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Supplementary Information for
Piscimetrics II$^{\$}$: Neural network models in fisheries research

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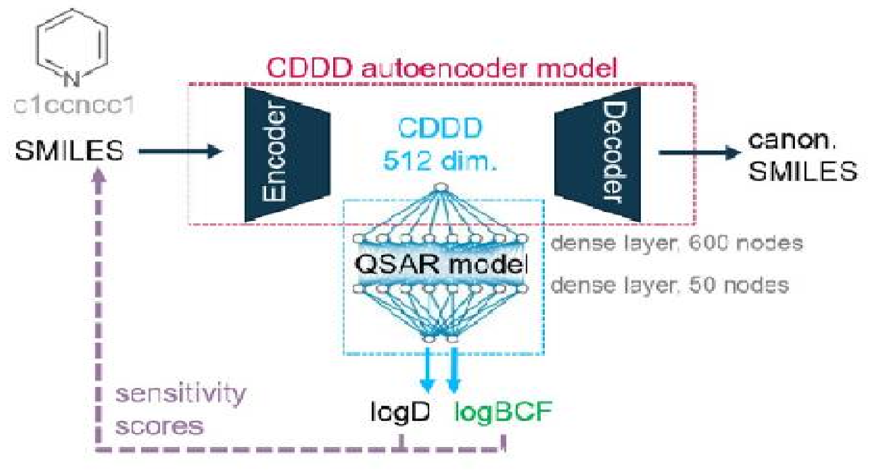
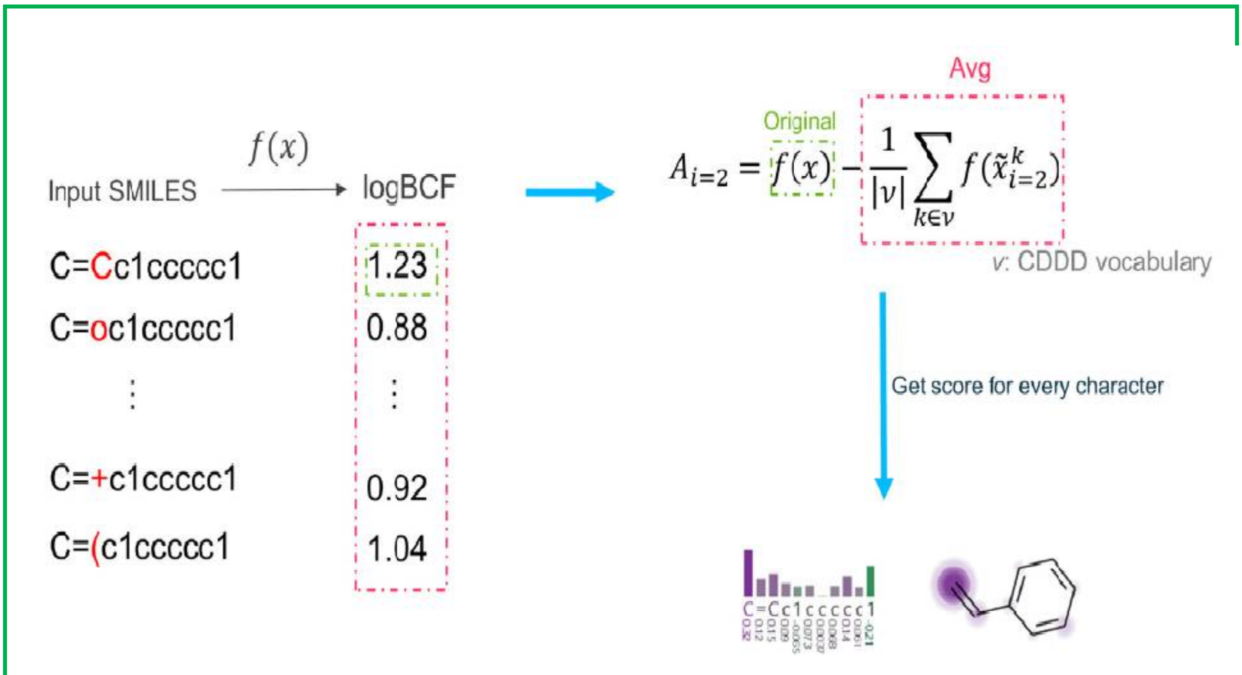
Sup Inf Fig (Sif-01)
Solutions for Typical tasks in fisheries with NNs , CNNs and Machine learning Algs.

Case Study
Zhao et al. [01] used explainable deep learning to model bioconcentration variables in fish

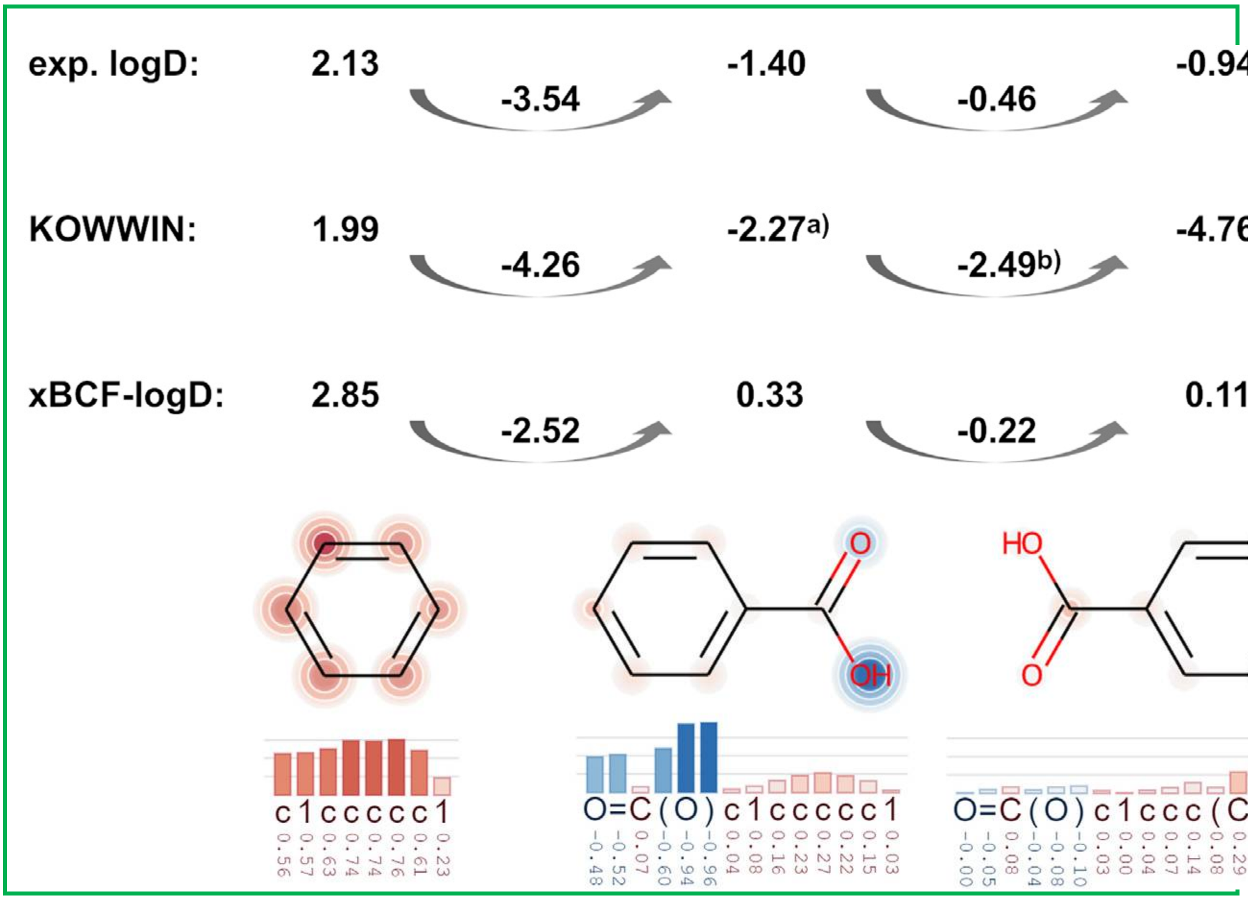
[01]	Zhao, L., Montanari, F., Heberle, H. and Schmidt, S., Modeling bioconcentration factors in fish with explainable deep learning, Artificial Intelligence in the Life Sciences, 2022, 2, .100047. https://doi.org/10.1016/j.ailsci.2022.100047

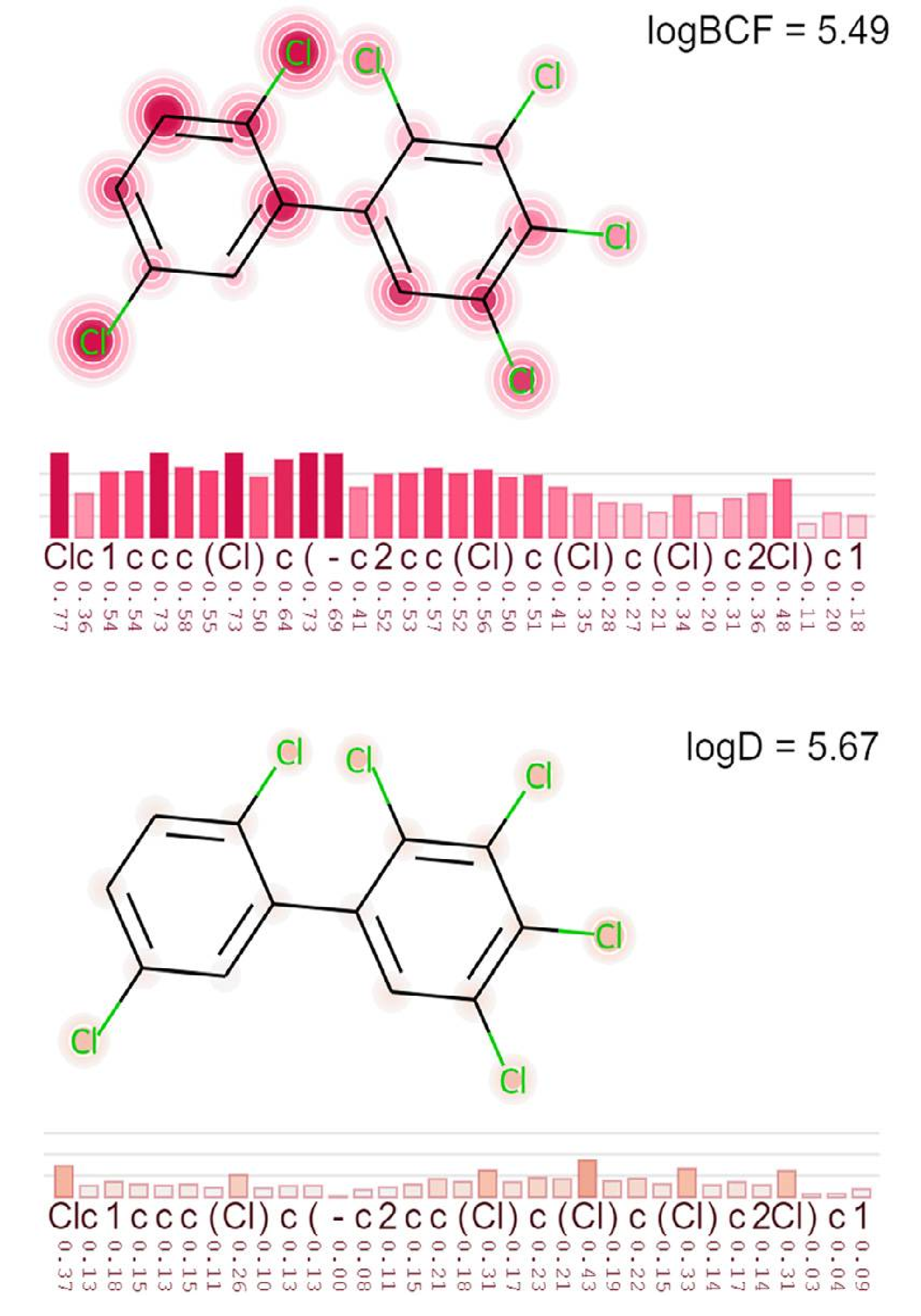


Model structure of the xBCF multitask model based on CDDD descriptors

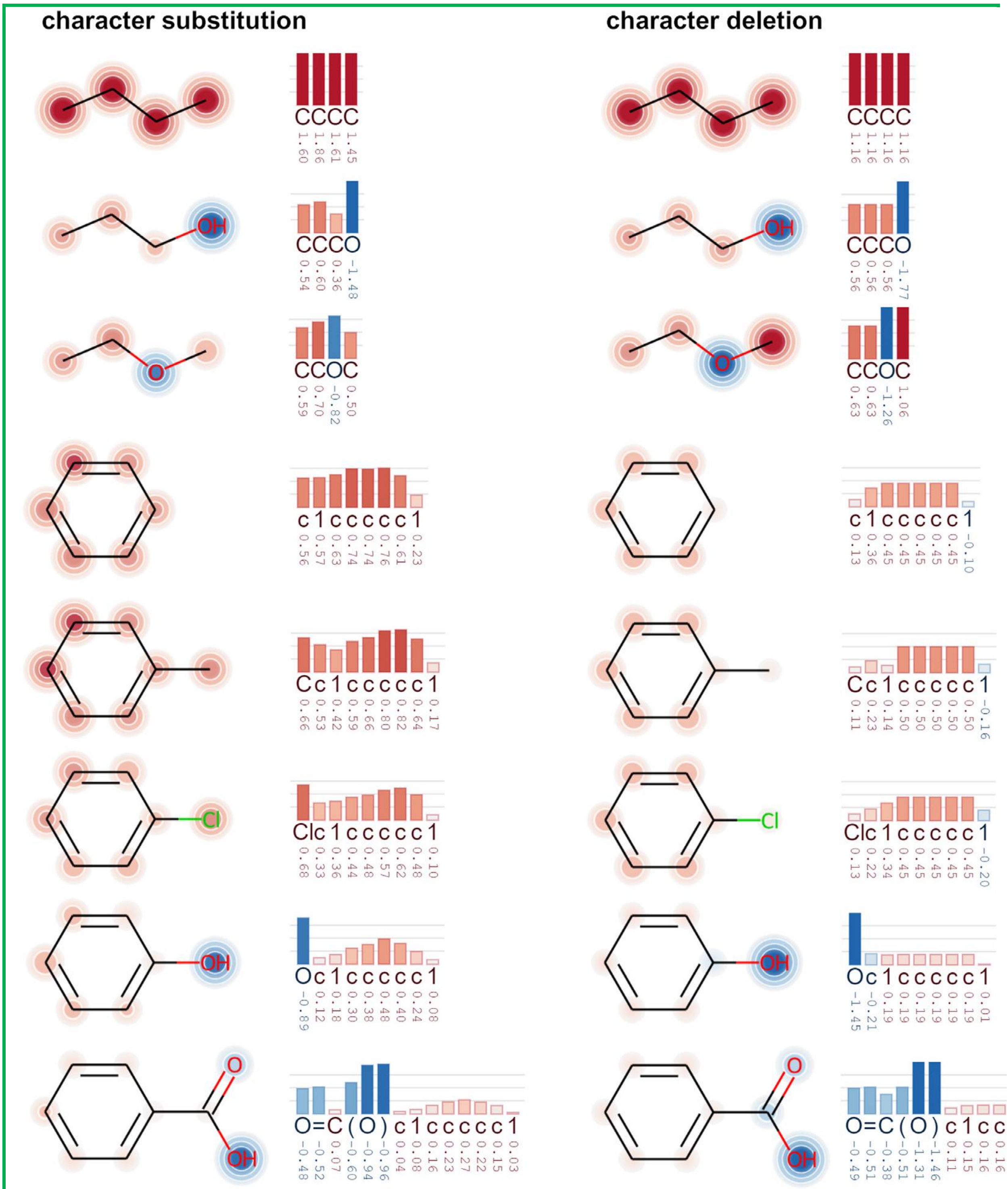


Character substitution method illustration

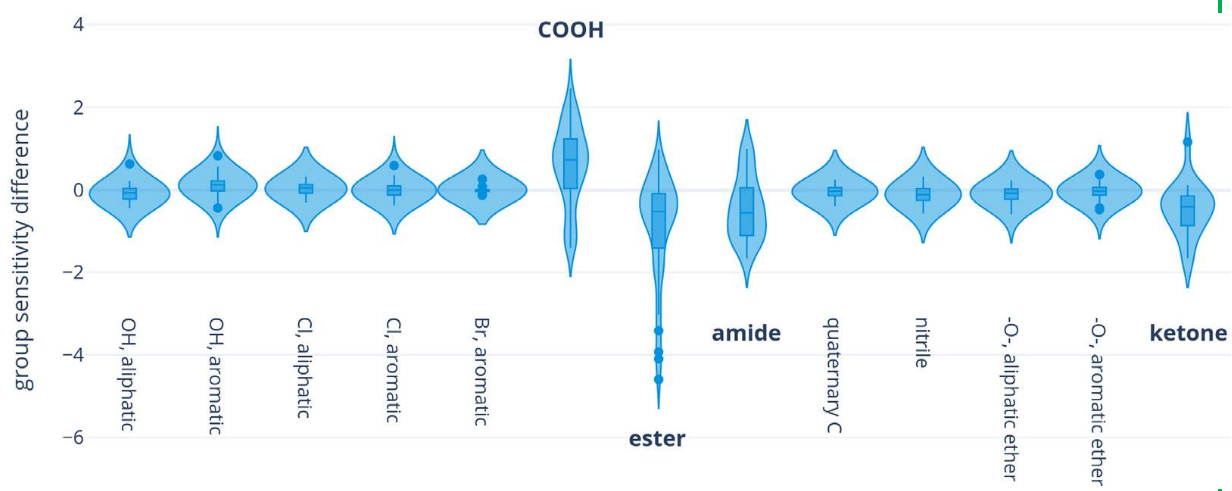




Sensitivity scores for a PCB molecule



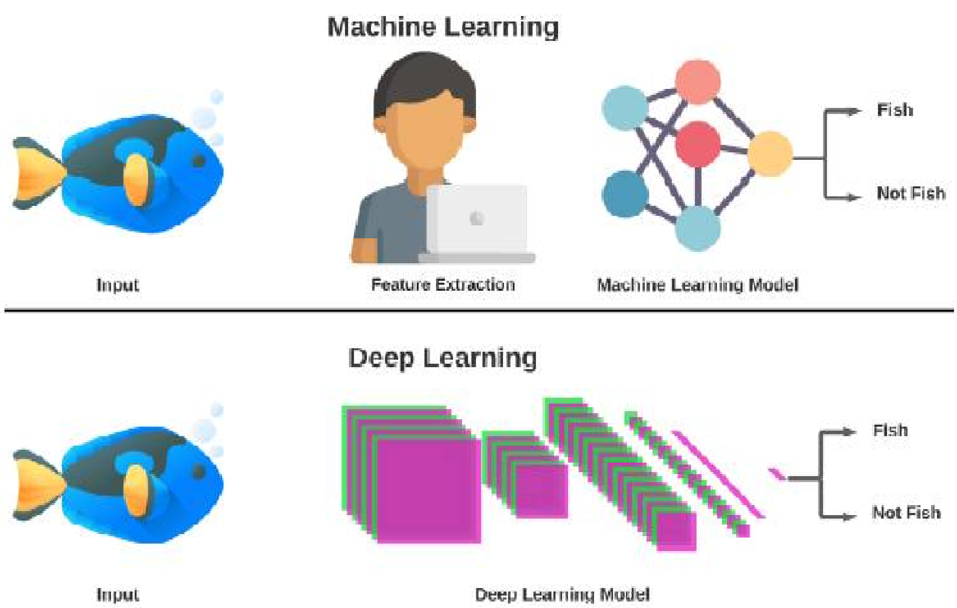
LogD sensitivity score visualizations for small molecules with single-character, single-atom or single-group changes



