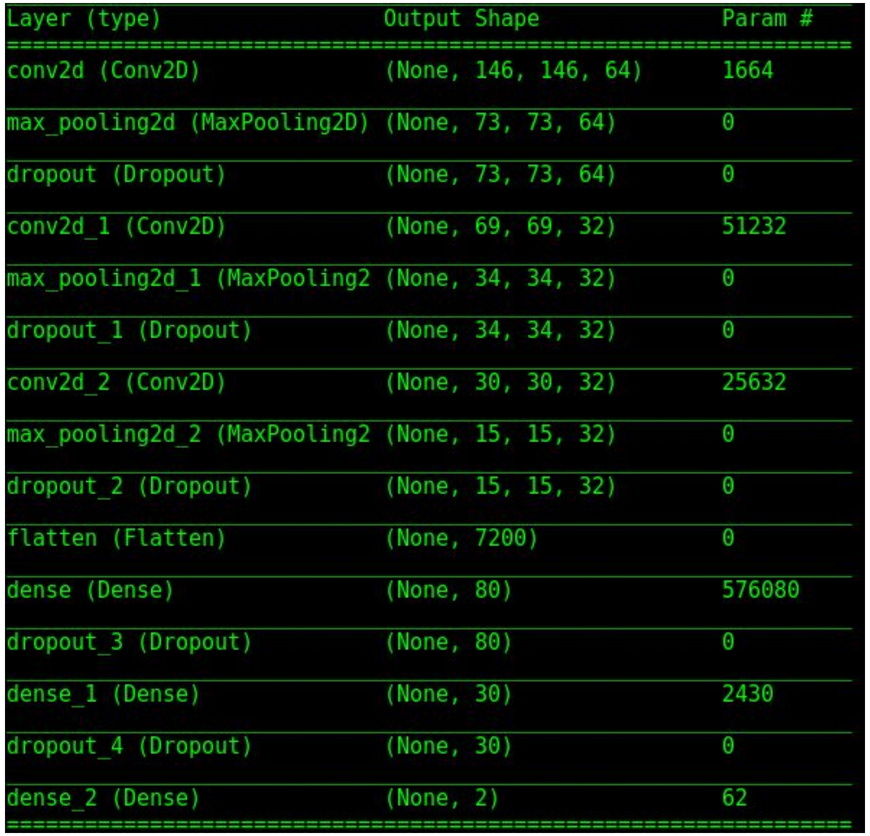
Processed Image

```
amount of white pixels: 110818
amount of black pixels: 116290
porosity: 51.0
```

MODEL CREATED WITH PARAMETERS

Depending on the **healthiness factor** [1*]

