

# Otolith age estimation by machine learning approaches

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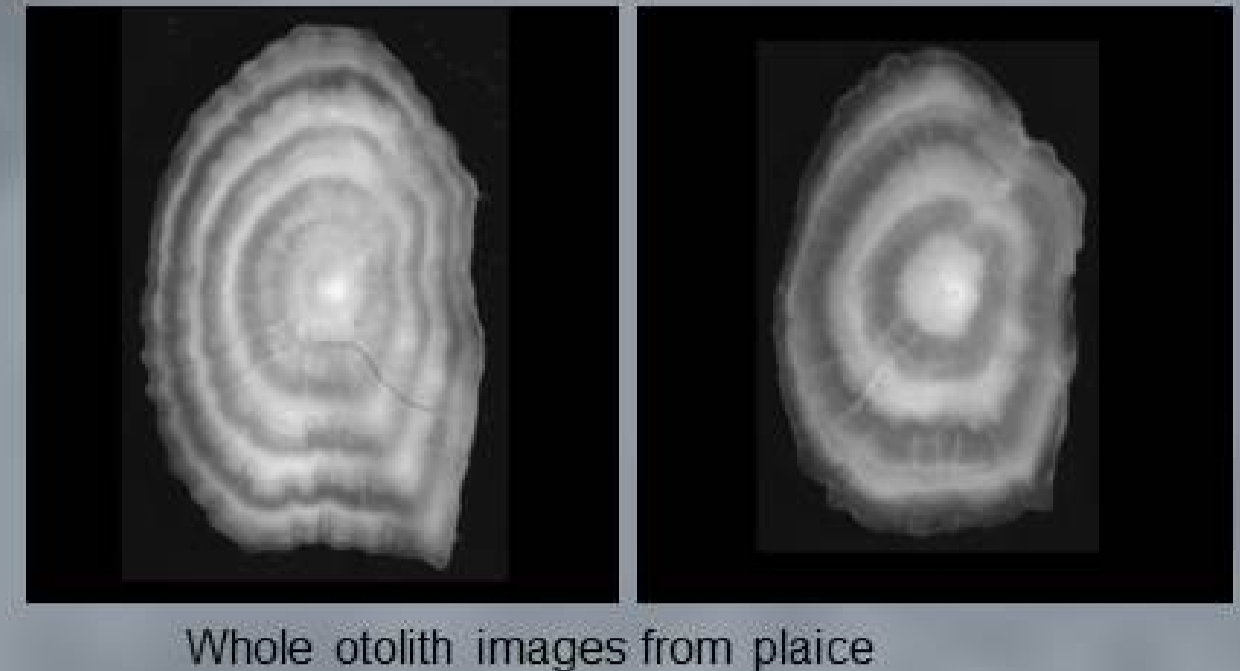


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## Otolith sampling and age estimation by Human experts

- Otoliths are paired calcified structures found in both inner ears of bony fish.
- Otoliths are used to determinate fish ages with different growth periodicities ranging from daily to annual increment.
- Between 800,000 and 1,000,000 otoliths are sampled and analysed per year
- Annual cost of approximately \$8 million
- The longest step in this process is the preparation and reading of otoliths by the experts.

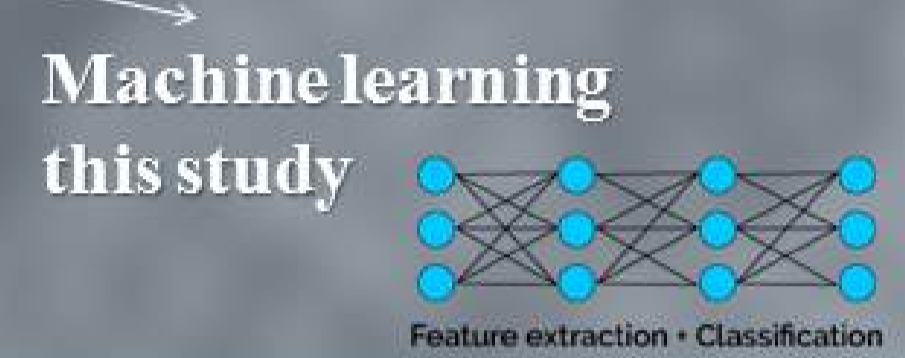
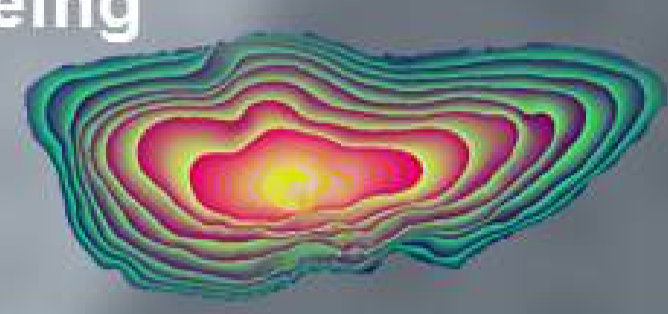