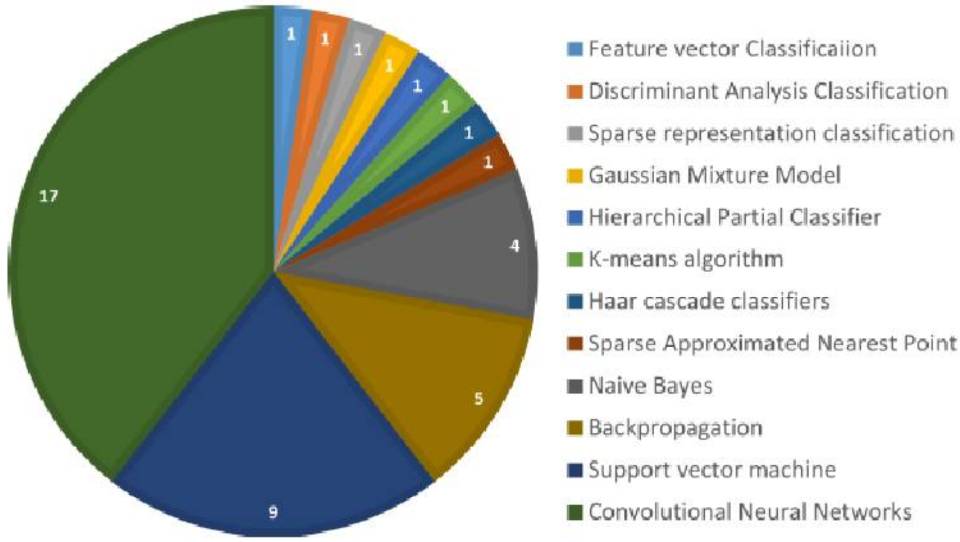
Sensitivity Difference between logBCF and logD for selected functional groups

Case Study
Deep Learning classification methods—Review Saleh et. Al [02] reviewed Deep Learning methods employed in classification of fish from underwater imaging surveys reported during the period 2003 to 2021.

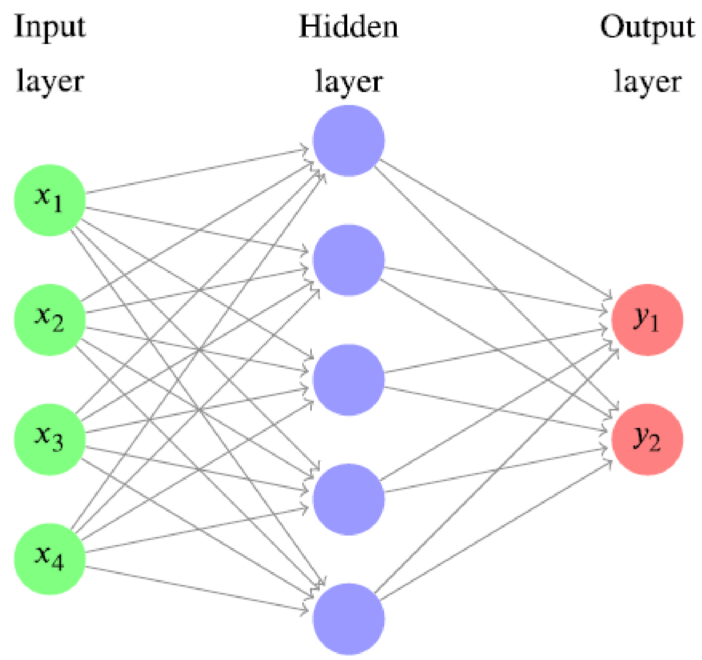
[02]	Saleh, A., Sheaves, M. and Rahimi Azghadi, M., Computer vision and deep learning for fish classification in underwater habitats: A survey, Fish and Fisheries, **2022**, 23(4), 977-999 https://doi.org/.



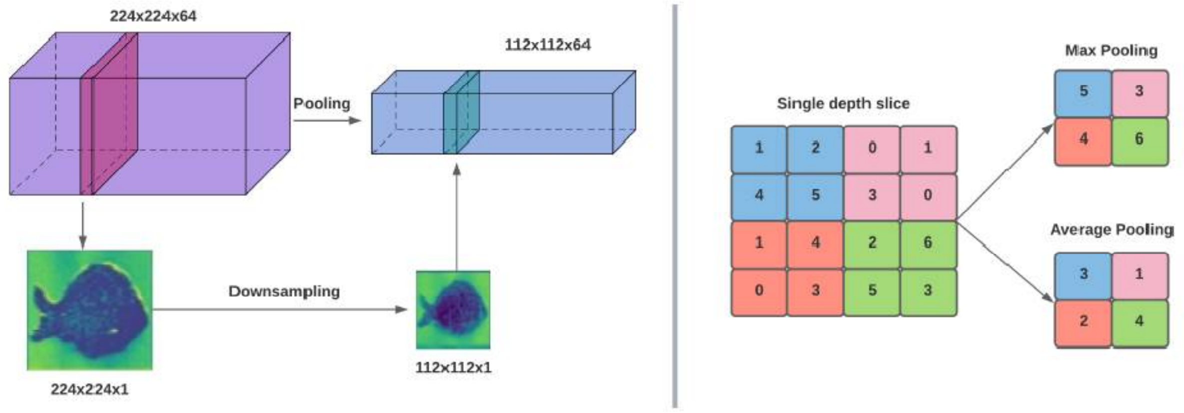
Mach Lrn: domain expert extracts features
Deep Lrn: Hidden layers of (MLP-NN, CNN) extract features



Classical, MachLrn, DeepNN, DeepLrn etc methods for fish classification (2003 to 2021)

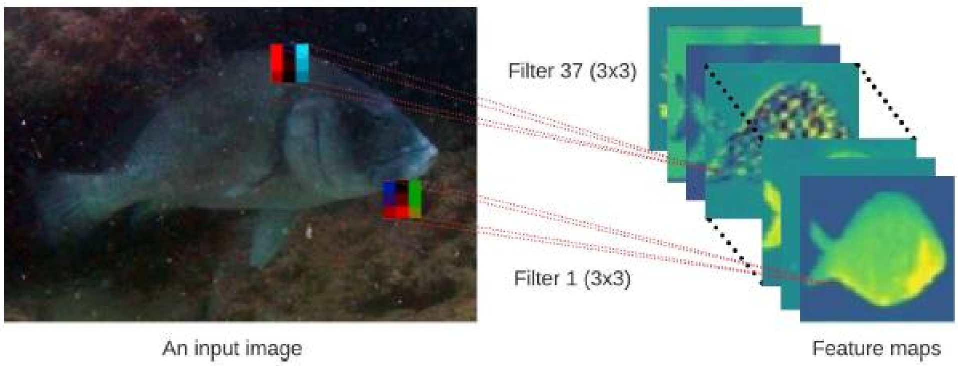


SLP-NN

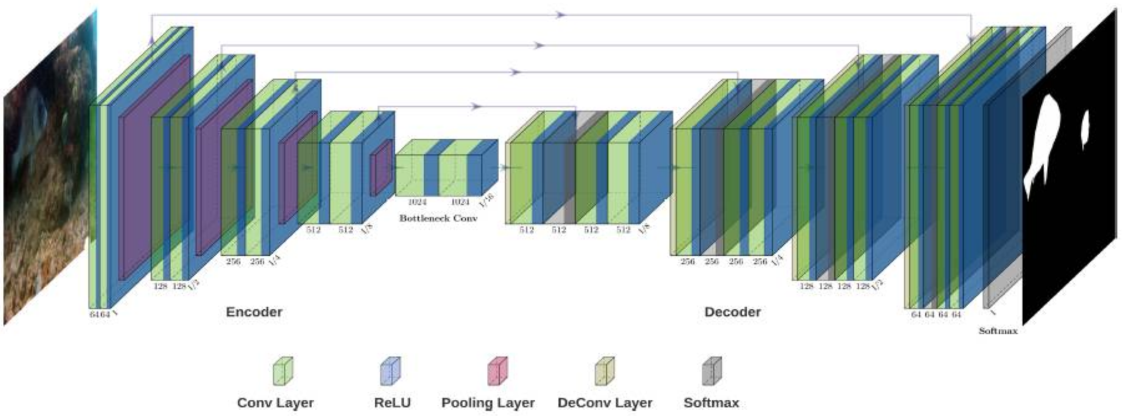


Pooling layer: (Left) single feature map spatially down sampled from a representation block with shape
224 × 224 × 1 to a new representation of shape 112 × 112 × 1.
(Right) types of pooling layers : [max pooling ; average pooling]

Schematic diagram of feature maps of CNN used in classification task



Filter (Kernel of 3 × 3) slid over the entire image to generate feature maps
Feature map is a 2D-representation of an input image

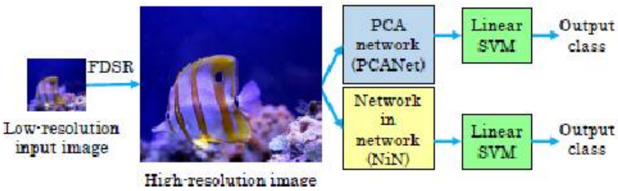


UNet
Encoder : extracts features from input image
Decoder : outputs per-pixel scores

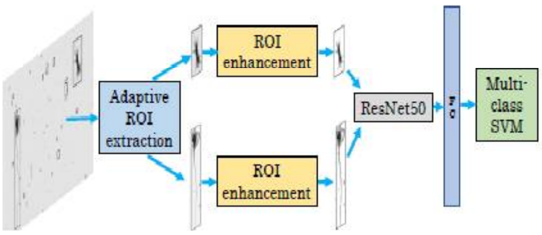
Different layers network: convolutional (Conv Layer), rectified linear unit (ReLU), pooling, deconvolutional (DeConv) and SoftMax layer

Mittal et al [04] narrated a survey of deep learning techniques for classification of under water images.

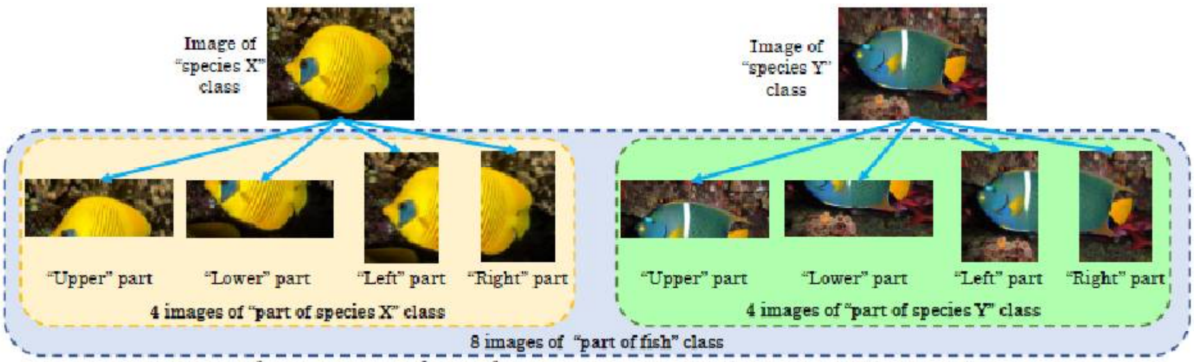
04	Mittal, S., Srivastava, S. and Jayanth, J.P., A survey of deep learning techniques for underwater image classification, IEEE Transactions on Neural Networks and Learning Systems, **2022**.



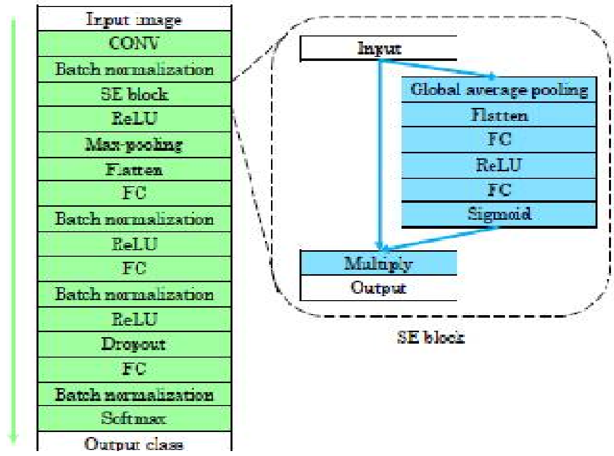
PCA,NiN, SVM models by Sun et al



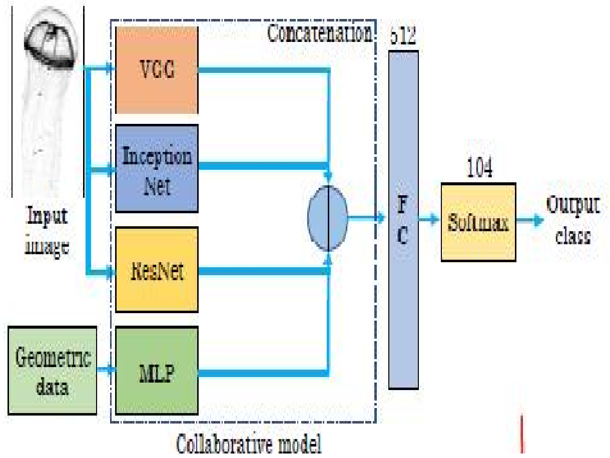
Architecture of Cheng et al.
685,520 images; seven classes
AlexNet, VGG, GoogLeNet, ResNet
Best model: ResNet50 + SVM



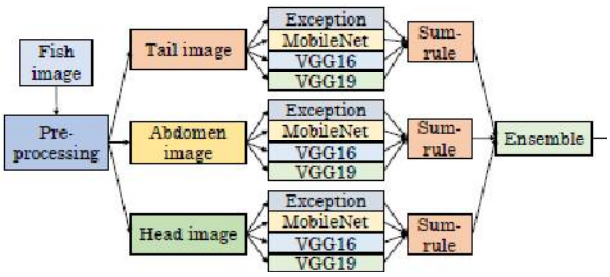
"Part of fish" and "part of species" classes



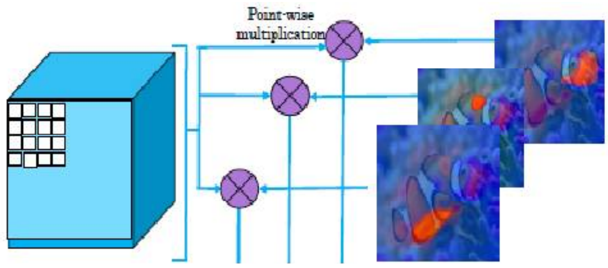
CNN-SENet proposed by Olsvik et al
SENet: "squeeze" "excitation" operations in Net



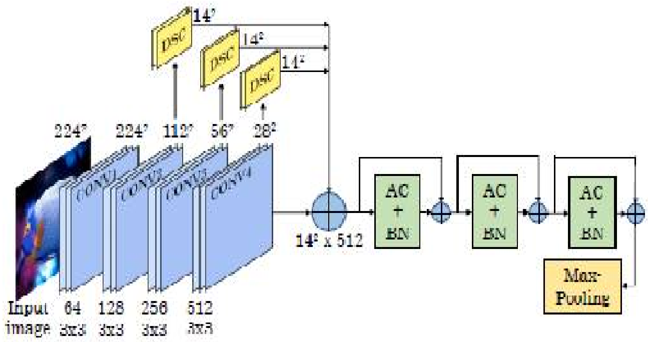
Architecture of Kerr



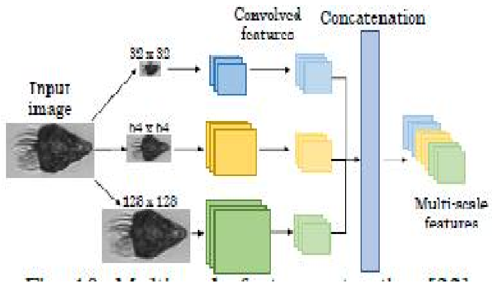
Architecture of Jose et al.