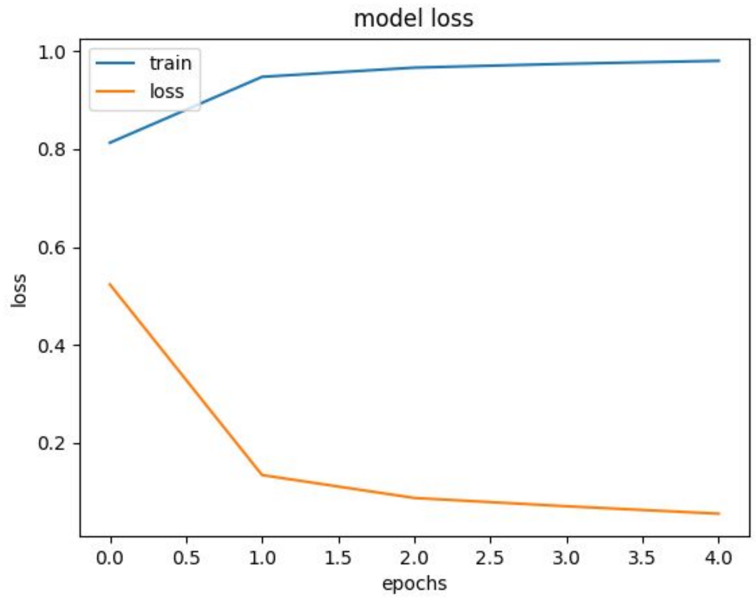




Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 146, 146, 64)	1664
max_pooling2d (MaxPooling2D)	(None, 73, 73, 64)	0
dropout (Dropout)	(None, 73, 73, 64)	0
conv2d_1 (Conv2D)	(None, 69, 69, 32)	51232
max_pooling2d_1 (MaxPooling2	(None, 34, 34, 32)	0
dropout_1 (Dropout)	(None, 34, 34, 32)	0
conv2d_2 (Conv2D)	(None, 30, 30, 32)	25632
max_pooling2d_2 (MaxPooling2	(None, 15, 15, 32)	0
dropout_2 (Dropout)	(None, 15, 15, 32)	0
flatten (Flatten)	(None, 7200)	0
dense (Dense)	(None, 80)	576080
dropout_3 (Dropout)	(None, 80)	0
dense_1 (Dense)	(None, 30)	2430
dropout_4 (Dropout)	(None, 30)	0
dense_2 (Dense)	(None, 2)	62

RESULTS

Training
Depending on health factor



Amount of epochs: **5**
Loss: **0.0558**
Accuracy: **97.98%**
Total time to train: **28.05 minutes**