8578 sampled Fishes

From surveys and fishing markets  
Period: 2010 - 2017  
Only Quarters 3 & 4  
Age: from 0 to 8+ year classes

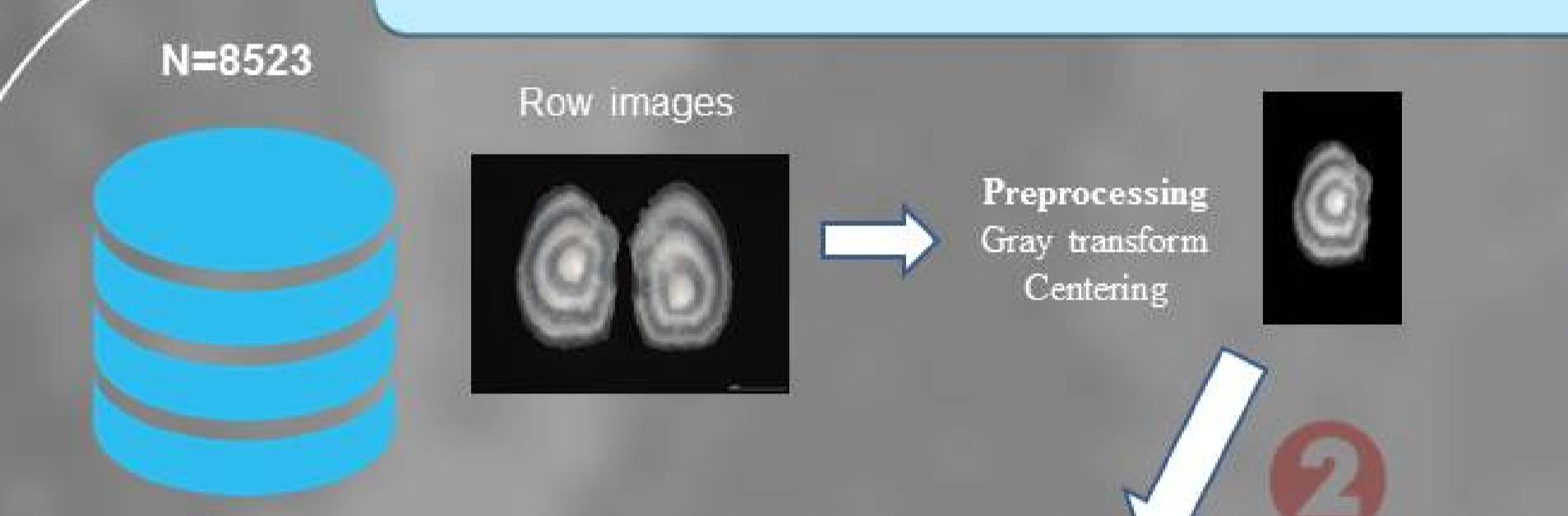


Automated FISH Ageing EU project (AFISA)  
Mahé, 2009

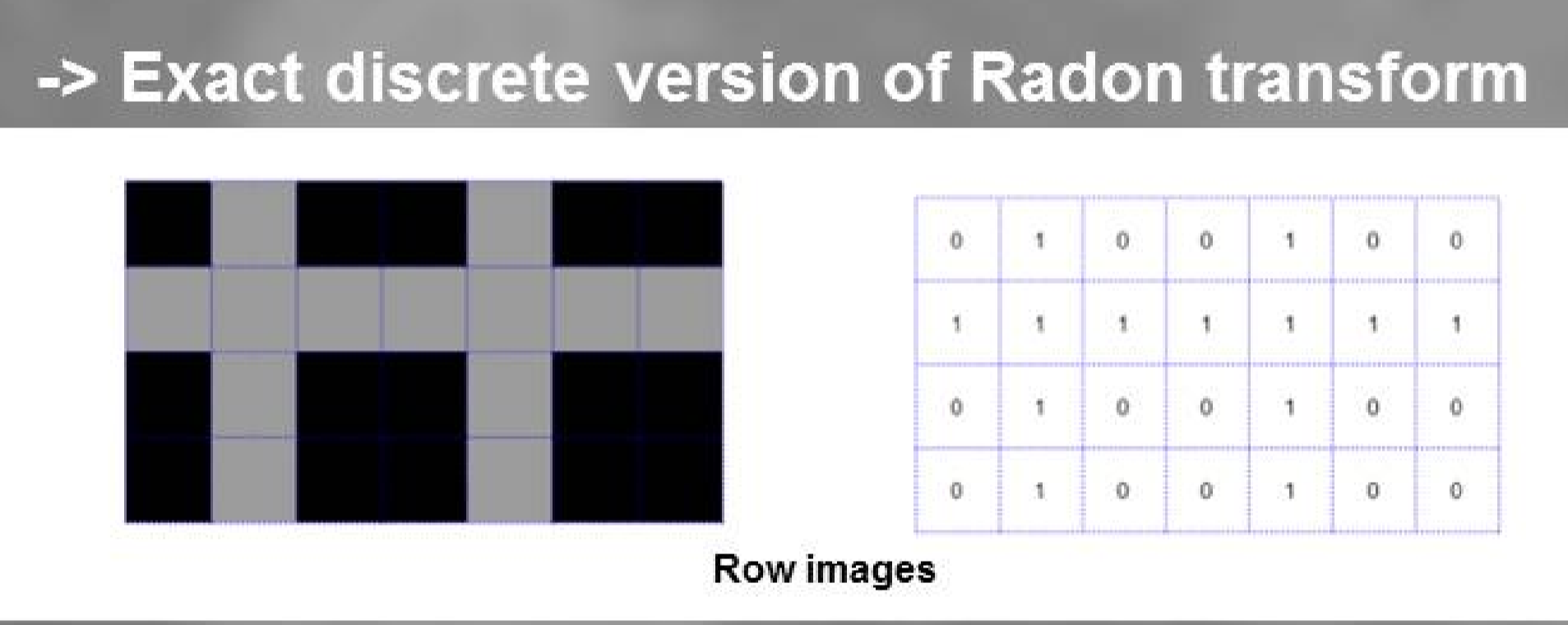


Automation of age reading ?