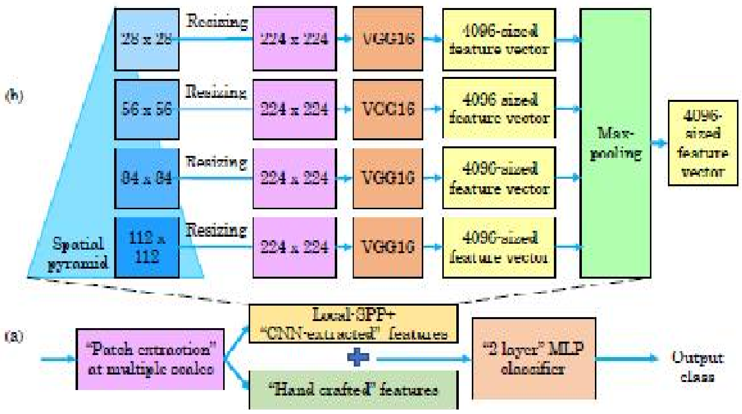
Cross convolutional layer pooling algorithm



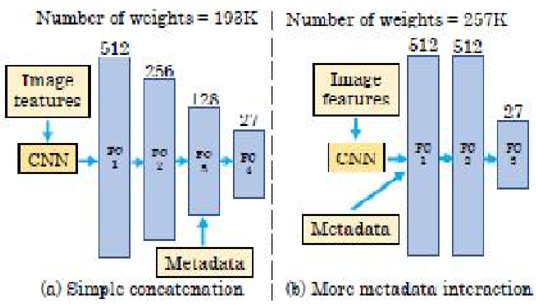
Architecture of Prasetyo et al.



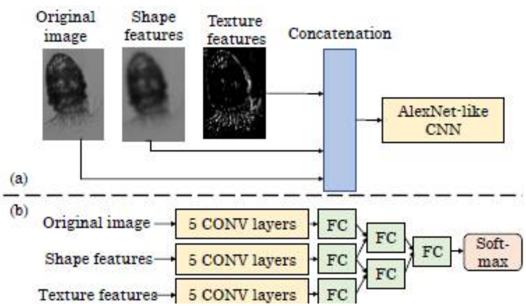
Multi-scale feature extraction

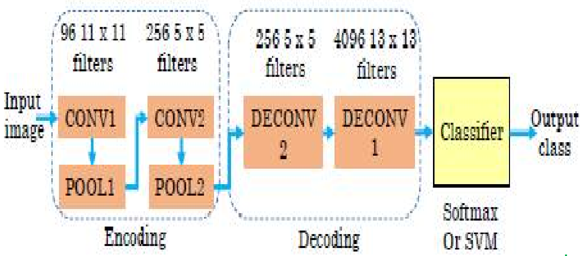


Local-SPP followed by CNN-based feature extraction model of Mahmood et al.

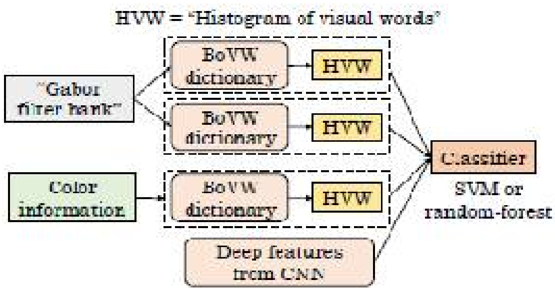


Architecture of Ellen et al.

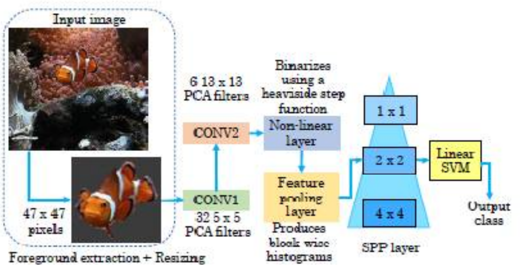




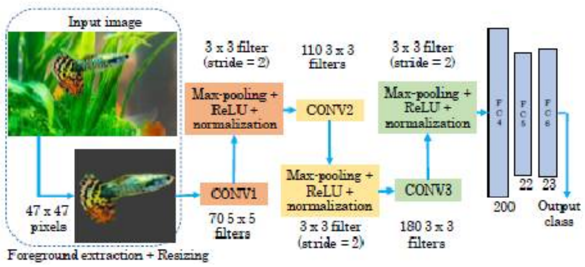
Architecture of Wang et al.



Architecture of (a) Cui et al. (b) Dai et al



Methods-Flow of the DeepFish-SVM model.



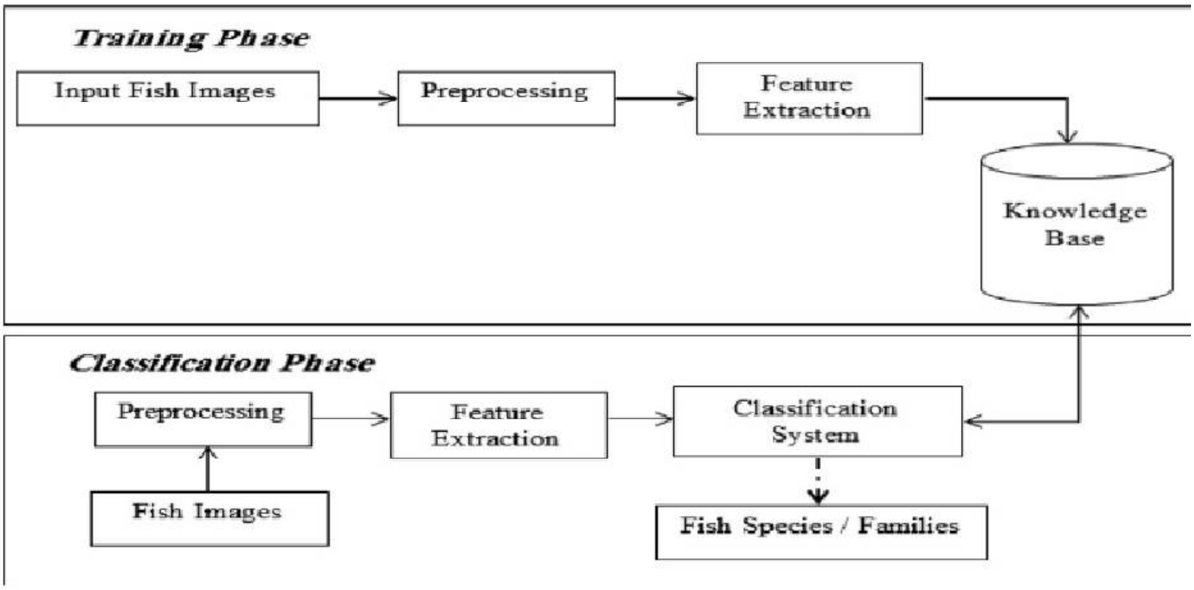
Methods-Flow of the Deep-CNN model

Case Study

Feature extraction with CNN, SVM, NN-BP etc.

Alsmdi et.al [03] summarized fish feature extraction/classification methods and data sets (Fish4-Knowledge (F4K), knowledge database, and Global Information System (GIS) on Fishes etc.) in their review comprising of 80 research publications. In fisheries research, Conventional features are categorized as shape , local (fish mouth length, anal fin length, fish head angle, eye-end mouth angle, and caudal fin length)/ global , color, texture, geometric (length of the body, anal fin, caudal fin, dorsal fin, pelvic fin,) and their combinations. The classification methods covered include SVM, BP NN, HGAGD-BPC, GAILS-BPC, Bayesian classifier, and CNN. The information is of relevance to industrial field, agriculture domain, and marine scientists.

[03]	Alsmadi, M.K. and Almarashdeh, I., A survey on fish classification techniques, Journal of King Saud University-Computer and Information Sciences, **2022**, 34(5), 1625-1638. https://doi.org/10.1016/j.jksuci.2020.07.005



Method(s)-Flow for Fish classification

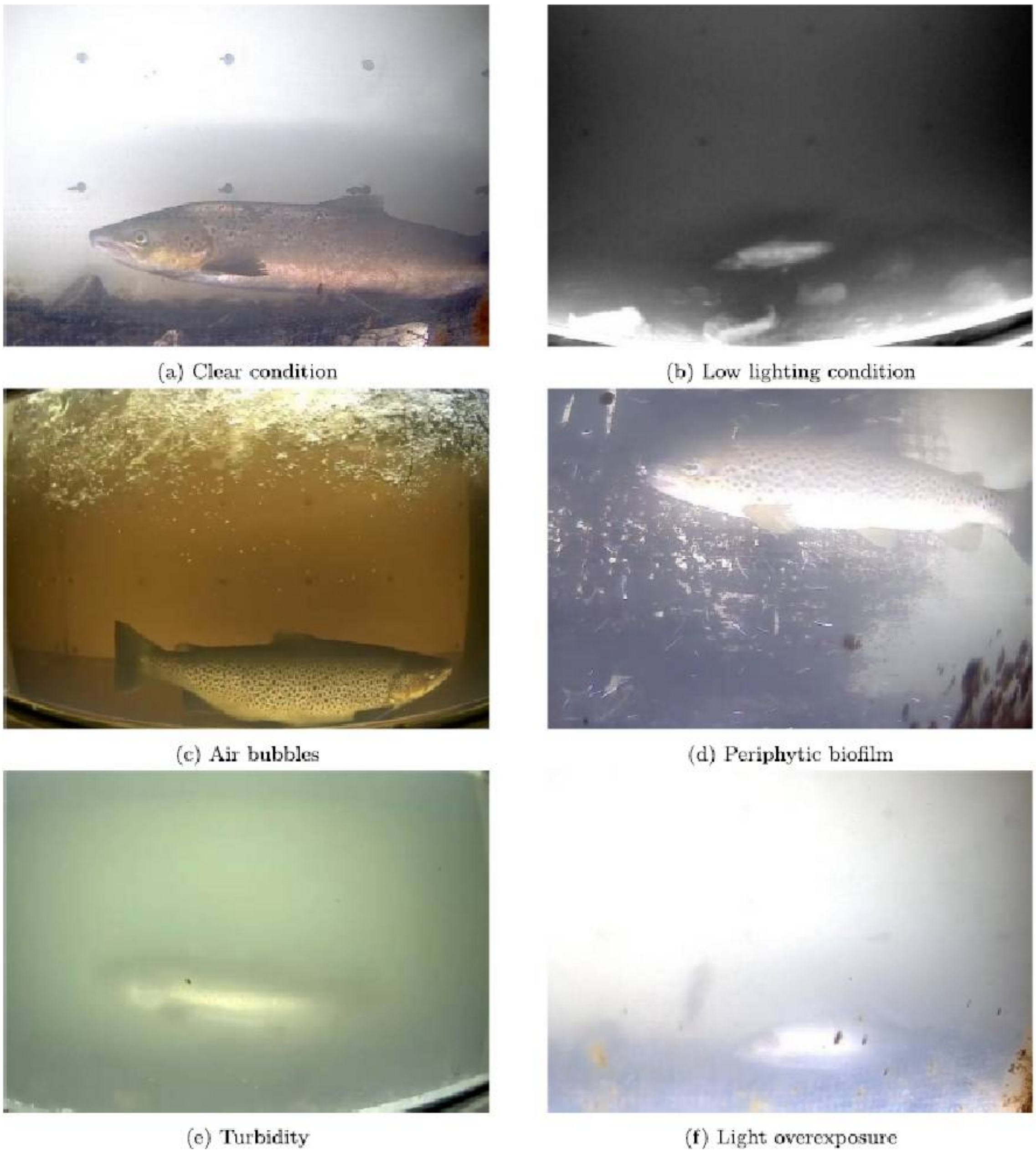
Case Study

Automatic detection of fish with CNN in binary classifier mode

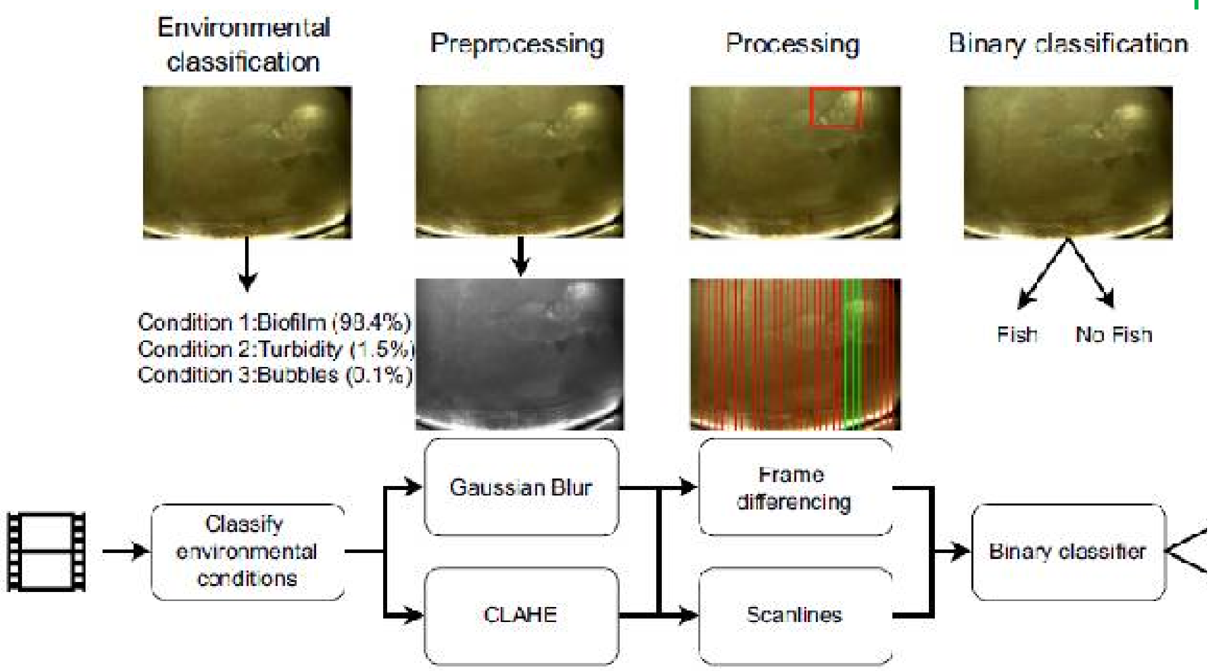
Soon et.al [4] validated a work-flow for automatic detection of fish and no-fish scenarios from 3000 underwater fish counter videos under varying environmental conditions like clear water, biofilm growth, bubbles, turbidity, low light and overexposure. These results illustrate a feasibility of a fast, accurate, and robust computer vision-based CNN binary classifier model for probing freshwater fish systems. The authors anticipate an environmentally-adaptive outdoor video monitoring system for birds as well as terrestrial animals.

04	Soom, J., Pattanaik, V., Leier, M. and Tuhtan, J.A., Environmentally adaptive fish or no-fish classification for river video fish counters using high-performance desktop and embedded hardware, Ecological Informatics, **2022**,72, 101817. https://doi.org/10.1016/j.ecoinf.2022.101817

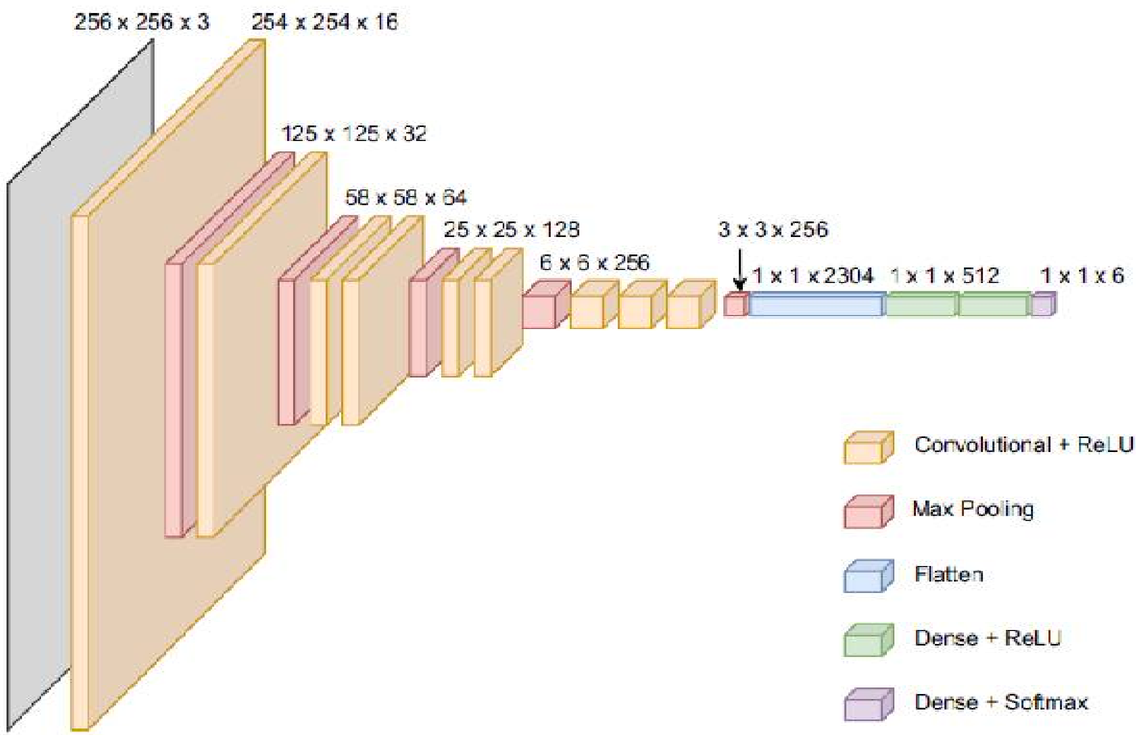
Different environmental conditions



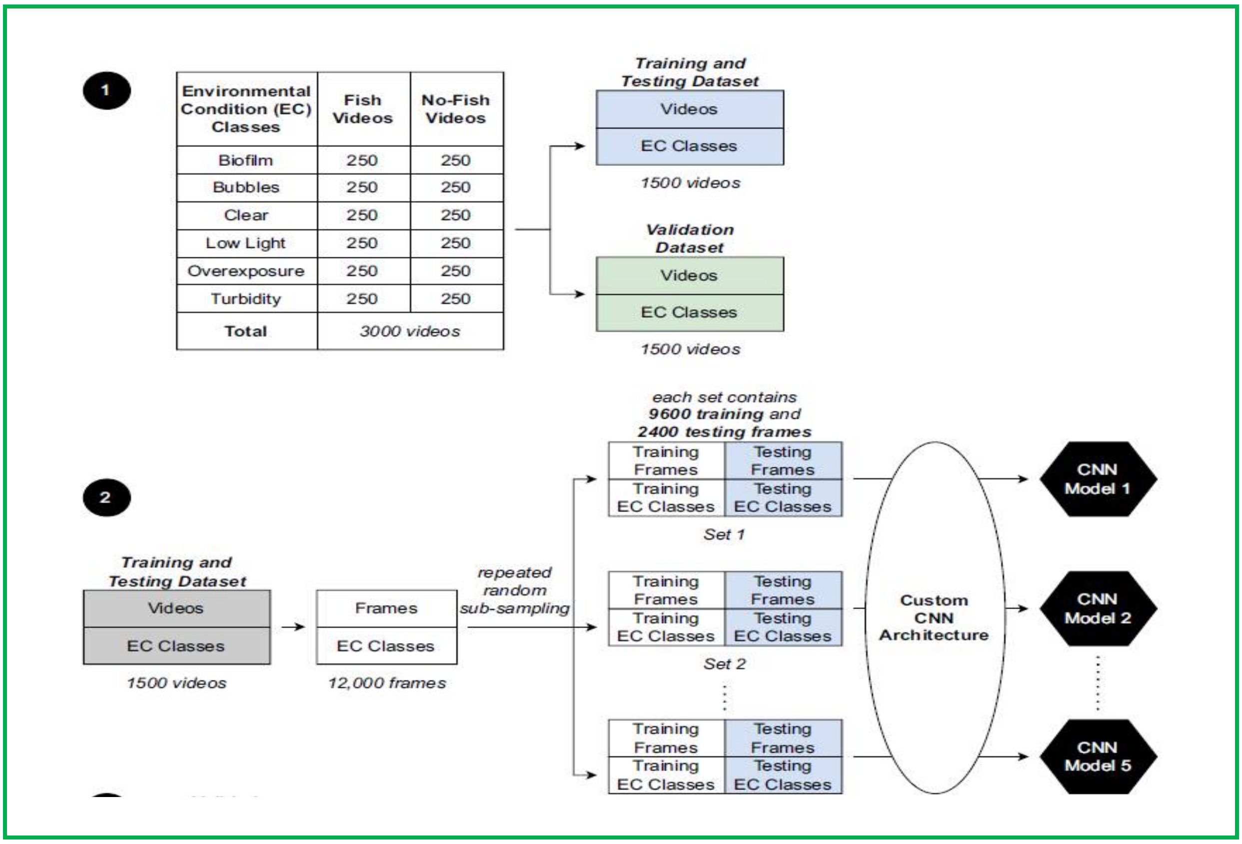
(f): Includes biofilm growth (d) and turbidity (e) in addition to light over exposure