Evaluation
Depending on health factor

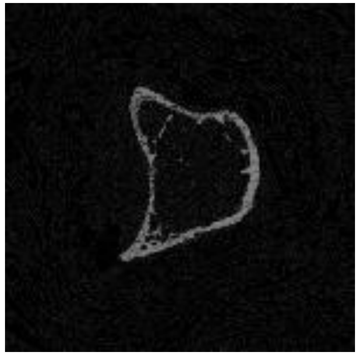
Accuracy of
99.13%

Loss of
0.029

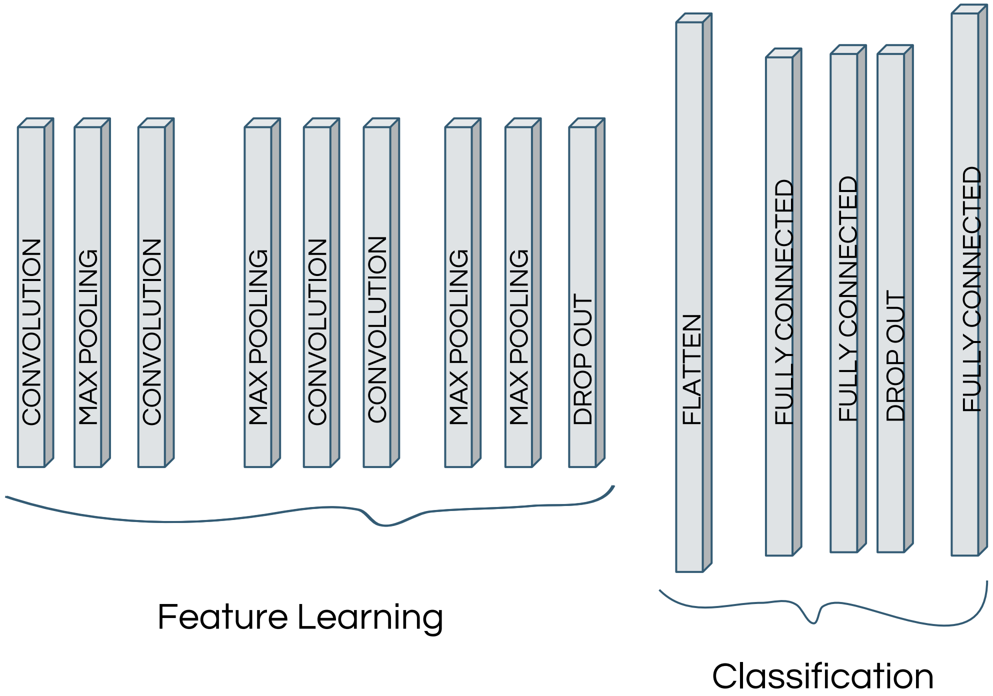
Predictions

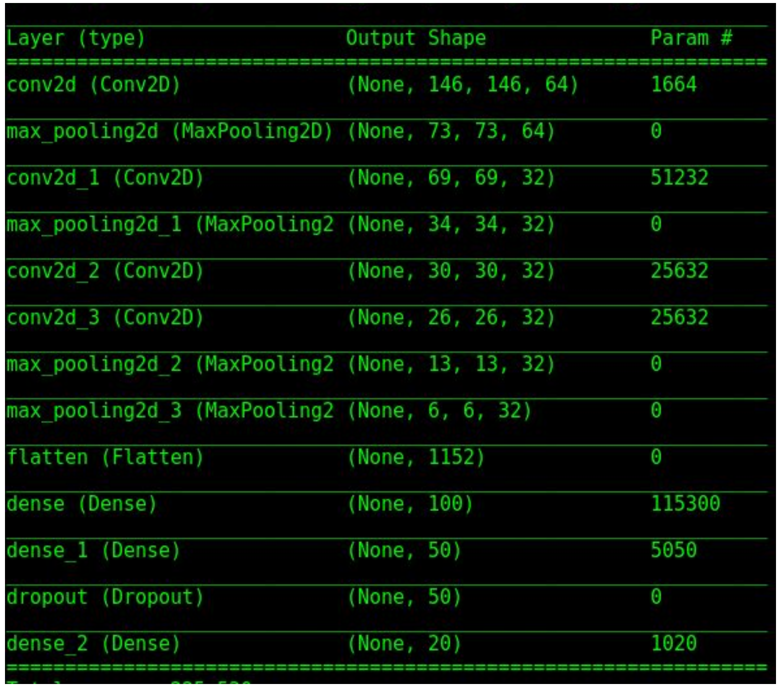
MODEL CREATED WITH PARAMETERS

Depending on the **porosity factor** [2*]



Input : 150 x 150 x 1

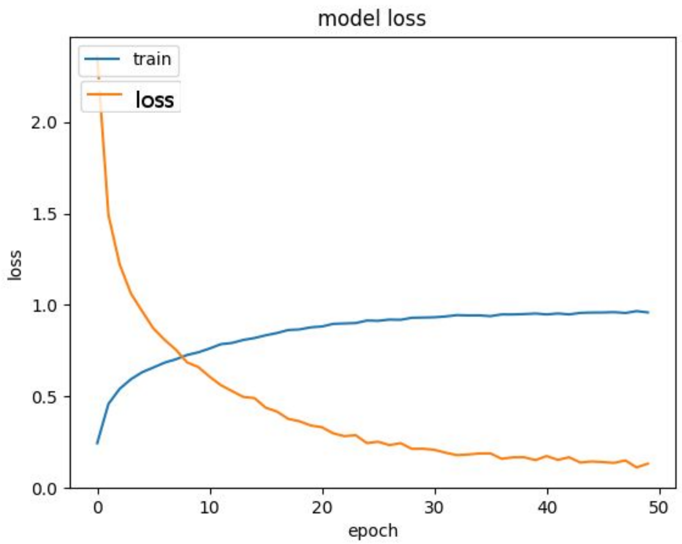




Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 146, 146, 64)	1664
max_pooling2d (MaxPooling2D)	(None, 73, 73, 64)	0
conv2d_1 (Conv2D)	(None, 69, 69, 32)	51232
max_pooling2d_1 (MaxPooling2	(None, 34, 34, 32)	0
conv2d_2 (Conv2D)	(None, 30, 30, 32)	25632
conv2d_3 (Conv2D)	(None, 26, 26, 32)	25632
max_pooling2d_2 (MaxPooling2	(None, 13, 13, 32)	0
max_pooling2d_3 (MaxPooling2	(None, 6, 6, 32)	0
flatten (Flatten)	(None, 1152)	0
dense (Dense)	(None, 100)	115300
dense_1 (Dense)	(None, 50)	5050
dropout (Dropout)	(None, 50)	0
dense_2 (Dense)	(None, 20)	1020