## Age estimation by Machine



### Mojette Transform

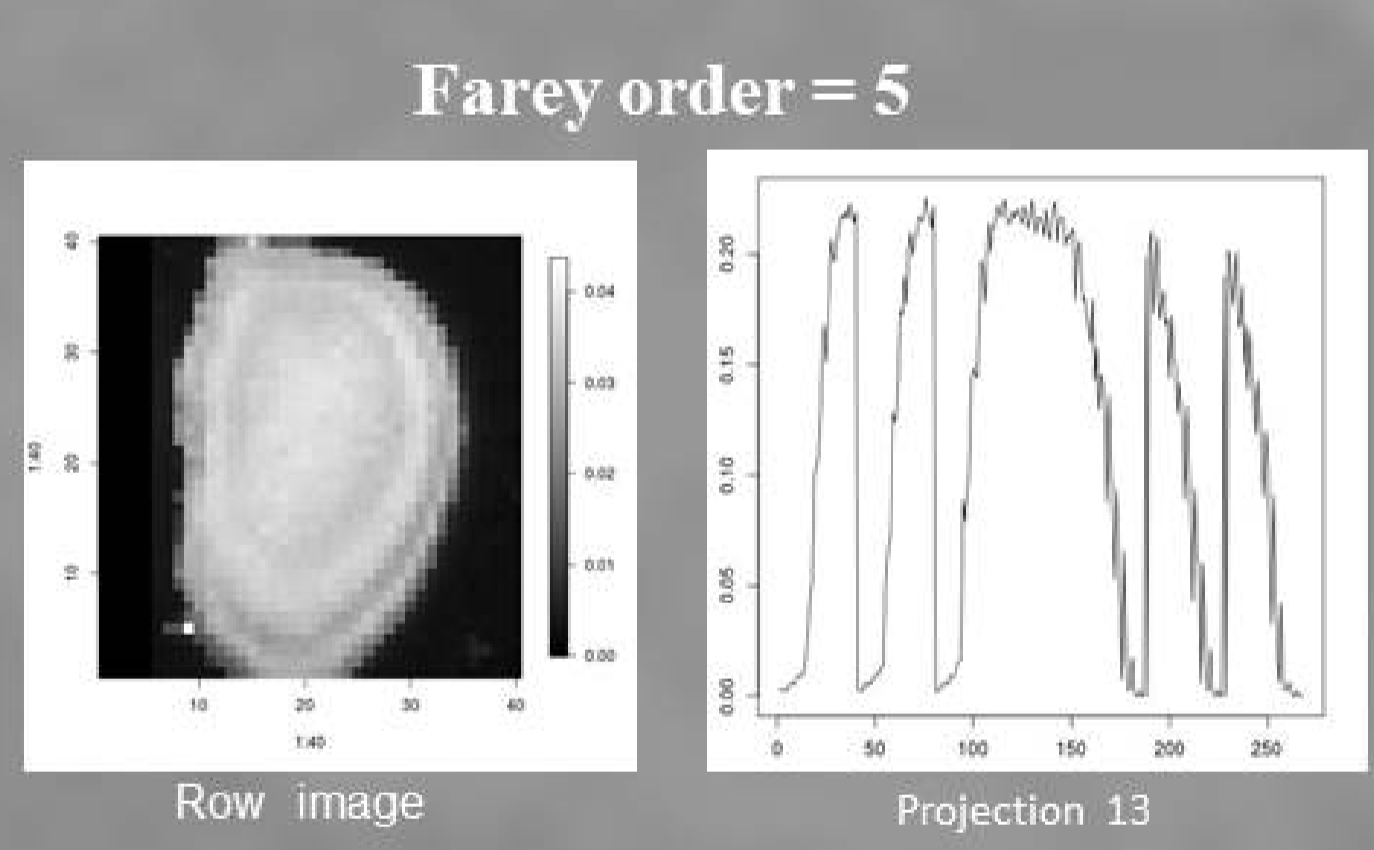
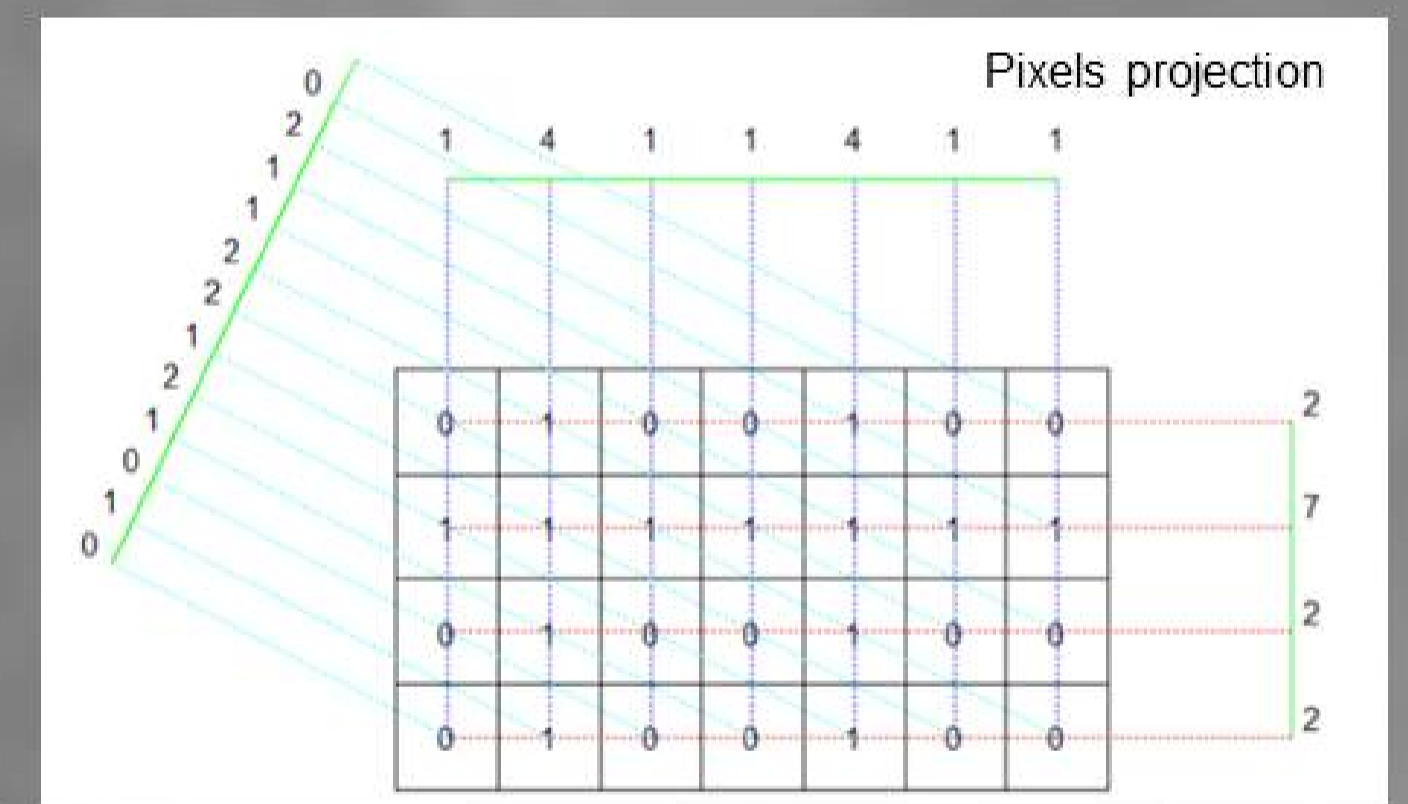