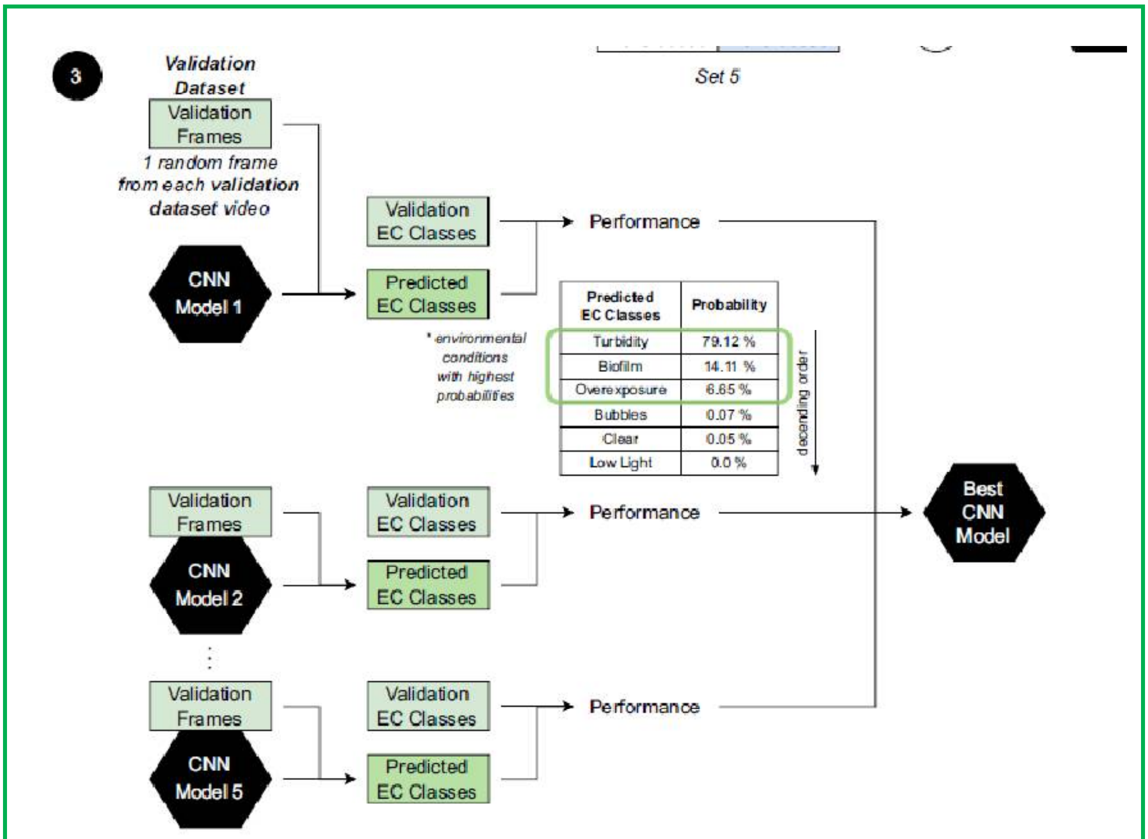


Four-stage underwater video classification pipeline
CLAHE: Contrast Limited Adaptive Histogram Equalization



CNN model architecture for environmental condition classification





Method flow Adapted from (Raschka, 2018)

		Predicted Labels					
		Biofilm	Bubbles	Clear	Low Light	Overexposure	Turbidity
True Labels	Biofilm	237	3	5	0	3	2
	Bubbles	2	240	0	0	2	6
	Clear	3	0	244	1	1	1
	Low Light	3	0	1	246	0	0
	Overexposure	0	0	0	0	250	0
	Turbidity	0	2	1	0	2	245

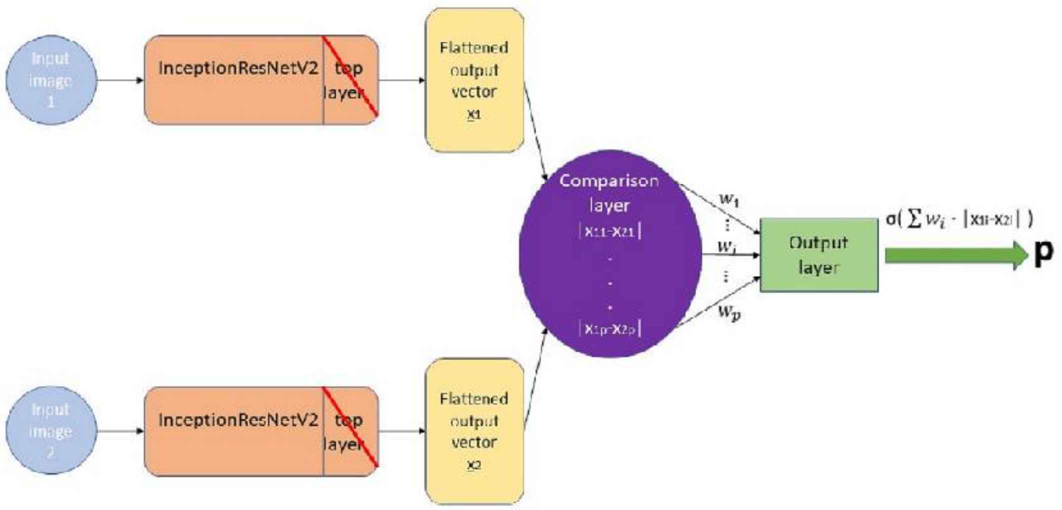
Confusion matrix of best CNN model

Case Study

Re-identificationof known/marked individual fish by Siamese-NN

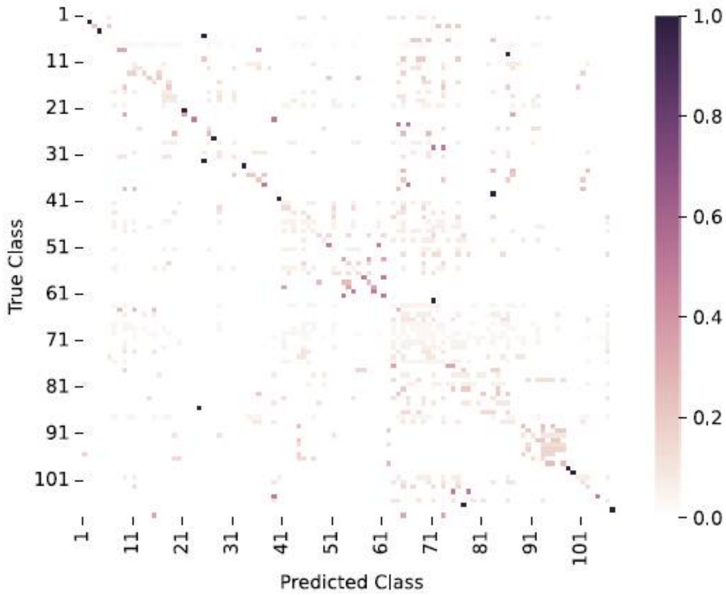
Vargas et al. [5] employed a Siamese neural network for photo-identification to discriminate individuals of the undulate skate (Raja undulata). This deep learning NN includes statistical fundamentals, It re-identifies known/marked individual fish up to 70% correctly. The recaptures here were about a year after the first shots.

05	Gómez-Vargas, N., Alonso-Fernández, A., Blanquero, R. and Antelo, L.T., Re-identification of fish individuals of undulate skate via deep learning within a few-shot context, Ecological Informatics, **2023**, 75, 102036. https://doi.org/10.1016/j.ecoinf.2023.102036



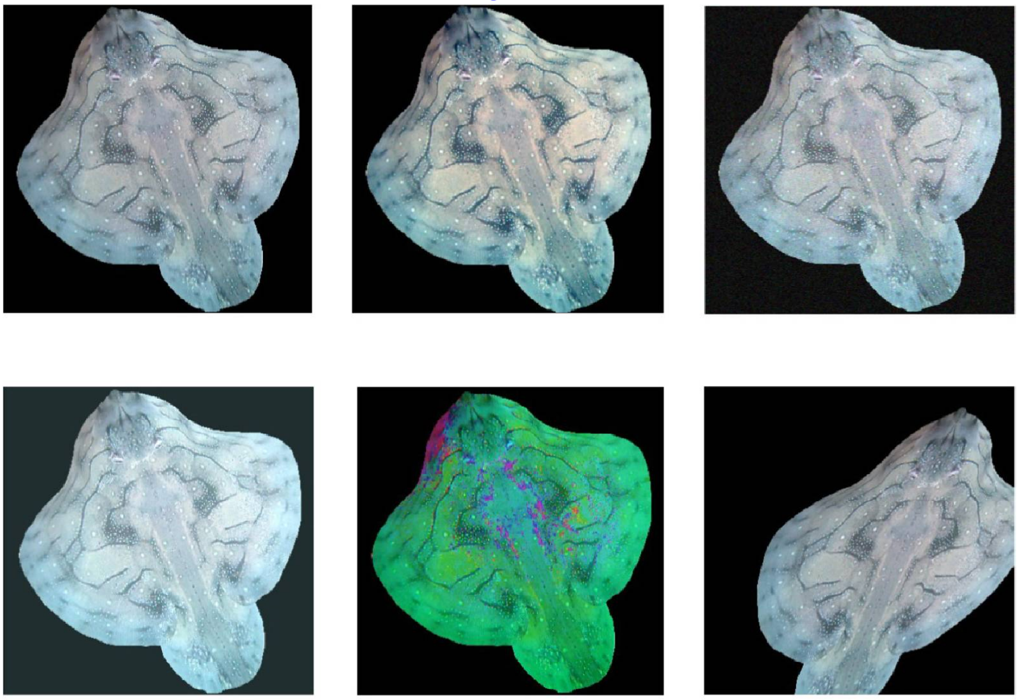
Siamese network

Heatmap of individual assignments in the predictions



- ✓ Map shows coloured ells (i,j) if individual in column j was predicted as identity for individual in row i, otherwise white
  - Strongest colour is for the case where only one individual was proposed as identity
  - Becomes clearer when the number of identities proposed in the majority vote procedure is greater

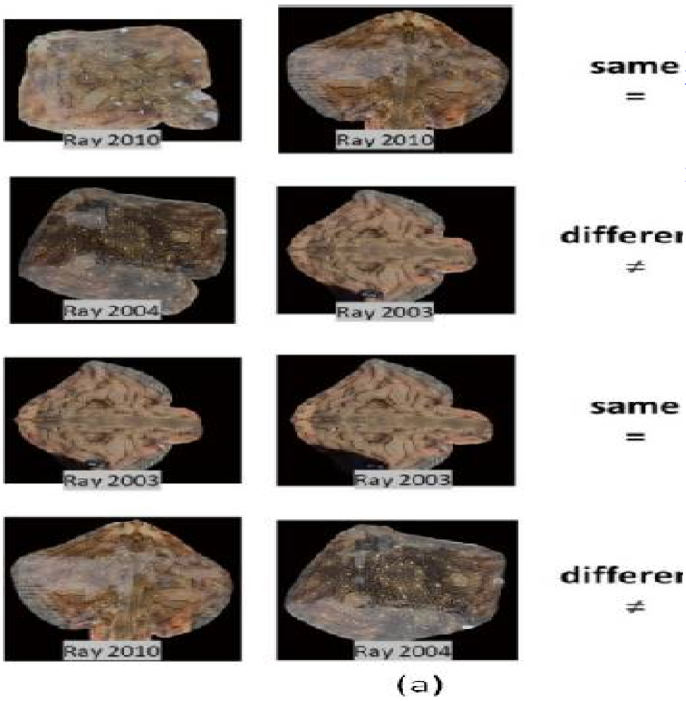
Data augmentation

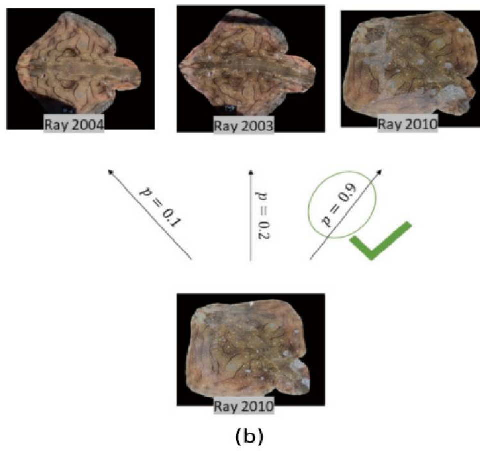


(a) Original image; (b) Contrast transformation; (c) Additive Gaussian noise transformation;	(d) Pixel sum transformation; (e) Hue and saturation transformation; (f) Affine transformations

Learning paradigm of Siamese network

(a) Verification model,: outputs probability that a particular pair belongs to the same class;
(b) One-shot task, which evaluates a new test sample in a pairwise manner score



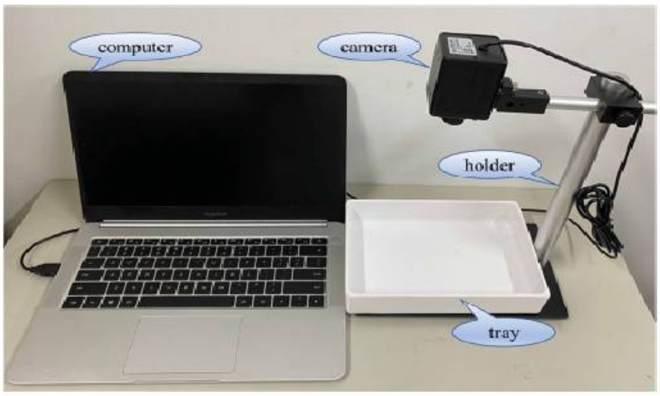


Case Study

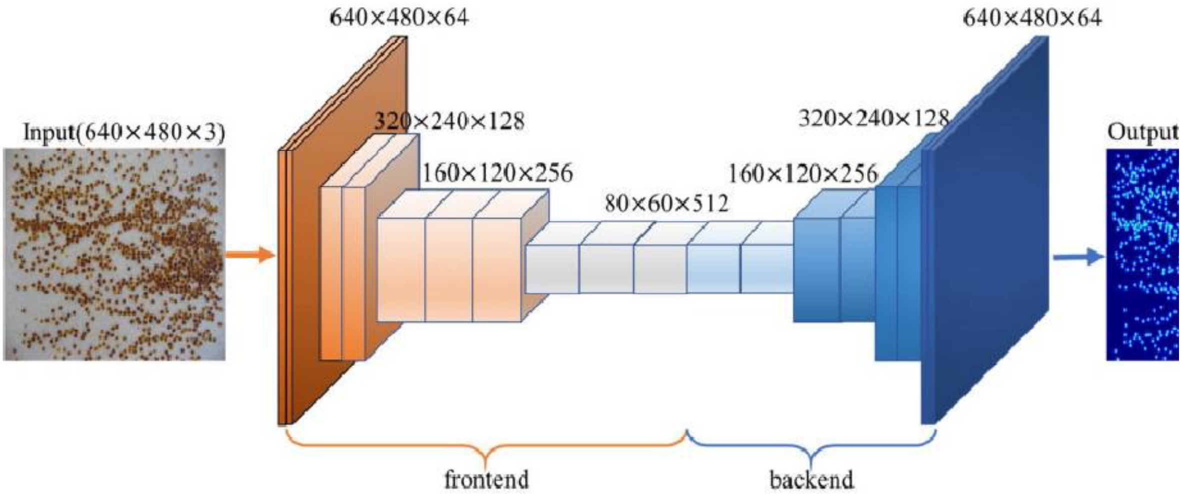
Srimp egg counting network (SECNet) >> for VGG-16, U-Net, or CSR-Net

Zhang et al. [06] reported an egg counting system making use Conv NN for shrimp. Around 450 images of the redclaw crayfish Cherax quadricarinatus (with about 272,000 eggs accurately annotated) were collected. This shrimp egg counting network (SECNet) is based on fully convolutional regression network (FCRN) and exploits the density map regression. It is more efficient in densely-distributed case even with severe occlusion. The accuracy reached 99.2 % which is greater than that for VGG-16, U-Net, or CSR (Congested Scene Recognition) Net.