RESULTS

Training
Depending on porosity factor



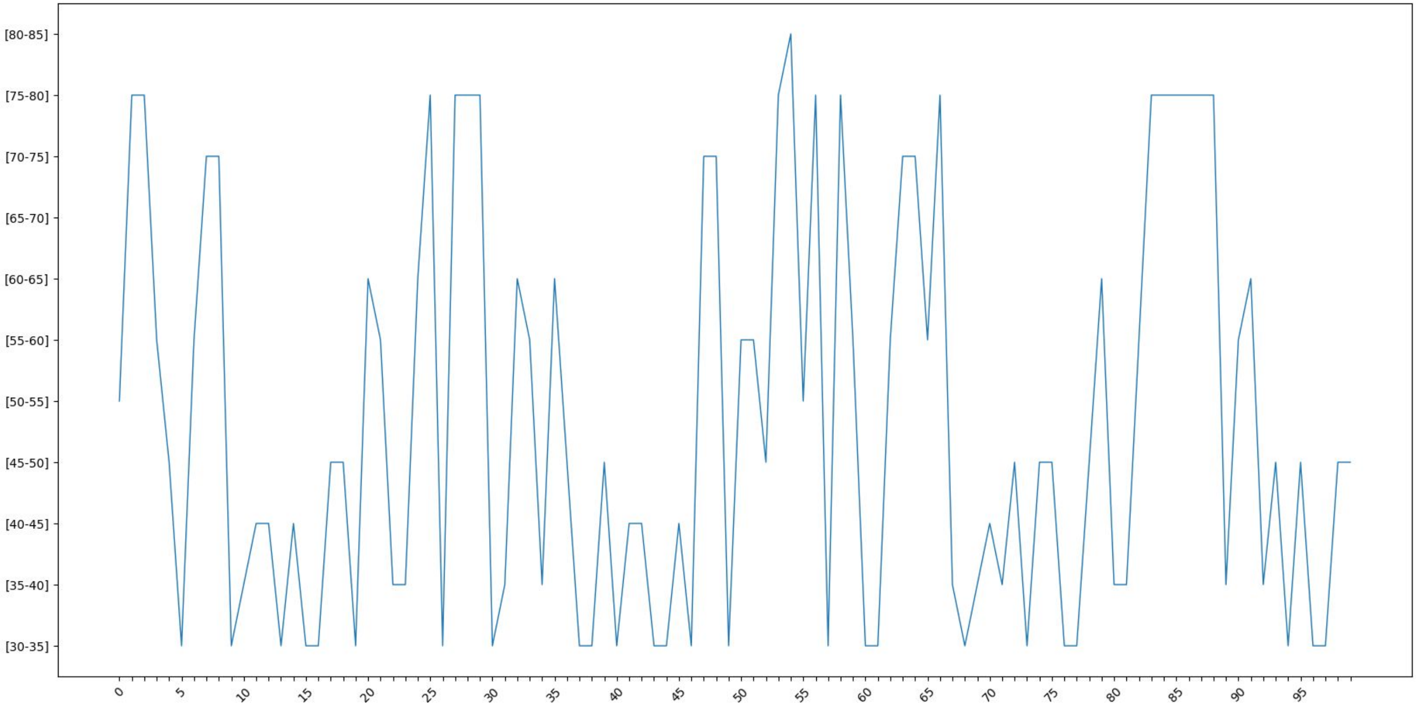
Amount of epochs: **50**
Loss: **0.15**
Accuracy: **95%**
Total time to train: **26 min**