-> To reduce the information by recording only few projections that allow to reconstruct original image

Each projection depends of its angle defined by (p,q) and it consists in a set of bin value M with b the index number of this bin.  
All angles are built according to the Farey suite with n order and symmetry  
A bin value M is the sum of pixel value f(i,j) according the direction characterized by (p,q).

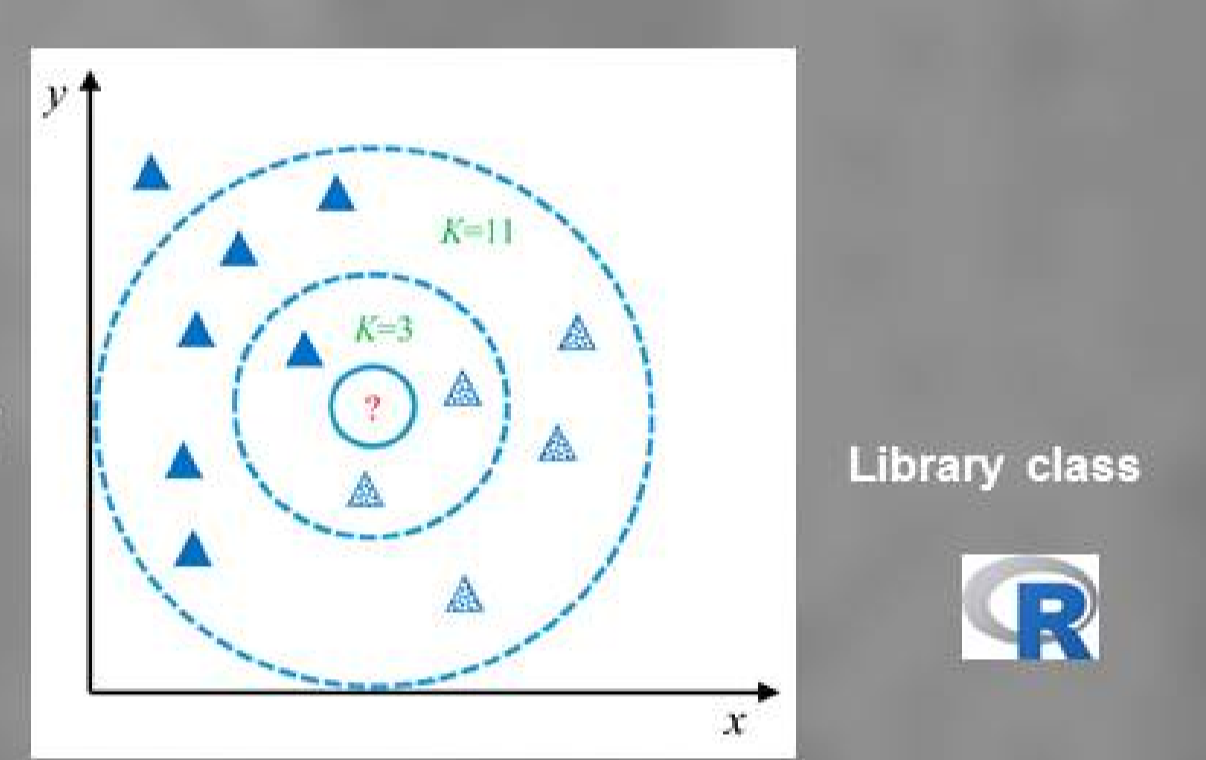
Katz Criterion to select the number of projection :  
sum(p) > P width or sum(q) > Q height.

$$M(b,p,q) = \sum_{i=-\infty}^{+\infty} \sum_{j=-\infty}^{+\infty} f(i,j) \times \Delta(b-p \times i + q \times j).$$