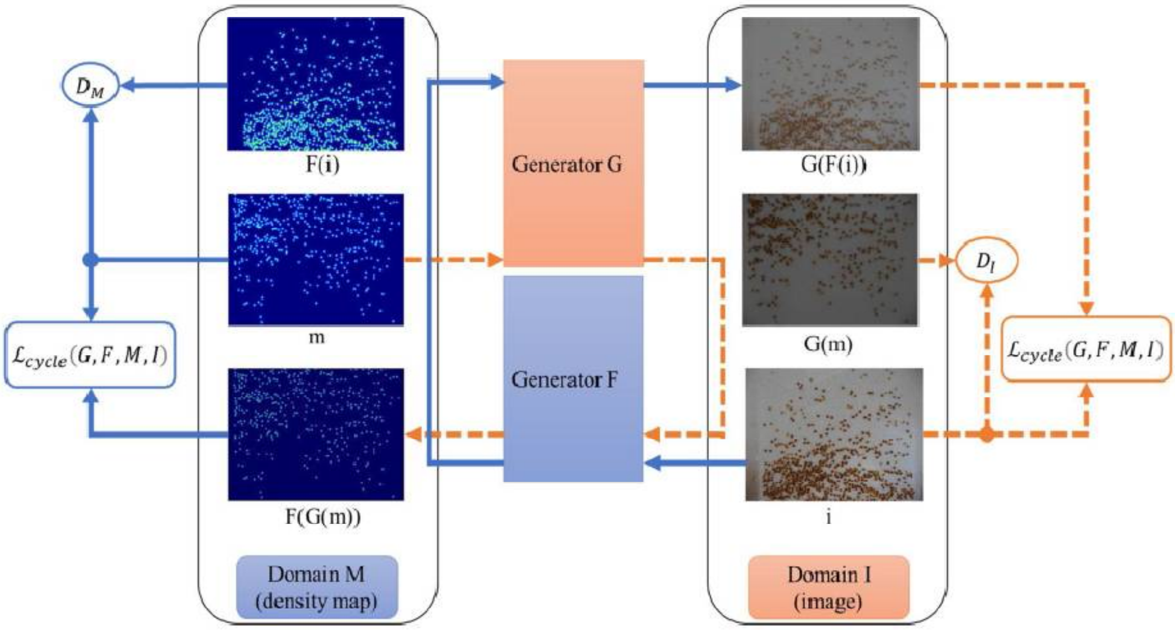
06	Zhang, J., Yang, G., Sun, L., Zhou, C., Zhou, X., Li, Q., Bi, M. and Guo, J., Shrimp egg counting with fully convolutional regression network and generative adversarial network, Aquacultural Engineering, **2021**, 94, 102175. https://doi.org/10.1016/j.aquaeng.2021.102175



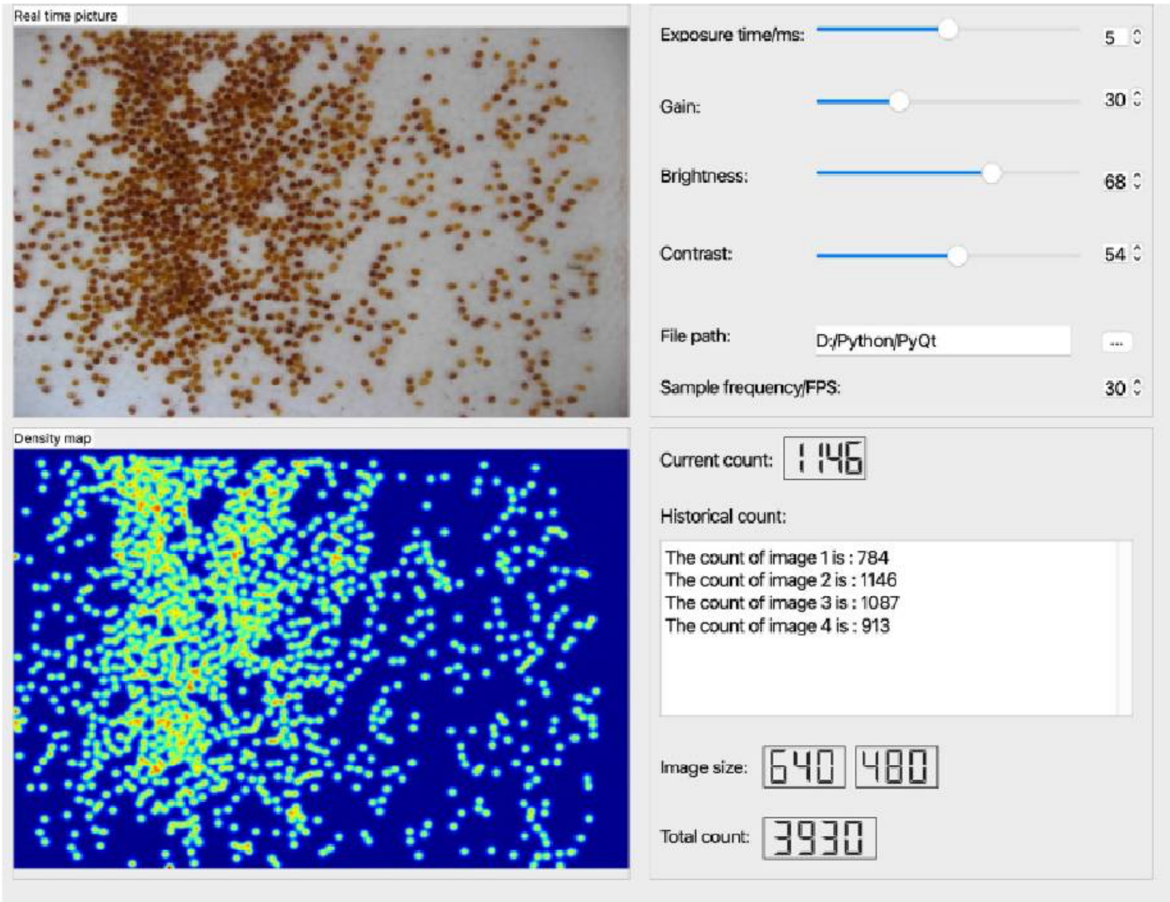
A computer vision setup



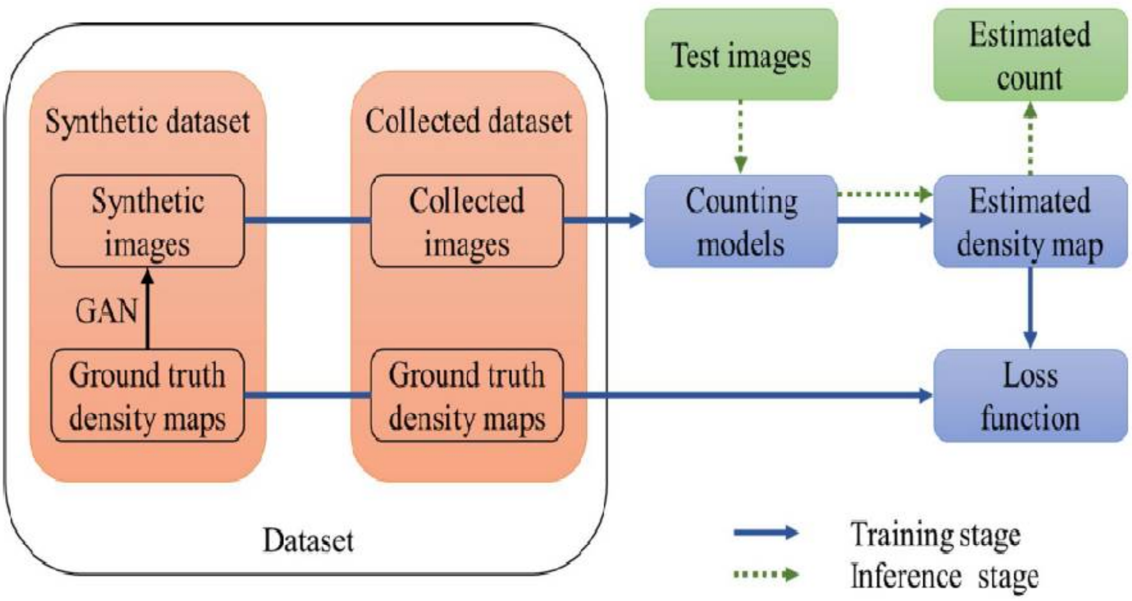
Shrimp egg counting (SEC)-Net architecture



Method-Flow of synthetic dataset generation

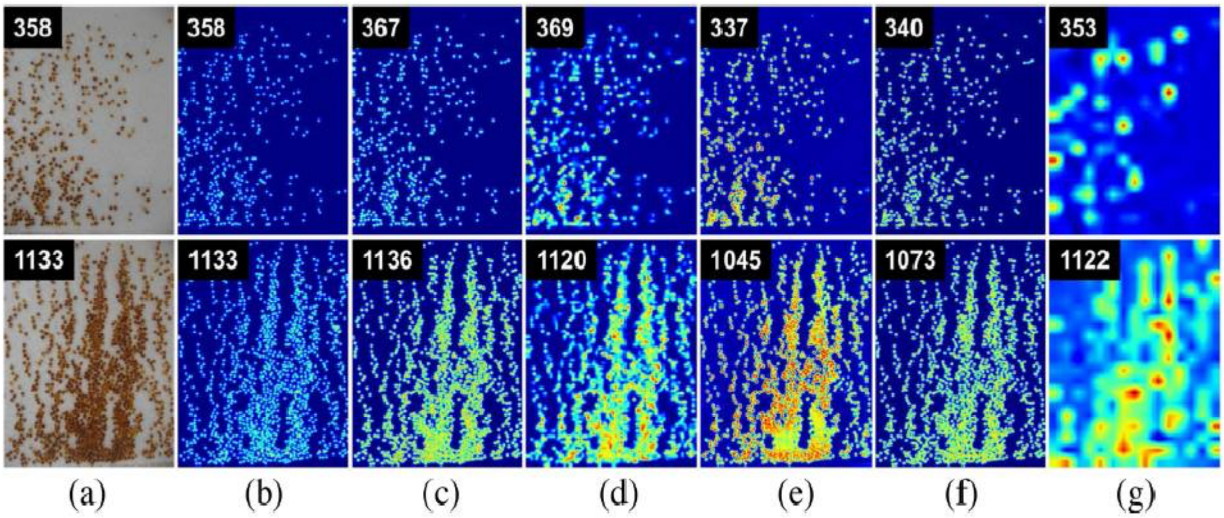


GUI of the operation program



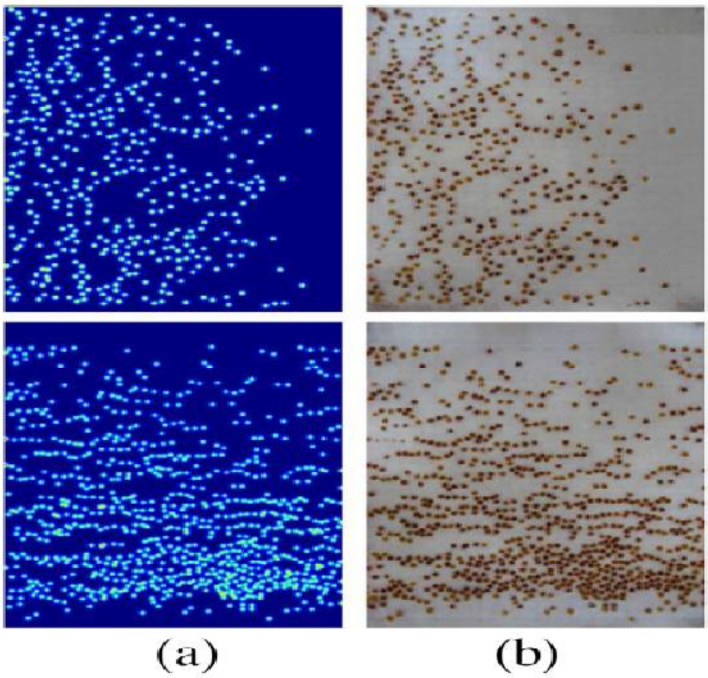
Framework of the counting system

Comparison of the results of different counting models

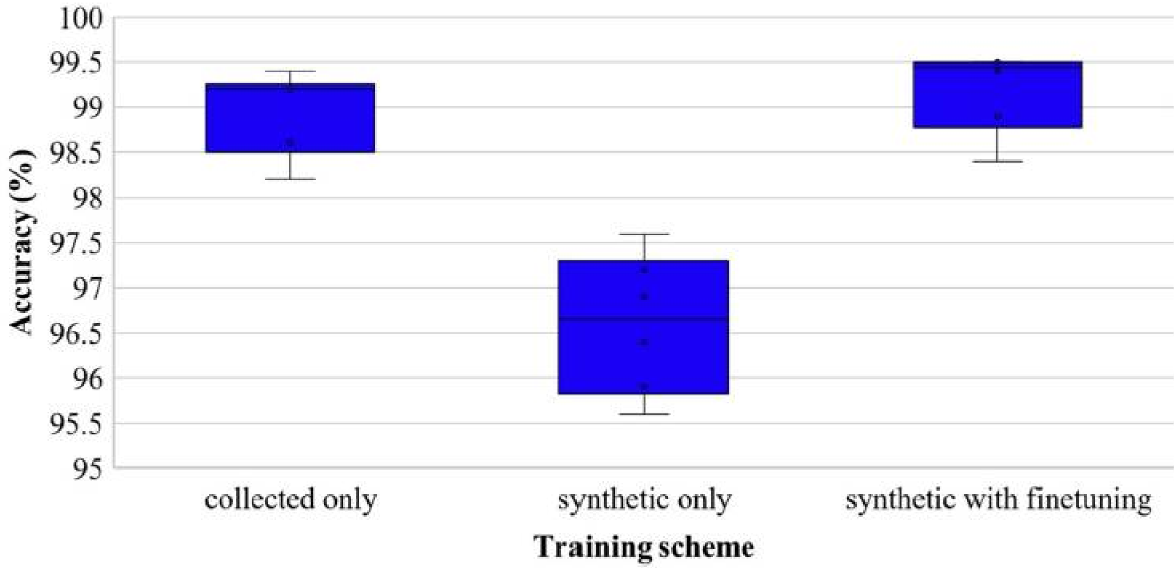


(a) Real images
(b) Ground truth density maps
(c) SECNet
(d) CSRNet
(whose 1/8-shrunk output image is resized to the same size as the input image)
(e) U-Net,
(f) SANet
(g) VGG-16
(whose 1/32-shrunk output image is resized to the same size as the input image)

Synthetic images generated by GAN-based generation model



(a) Randomly-generated ground truth density maps
(b) Synthetic mages



Box plot: Comparison of counting accuracies of SECNet trained with different training schemes

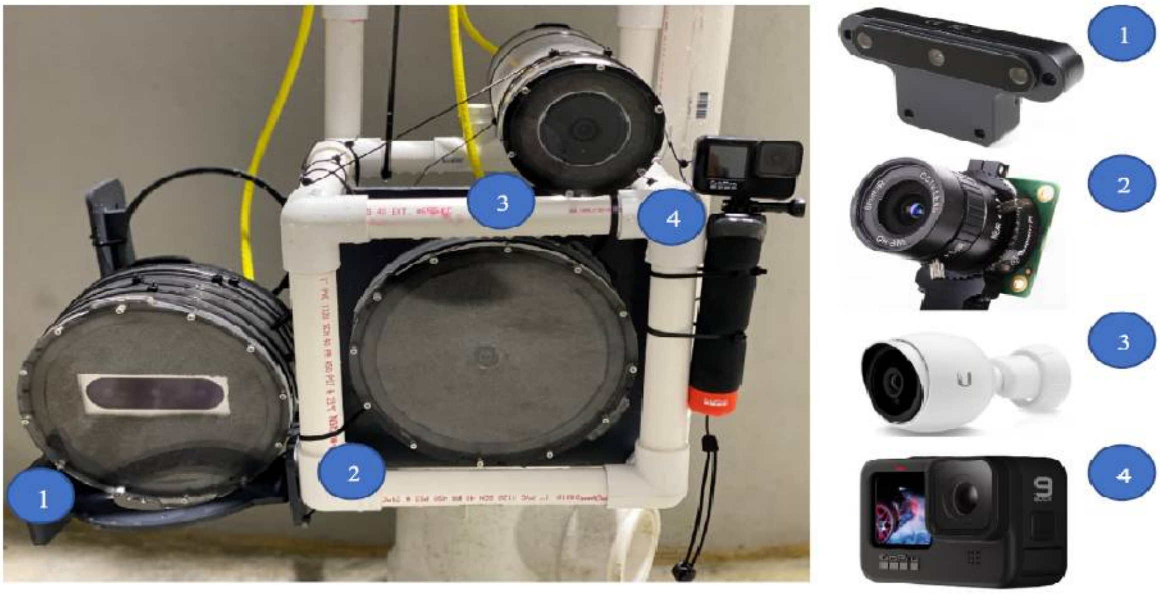
Case Study

Fish detection from under water images using yolov5 CNN-model

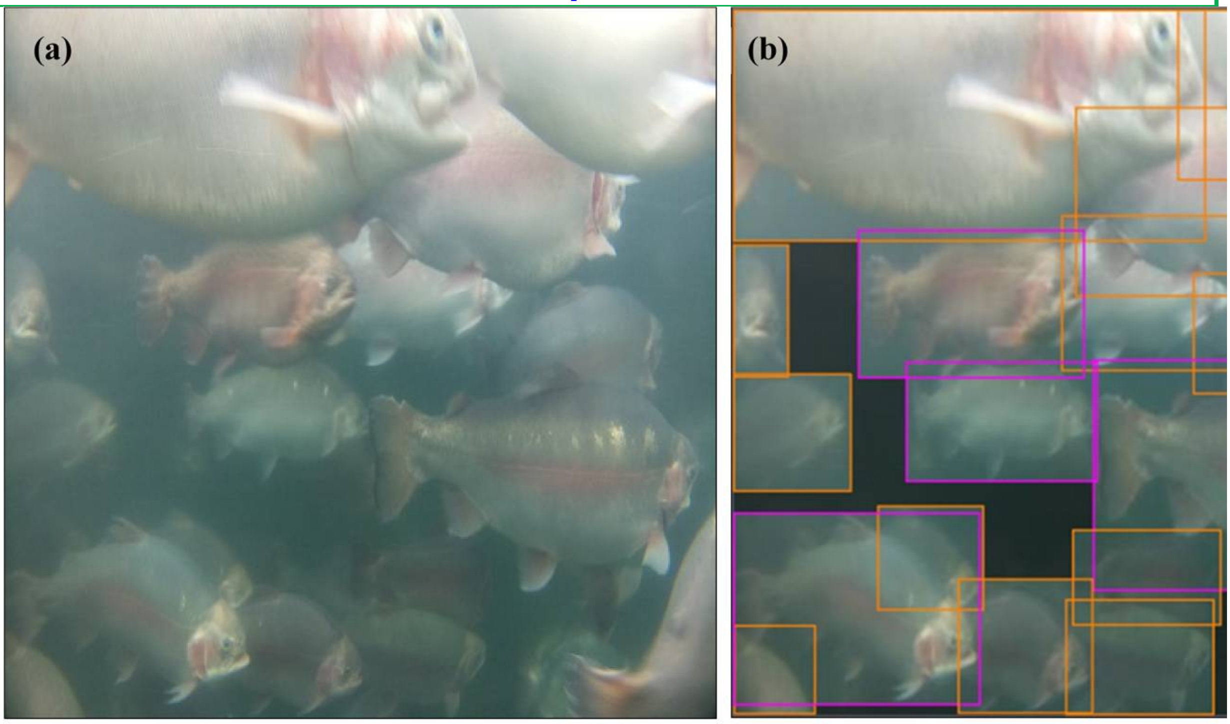
Ranjan et al. [7] trained under water fish images with YOLOv5 CNN-model. Around 100 images were acquired under ambient and supplemental light conditions. Augmentation method was adopted to increase the size of input images to 700. The focus of the investigation was on surmounting hurdles in high fish density, water turbidity and low-quality underwater image acquisition schedules. The effects of sensor selection, data size, annotation and pre-processing methods on the machine learning model accuracy for fish detection were probed.