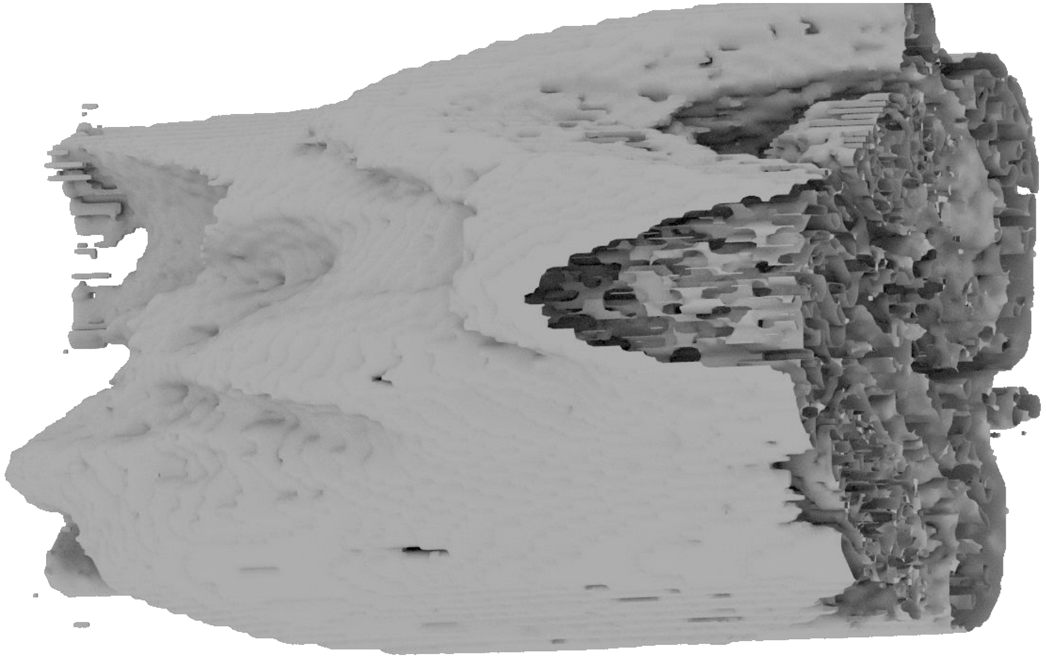
Evaluation
Depending on porosity factor

Accuracy of
95%

Loss of
0.15

Predictions

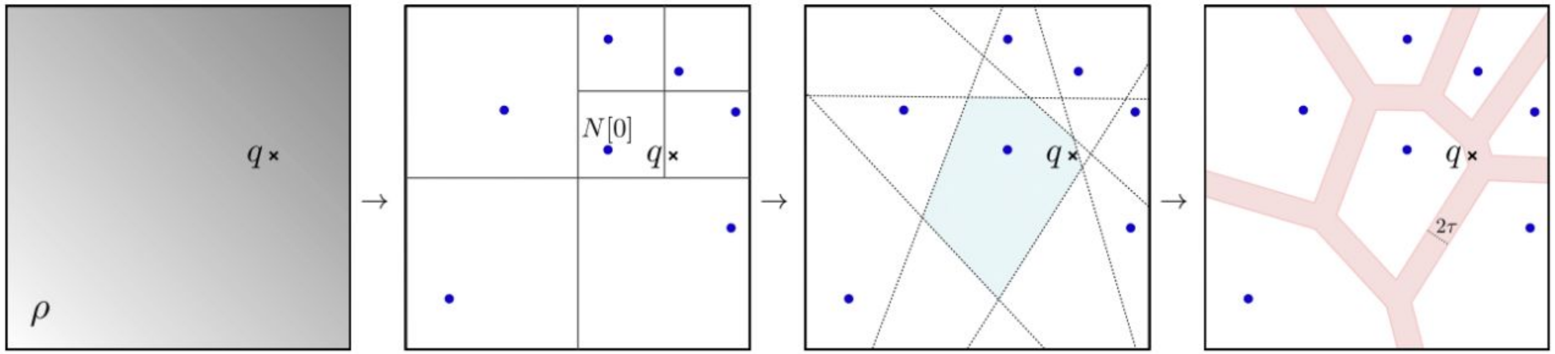




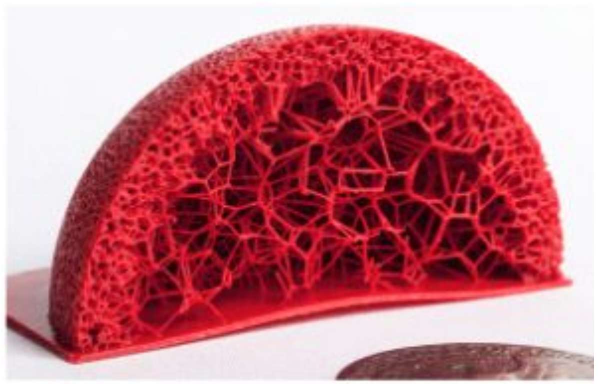
Future Work

- Reconstruct a 3D model based on the porosity factor [4]
  - Paper: Procedural voronoi foams for additive manufacturing (SIGGRAPH 2016)
  - This method depends on two parameters the density (porosity factor) and the radius of a beam (hole)

- 3D print the porous object



(a) Density field. (b) Gather seeds. (c) Evaluate structure. (d) Voronoi edge beams.



Q&A

Parameters

[1*]

Convolution	Amount of nodes = 64	kernel_size = 5	activation = ‘relu’	input_shape = (150,150,1)
Max Pooling		pool_size = (2,2)		
Drop out	rate = 0.4			
Convolution	Amount of nodes = 32	kernel_size = 5	activation = ‘relu’	
Max Pooling		pool_size = (2,2)		
Drop out	rate = 0.4			
Convolution	Amount of nodes = 32	kernel_size = 3	activation = ‘relu’	
Max Pooling		pool_size(2,2)		
Drop out	rate = 0.5			
Flatten				
Dense	Amount of nodes = 80		activation = ‘relu’	
Drop out	rate = 0.3			
Dense	Amount of nodes = 30		activation = ‘relu’	
Drop out	rate = 0.5			
Dense	Amount of nodes = 2		activation = ‘softmax’	

Parameters

[2*]

Convolution	Amount of nodes = 64	kernel_size = 5	activation = ‘relu’	input_shape = (150,150,1)
Max Pooling		pool_size = (2,2)		