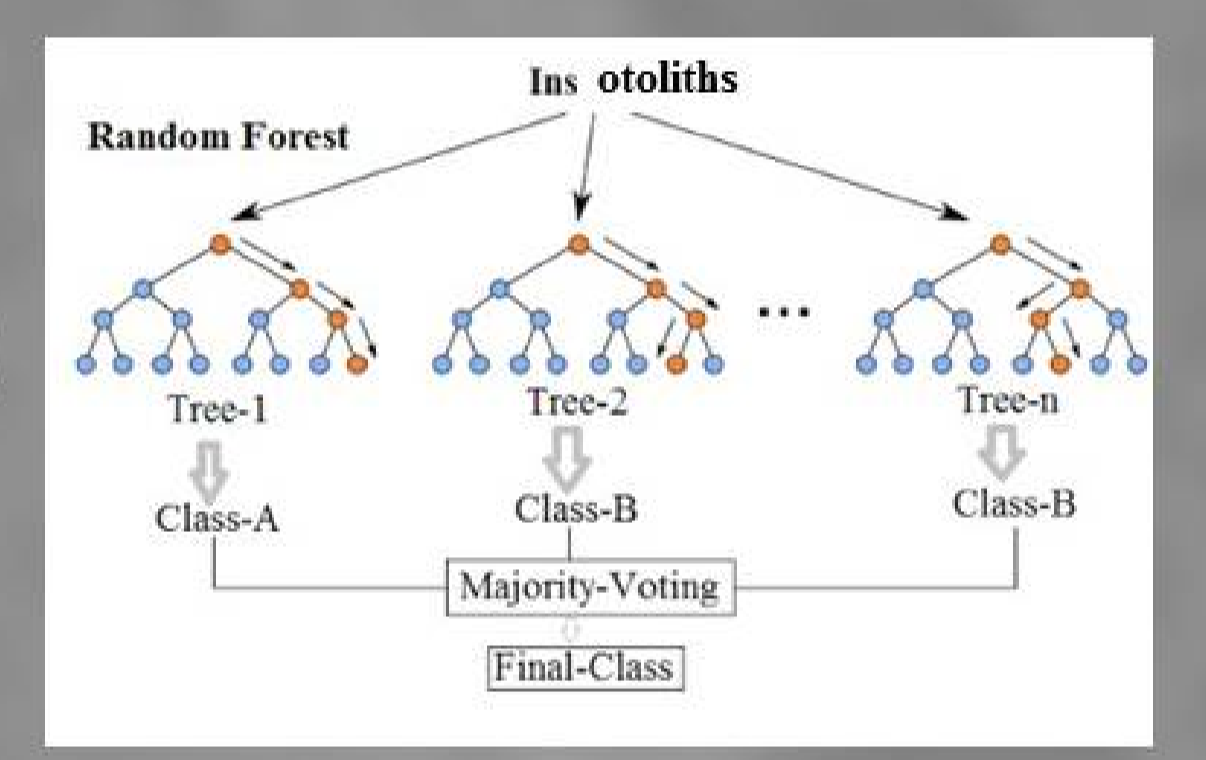


## Machine Learning : 3 classifiers

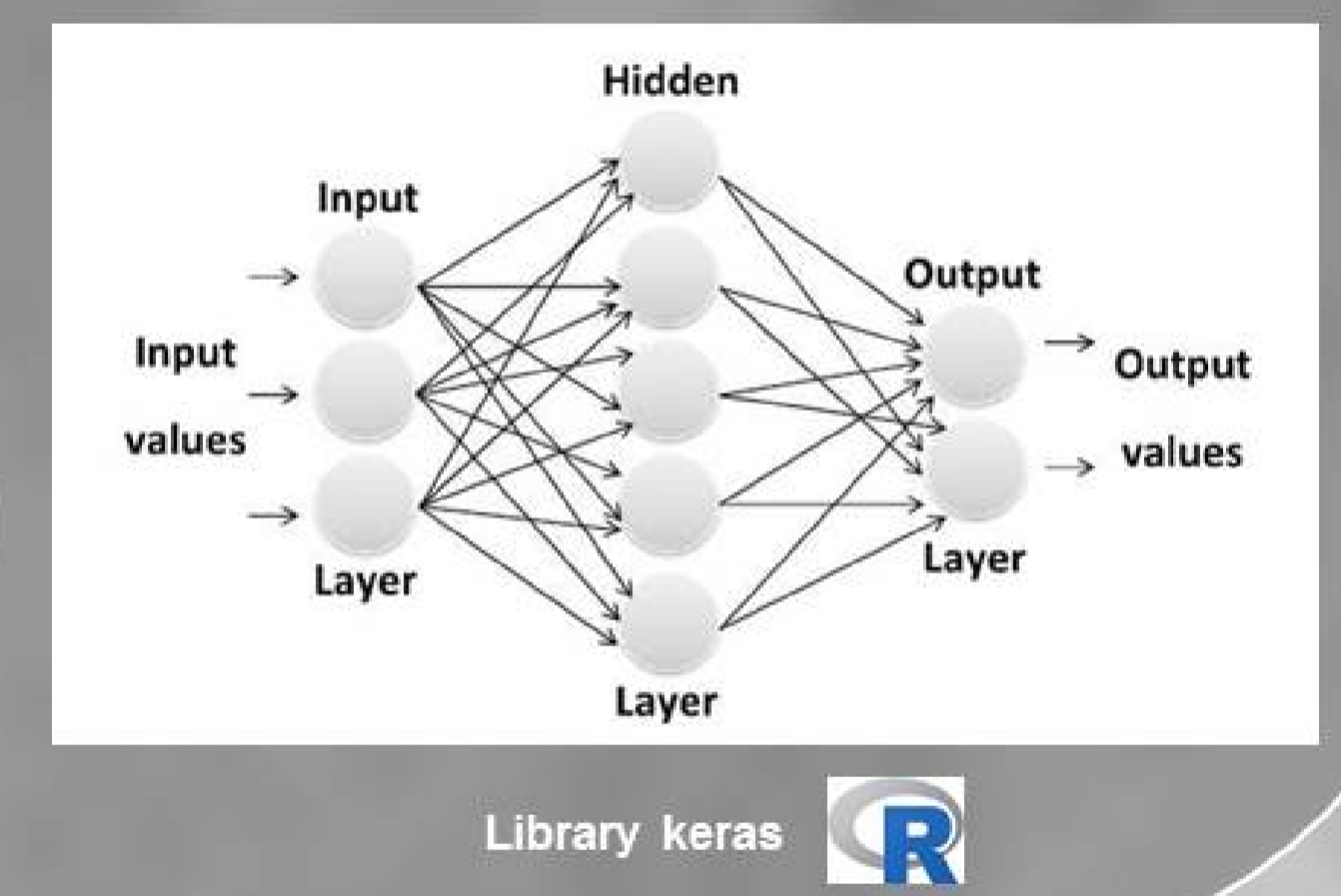
k-NN  
k-Nearest Neighbors



Random Forest



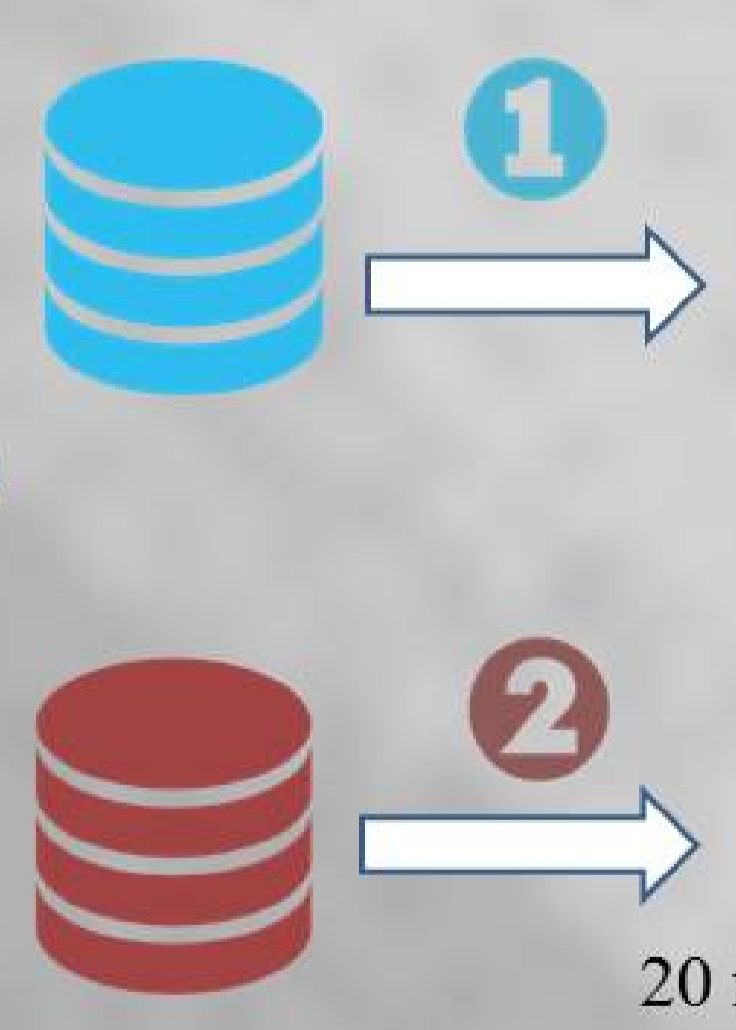
MLP  
Multi-Layer Perceptron



## Results

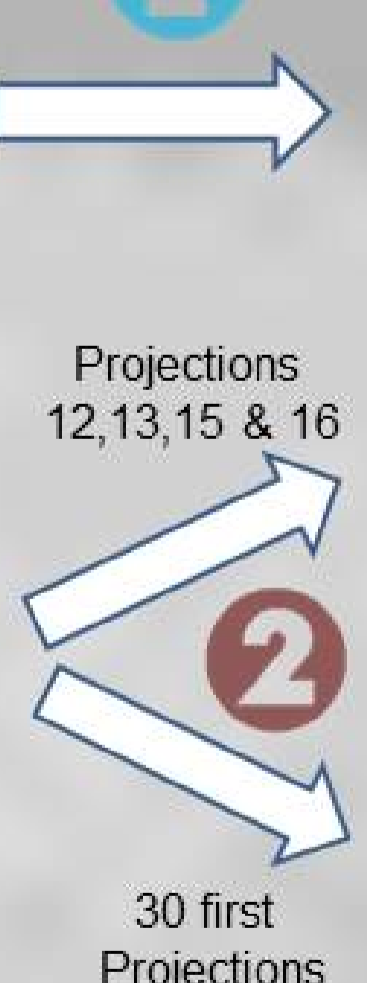
Human Expert

Age class	Training set	Test set
Age 0	116	49
Age 1	843	406
Age 2	1397	685
Age 3	1468	782
Age 4	1134	523
Age 5	419	237
Age 6	180	92
Age 7	130	54
Age 8+	71	37



### Machine Learning

- k-nn : k=1/5/10
- Random Forest : mtry=16 ntree=50/100/500
- MLP : linear/1hidden layer 20 neurons/sigmoid function output :softmax activation 9 classes



		k-NN			Random Forest			MLP	
		1-nn	5-nn	10-nn	RF-50	RF-100	RF-500	Linear-MLP	20-MLP
Database	Precision	98,5	64,3	57,9	98,4	98,5	98,5	46,1	51,7
Training	± 0 year	99,5	88,6	87,1	99,5	99,5	99,5	84,3	87,8
Training	± 1 year	42,8	47,3	48,0	51,6	51,3	52,4	42,5	45,7
Test	± 0 year	79,6	84,2	85,2	88,7	88,9	89,2	83,0	85,5