7	Ranjan, R., Tsukuda, S. and Good, C., Effects of image data quality on a convolutional neural network trained in-tank fish detection model for recirculating aquaculture systems, Computers and Electronics in Agriculture, **2023**, 205, 107644. https://doi.org/10.1016/j.compag.2023.107644

07-



Underwater sensing platform (RASense1.0) with four on-board RGB sensors for in-tank image acquisition



CNN models YOLOv5 ; Faster R-CNN
(a) pre-processed input image
(b) ground truth image and corresponding
(c) model predicted image

- robust model performance
- detecting whole (marked with solid 'pink' bounding box) and partial (marked with solid 'orange' bounding box) fish.
- dotted rectangular box in 'red' highlights a fish that was identified as both partial and whole fish by the model.

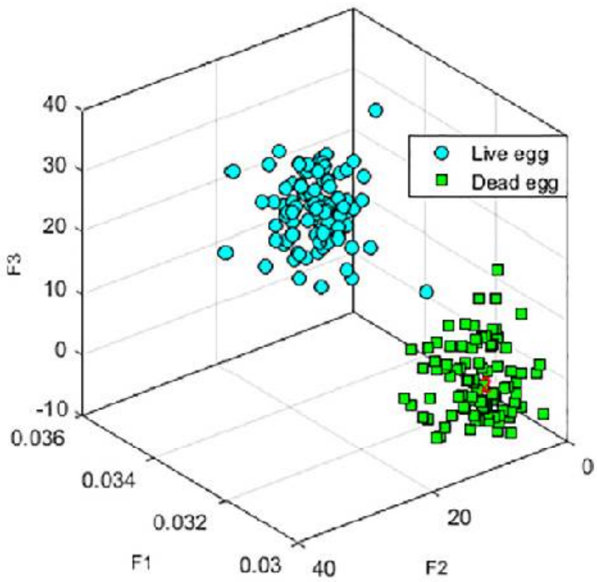
07	Ranjan, R., Tsukuda, S. and Good, C., Effects of image data quality on a convolutional neural network trained in-tank fish detection model for recirculating aquaculture systems, Computers and Electronics in Agriculture, **2023**, 205, 107644.https://doi.org/10.1016/j.compag.2023.107644

Case Study

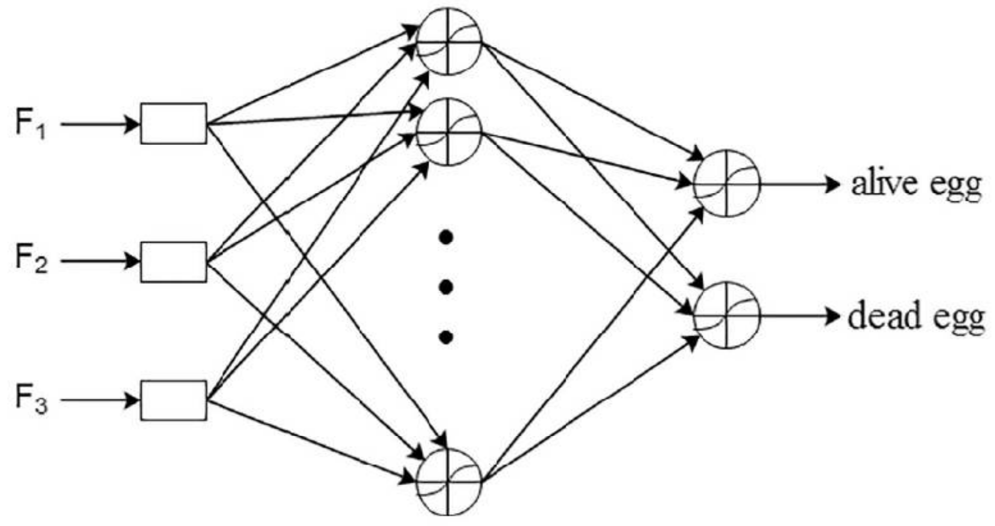
Discrimination of trout fishes from dead eggs using MLP-NN, SVM

Rohani et al. [08] made use of MLP-NN and SVM to distinguish live rainbow trout fishes from dead eggs. 15 causative variables were extracted from 200 images employing subtle image processing methods. Around 10 influential features were chosen for the binary classification arriving at a minimum of three for valid classification task.

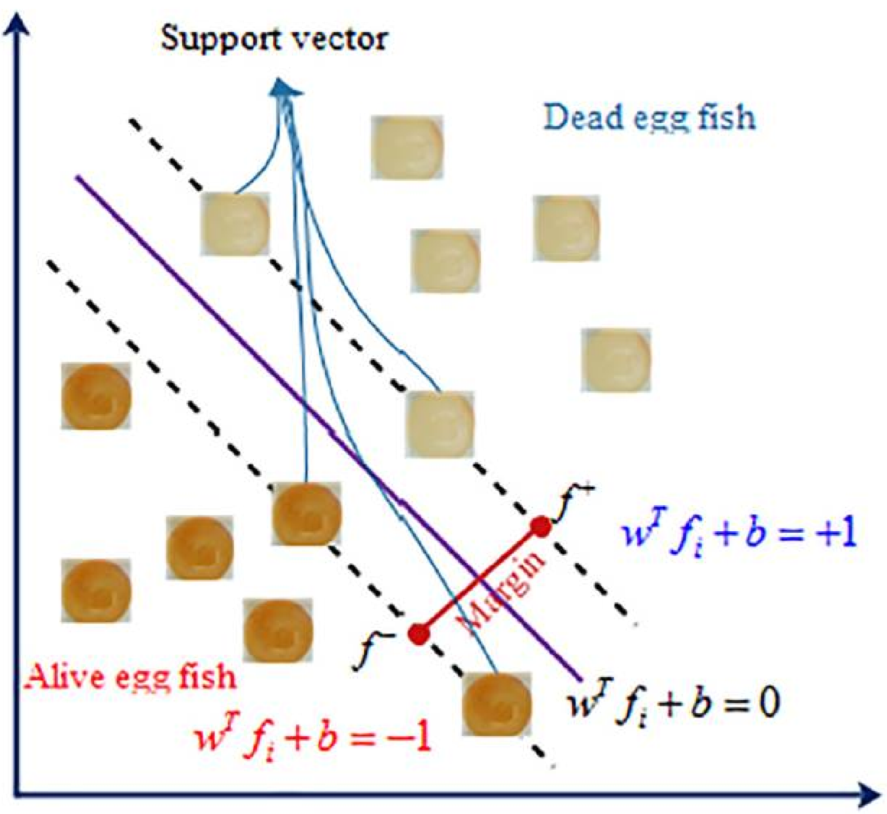
08	Rohani, A., Taki, M. and Bahrami, G., Application of artificial intelligence for separation of live and dead rainbow trout fish eggs, Artificial Intelligence in Agriculture, **2019**, 1, 27-34. https://doi.org/10.1016/j.aiia.2019.03.002



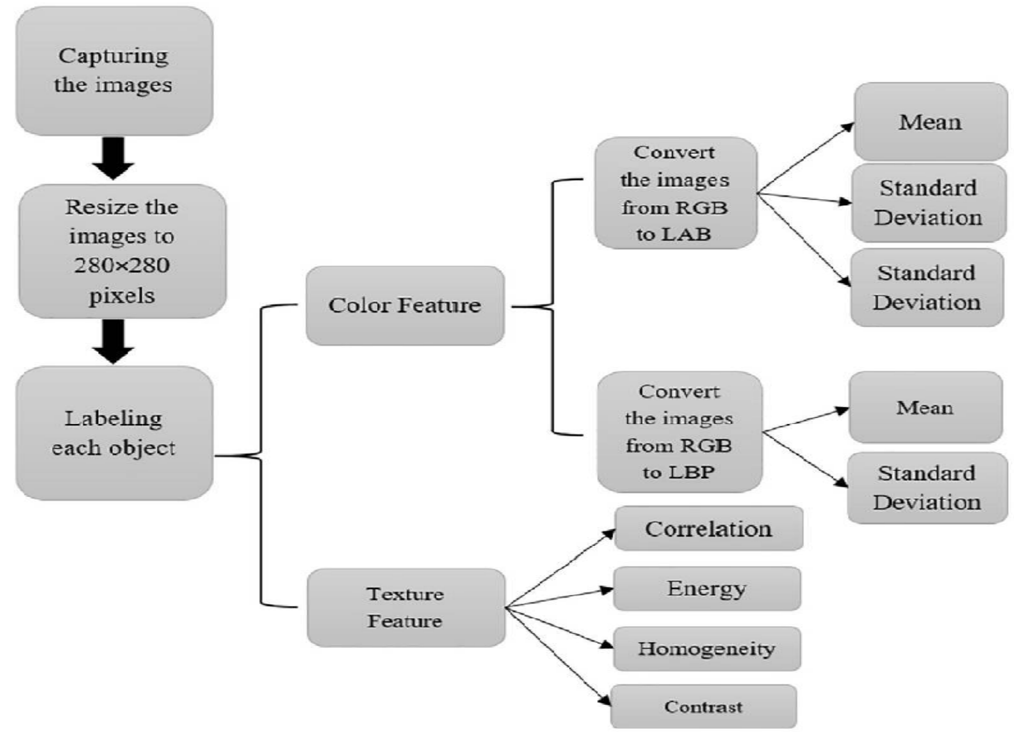
Dispersion of two classes of alive and dead eggs based on the three selected variables.



SLP-classifier-NN with three inputs and two outputs



Linear SVM classifier



I/O Flow chart for image pre-processing

Case Study

Detection of Microfossil fish teeth using Mask R–CNN and EfficientNet-V2

Mimura et al. [09a] reported automatic detection of Microfossil fish teeth (referred as ichthyoliths) using NN methods. The regions for segmentation from microscopic images were defined with Mask R–CNN. The detected regions are re-classified by operation of EfficientNet-V2 module. 90% of the predicted lengths are within ±20% of measured values.

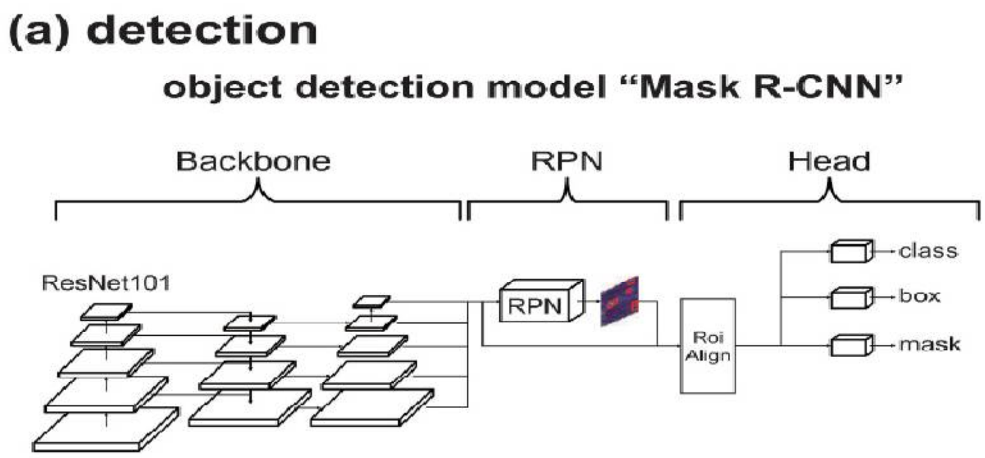
These authors (Mimura et al. [09b]) described three datasets for training, validating, and testing deep learning models to detect microfossil fish teeth.

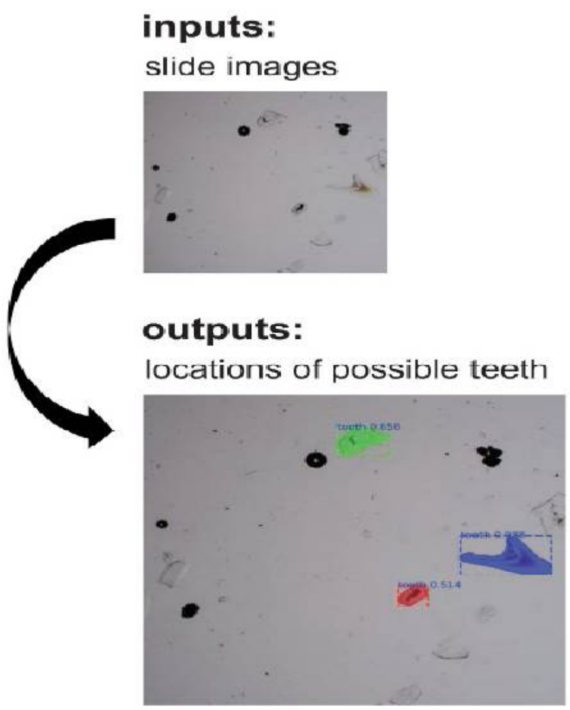
	Training/ Validation	Model
Dataset 1	866 images + annotation file 92 images + annotation file	Mask R-CNN
Dataset 2	17,400 images of teeth + 15,036 images of noise (particles other than teeth)	EfficientNet- V2
Dataset 3	5177 images + annotation files for 431 locations teeth	Mask R-CNN + EfficientNet- V2

09a	Kazuhide Mimura, Shugo Minabe, Kentaro Nakamura, Kazutaka Yasukawa, Junichiro Ohta, Yasuhiro Kato, Automated detection of microfossil fish teeth from slide images using combined deep learning models, Applied Computing and Geosciences 16 (2022) 100092, https://doi.org/10.1016/j.acags.2022.100092

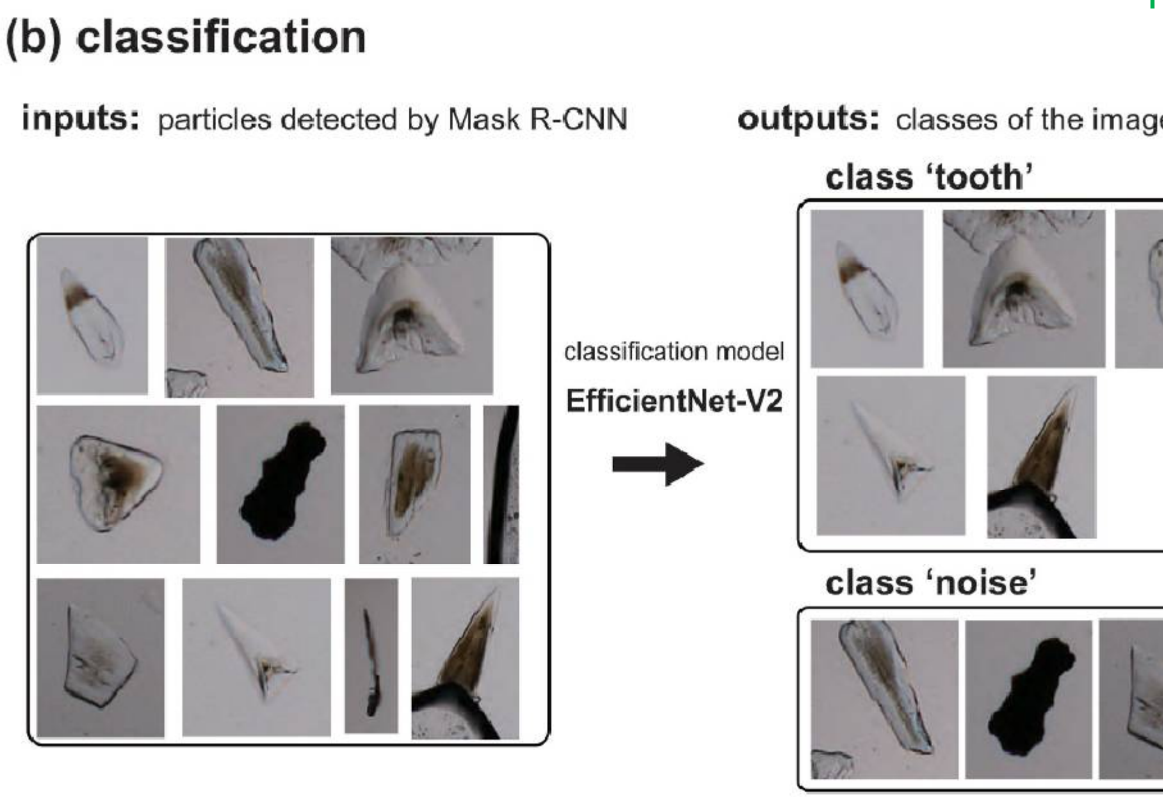
09b	Mimura, K. and Nakamura, K., Datasets for training and validating a deep learning-based system to detect microfossil fish teeth from slide images, Data in Brief, **2023**, 202347, 108940. https://doi.org/10.1016/j.dib.2023.108940

Ichthyolith detection system





Single-class object detection model ‘Mask R–CNN’
Possible regions of fish teeth in slide images



Precise classes of particles detected by Mask R–CNN were re-predicted by a two-class image classification model, EfficientNet-V2.