Convolution	Amount of nodes = 32	kernel_size = 5	activation = ‘relu’	
Convolution	Amount of nodes = 32	kernel_size = 5	activation = ‘relu’	
Max Pooling		pool_size = (2,2)		
Max Pooling		pool_size = (2,2)		
Flatten				
Dense	Amount of nodes = 100		activation = ‘relu’	
Dense	Amount of nodes = 50		activation = ‘relu’	
Drop out	rate = 0.5			

REFERENCES

[1] Micro-computed tomography reconstructions of tibiae of stem cell transplanted osteogenesis imperfecta mice - Ranzoni, A.M., Corcelli, M., Arnett, T.R., & Guillot, P.V. *Figshare.* https://dx.doi.org/10.6084/m9.figshare.c.3795019

[2] Baravalle, R., Scandolo, L., Delrieux, C., García Bauza, C., and Eisemann, E. (2017) Realistic modeling of porous materials. *Comp. Anim. Virtual Worlds*, 28: e1719. doi: 10.1002/cav.1719.

[3] Passioura, J.B., 2002. Soil conditions and plant growth. https://doi.org/10.1046/j.0016-8025.2001.00802.x

[4] Jonàs Martínez, Jérémie Dumas, Sylvain Lefebvre. Procedural Voronoi Foams for Additive Manufacturing. ACM Transactions on Graphics, Association for Computing Machinery, 2016, 35, pp.1 - 12. <10.1145/2897824.2925922>.

[5]https://orthofeed.com/2017/10/30/9-3m-just-in-time-3d-printed-bone-implant-project-in-australia-set-to-transform-tumour-surgery/

[6] Eduard Reithmeier Nina Loftfield, Markus Kastner. 2017. 3D Reconstruction And Characterization Of The Porous Microstructure Of AL2O3–CoatinBasedSurfaceData.(2017)