Test	± 1 year	42,8	45,7	45,9	49,6	50,8	51,3	40,6	41,5
Database	Precision	98,5	63,5	57,1	98,4	98,5	98,5	-	47,7
Training	± 0 year	99,5	88,6	87,3	99,5	99,5	99,5	-	87,4
Training	± 1 year	43,7	45,5	47,6	50,7	51,7	51,9	-	44,6
Test	± 0 year	81,4	84,3	85,6	88,3	88,6	88,9	-	85,9
Test	± 1 year	-	-	-	-	-	-	-	-

30 first projections  
Random Forest Classifier  
Test dataset : 2865 otoliths

51,9% of Correct Classification

Predicted age (year)

Age group	Age 0	Age 1	Age 2	Age 3	Age 4	Age 5	Age 6	Age 7	Age 8+
Age 0	22	23	4	0	0	0	0	0	0
Age 1	4	303	84	9	6	0	0	0	0
Age 2	2	90	408	159	33	1	0	0	0
Age 3	3	24	169	439	145	2	0	0	0
Age 4	0	7	38	187	277	13	1	0	0
Age 5	0	1	9	33	152	35	2	5	0
Age 6	0	0	1	13	54	10	5	5	0
Age 7	0	1	0	8	29	4	11	1	0
Age 8+	0	0	0	1	7	16	3	7	0

## Contacts

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## Conclusion & Prospects

- Mojette transform results are very close to raw image analysis.
- k-sensibility in k-nn were correlated with the high intra-class variability and close inter-class size.
- Database size is not sufficient to build an efficient neuronal network (MLP).
- Random Forest seemed to be the best classifier according to raw image or Mojette bins.
- The database was built from all otolith images (n=8578) used for stock assessment without prior filtering or images cleaning -> image quality (broken otoliths, dirty otoliths) impacts the results and must be evaluated.
- These results could be improved by optimizing machine learning parameters and by selecting discriminant projections.

## References

Mahé, K. (2009). Project no. 044132 Automated FISH Ageing (AFISA): Final Activity 831 Report. <http://cordis.europa.eu/documents/documentlibrary/124722831EN6.pdf>  
 Breiman, L., Ghahramani, Z. (2004). Consistency for a simple model of random forests. Statistical Department, University of California at Berkeley. Technical Report (670).  
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