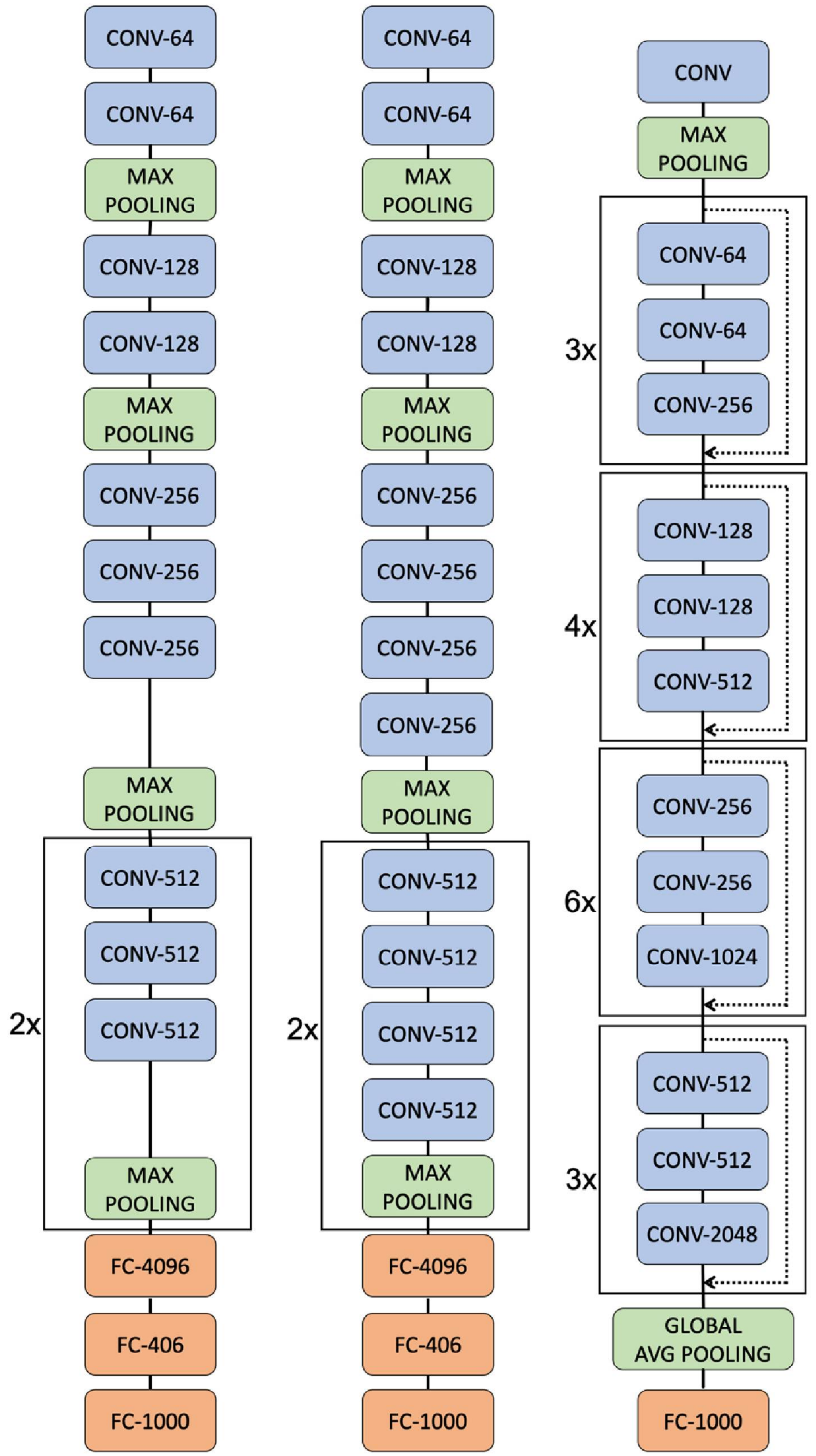
Case Study

Classification of order, family and species of fishes in Pantanal region with multi-branch (VGG-16, VGG-19, ResNet) CNN

Santos and Gonçalves [08] proposed a CNN-base with three branches for classification of fishes in Pantanal region. The first branch looks for order, the second one for family and the last one for species of fishes. This multi-level probing improves recognition of the fish with similar characteristics and down-ward passing of information from order to family and then to species. It improves the accuracy to 0.873 against a value of 0.864 when traditional CNN was employed to recognise 68 types of fish species.

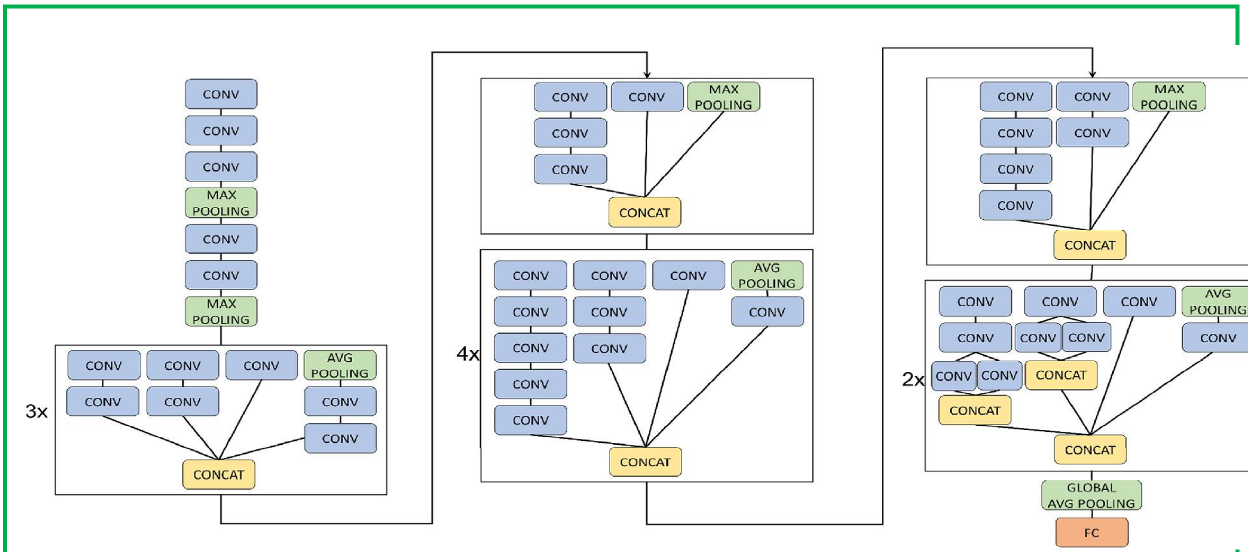
8	dos Santos, A.A. and Gonçalves, W.N., Improving Pantanal fish species recognition through taxonomic ranks in convolutional neural networks, Ecological Informatics, **2019**, 53, 100977. https://doi.org/10.1016/j.ecoinf.2019.100977

08

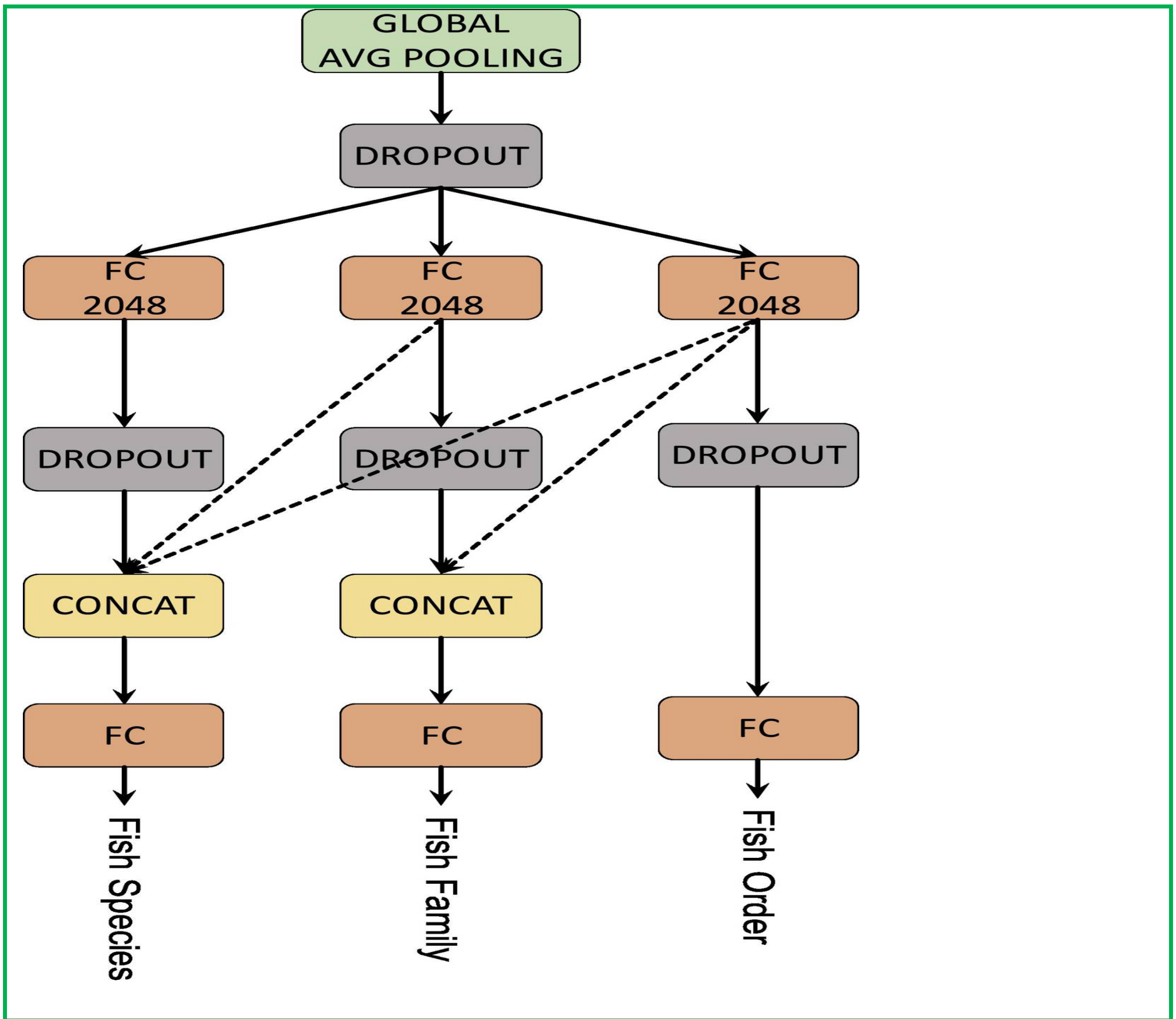


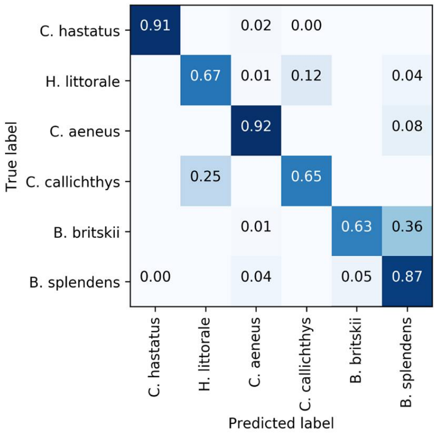
(a) VGG16 (b) VGG19 (c) ResNet

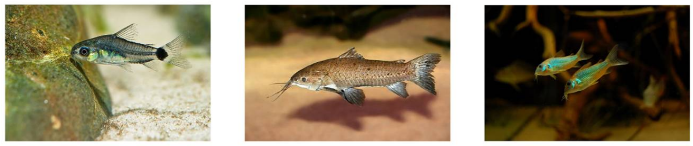
Representation of the layers of the $$CNNs
(a) VGG16, (b) VGG19, (c) ResNet
Number next to the layer name represents the number of filters



Overview of Inception layers







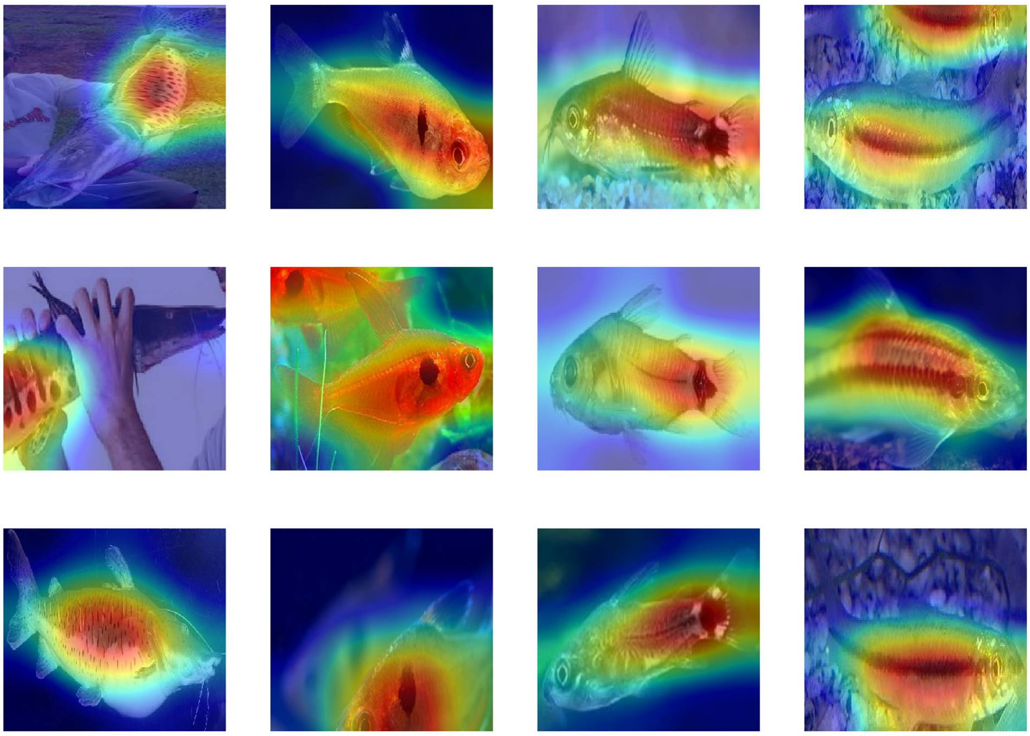
(b) C. hastatus (c) H. littorale (d) C. aeneus

(e) C. callichthys (f) B. britskii (g) B. splendens

(a) Confusion matrix

xAI-
grad-CAM-Method

grad-CAM



(a) Pincachara (b) H. eques (c) C. hastatus (d) A. affinis

Gradients obtained by grad-CAM for typical fish species

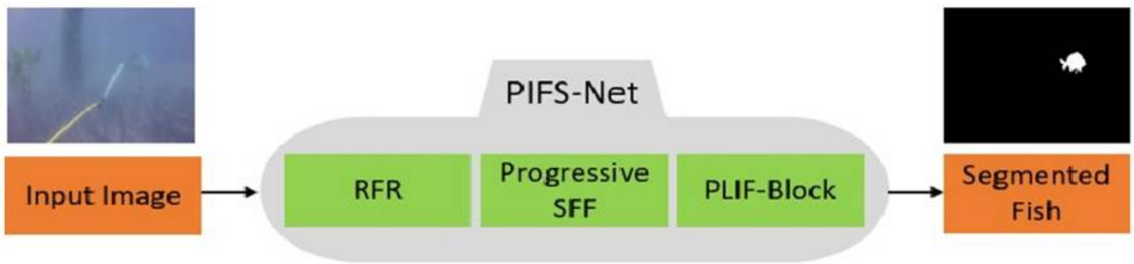
Case Study

Computer-aided fish segmentation with 2 million tunable parameters

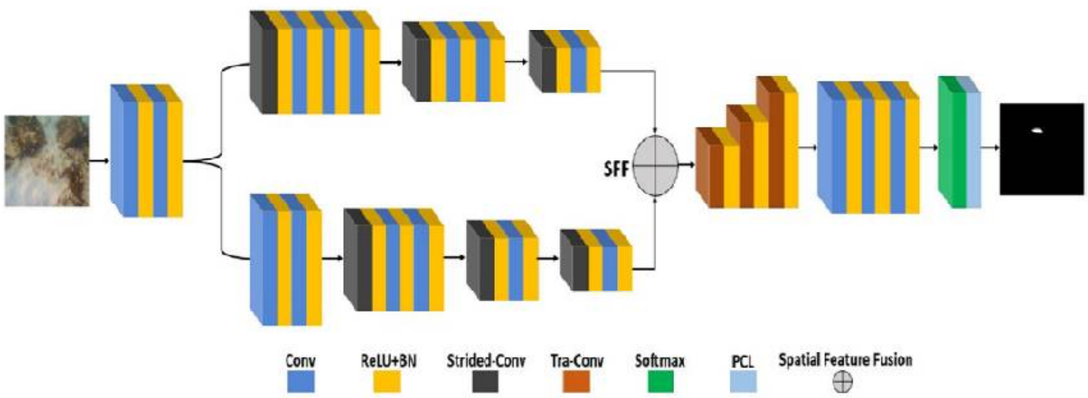
Haider et.al. [06] reported automatic high-performance computer-aided fish segmentation and assessment Modelling system. This study paves way to the development of an intelligent aquatic ecosystem in near future. PFFS-Net (parallel feature fusion-based segmentation network) is the base model to fuse parallel feature streams for pixel-wise fish segmentation. PIFS-Net (progressive information fusion-based segmentation network) employs rapid feature reduction and pre-prediction low-level information fusion blocks which further boost performance. PIFS-Net has 2.02 million trainable parameters. PIFS-Net is the final step of model using a progressive spatial feature fusion (SFF) mechanism. It enhances segmentation accuracy. RFR and PLIF-Blocks enabled diversified learning and further improved prediction accuracy. These models made use of publicly available (i.e., semantic segmentation of underwater imagery) databases which have diverse variations in the size, background, illumination, and shadows.

06	Haider, A., Arsalan, M., Nam, S.H., Sultan, H. and Park, K.R., Computer-aided fish assessment in an underwater marine environment using parallel and progressive spatial information fusion, Journal of King Saud University-Computer and Information Sciences, **2023**, 35(3), 211-226. https://doi.org/10.1016/j.jksuci.2023.02.016

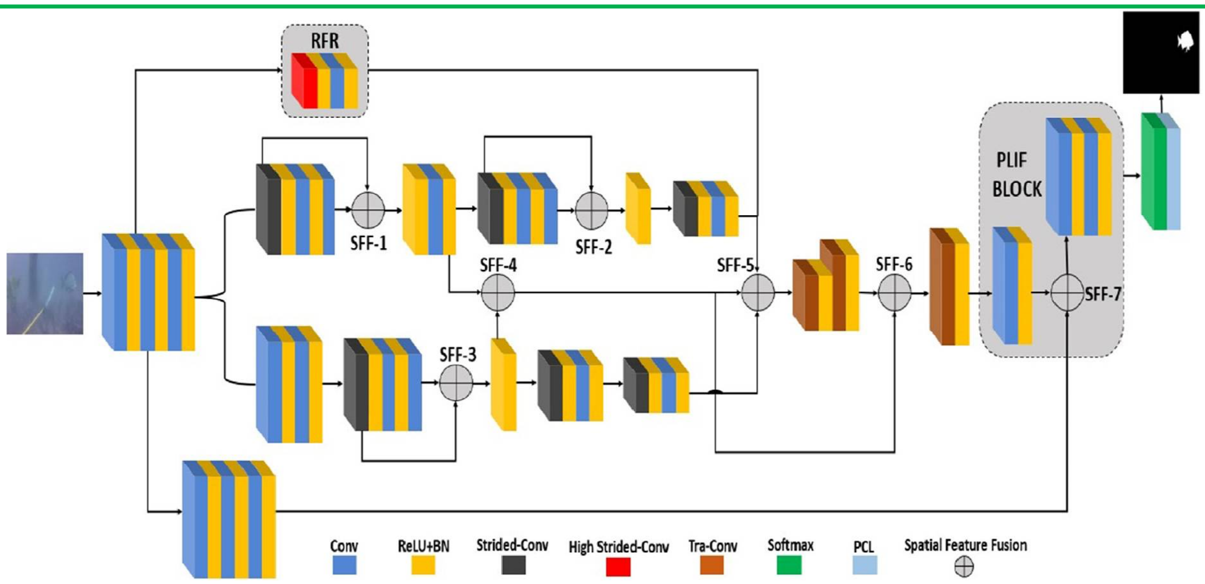
06



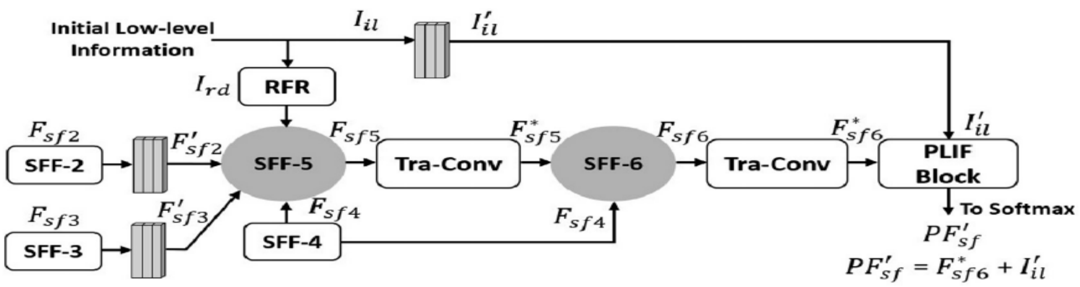
Method-flow overview



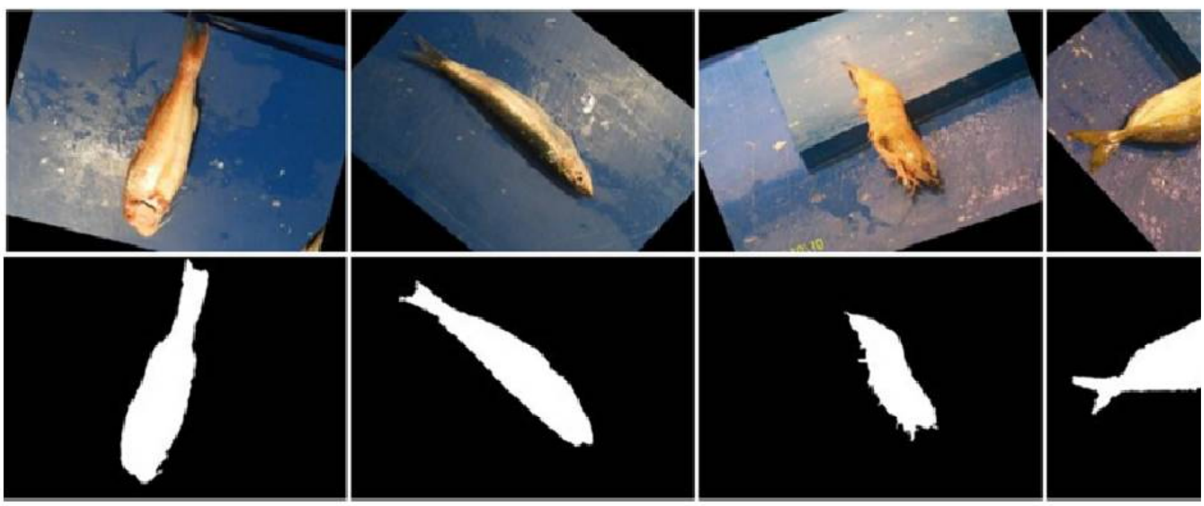
PFFS-Net architecture
Parallel feature fusion-based segmentation network



Architecture of PIFS- Net
Progressive information fusion-based segmentation network



Progressive feature fusion operations

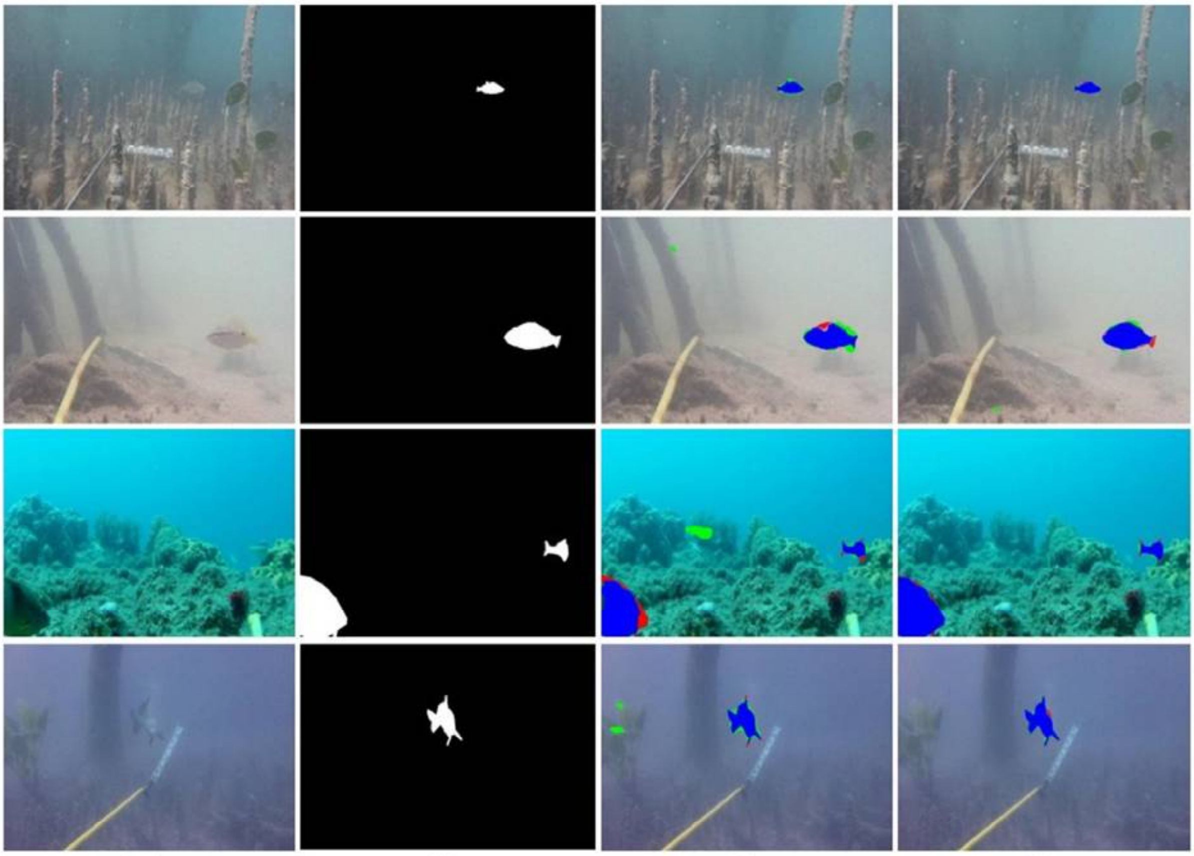


Sample images from Large-scale fish database along with corresponding ground truth images

PIFS-Net layers configuration along with parameters requirement.
resized image dimension of 400 x 400
Tra-Conv: Transposed convolutional layer; PB: PLIF-Block; SC: Skip connection;
RFR: Rapid feature reduction; Str-Conv: Strided convolutional layer

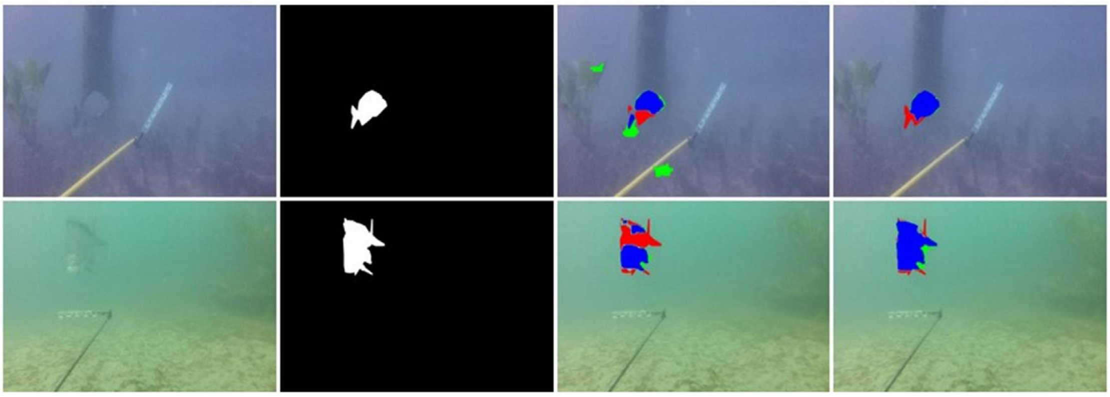
Layers name	Size	filters	Output final featuremap size (width × height × channels)	Required Paramet
Conv-1 + ReLU-1	3 × 3 × 16	16	400 × 400 × 16	448
BN-1	–	–		32
Conv-2 + ReLU-2	3 × 3 × 32	32	400 × 400 × 32	4640
BN-2	–	–		64
Conv-3 + ReLU-3	3 × 3 × 32	32		9248
BN-3	–	–		64
Conv-4 + ReLU-4	3 × 3 × 64	64	400 × 400 × 64	18,496
BN-4	–	–		128
Conv-5 + ReLU-5	3 × 3 × 64	64		36,928
BN-5	–	–		128
Str-Conv-1 + ReLU	3 × 3 × 64	64	200 × 200 × 64	36,928
BN-Str-1	–	–		128
Conv-6 + ReLU-6	3 × 3 × 64	64		36,928
BN-6	–	–		128
Conv-7 + ReLU-7	3 × 3 × 64	64		36,928
BN-7	–	–		128
Str-Conv-2 + ReLU	3 × 3 × 64	64	100 × 100 × 64	36,928
BN-Str-2	–	–		128
Conv-8 + ReLU-8	3 × 3 × 128	128	100 × 100 × 128	73,856
BN-8	–	–		256
Str-Conv-3 + ReLU	3 × 3 × 128	128	50 × 50 × 128	147,584
BN-Str-3	–	–		256
Conv-9 + ReLU-9	3 × 3 × 128	128	50 × 50 × 256	295,168
BN-9	–	–		512
Str-Conv-4 + ReLU	3 × 3 × 32	32	200 × 200 × 32	9248
BN-Str-4	–	–		64
Conv-10 + ReLU	3 × 3 × 32	32		9248
BN-10	–	–		64
Conv-11 + ReLU	3 × 3 × 32	32		9248
BN-11	–	–		64
Conv-12 + ReLU	3 × 3 × 64	64	200 × 200 × 64	18,496
BN-12	–	–		128
Str-Conv-5 + ReLU	3 × 3 × 64	64	100 × 100 × 64	36,928
BN-Str-5	–	–		128
Conv-13 + ReLU	3 × 3 × 64	64		36,928
BN-13	–	–		128
Conv-14 + ReLU	3 × 3 × 64	64		36,928
BN-14	–	–		128
Str-Conv-6 + ReLU	3 × 3 × 128	128	50 × 50 × 128	73,856
BN-Str-6	–	–		256
Conv-15 + ReLU	3 × 3 × 256	256	50 × 50 × 256	295,168
BN-15	–	–		512
Conv-16-SC + ReLU	3 × 3 × 32	32	400 × 400 × 32	9248
BN-16	–	–		64
Conv-17-SC + ReLU	3 × 3 × 32	32		9248
BN-17	–	–		64
Conv-18-SC + ReLU	3 × 3 × 32	32		9248
BN-18	–	–		64
Str-Conv-6-RFR + ReLU	3 × 3 × 128	128	50 × 50 × 128	36,992
BN-Str-6	–	–		256
Conv-19-RFR + ReLU	3 × 3 × 256	256	50 × 50 × 256	295,168
BN-19	–	–		512
Tra-Conv-1 + ReLU	3 × 3 × 128	128	100 × 100 × 128	295,040
BN-Tra-1	–	–		256
Tra-Conv-2 + ReLU	3 × 3 × 64	64	200 × 200 × 64	73,792
BN-Tra-2	–	–		128
Tra-Conv-3 + ReLU	3 × 3 × 32	32	400 × 400 × 32	18,464
BN-Tra-3	–	–		64
Conv-20-PB + ReLU	3 × 3 × 32	32		9248
BN-20	–	–		64
Conv-21-PB + ReLU	3 × 3 × 16	16	400 × 400 × 16	4624
BN-21	–	–		32
Conv-22-PB + ReLU	3 × 3 × 2	2	400 × 400 × 2	290
BN-22	–	–		4
Required total number of parameters				2,026,422

Good comparative visual performance of PFFS- and PIFS-Nets with DeepFish database



(A) (B) (C) (D)

Poor comparative visual performance of PFFS- and PIFS-Net with DeepFish database



(A) (B) (C) (D)

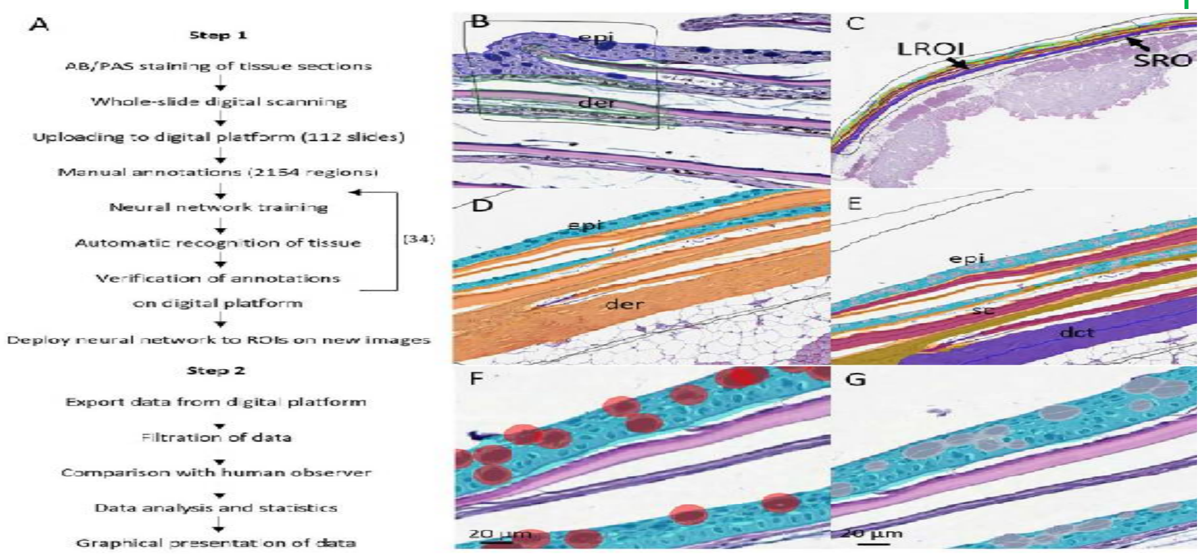
Testing images, (B) ground truth, (C) pixel-wise segmented results attained using PFFS-Net
(D) pixel-wise segmented images obtained using PIFS-Net
Blue and green colors in segmented images refer to tp and fp pixels
Red color shows the fn pixels

Case Study

Segmentation of Atlantic salmon Fish skin by CNN

Sveen et al. [10] proposed a CNN algorithm which is fully cloud-embedded Aiforia™ to detect multi-class segmentation of skin of Atlantic salmon. 122 digitalized skin sections were used in the comparison of this AI model with manual analysis carried out by two experienced histologists.

10	Sveen, L., Timmerhaus, G., Johansen, L.H. and Ytteborg, E., Deep neural network analysis-a paradigm shift for histological examination of health and welfare of farmed fish, Aquaculture, 2021, 532, 736024. https://doi.org/10.1016/j.aquaculture.2020.736024



Workflow and tissue structure identification.

Case Study

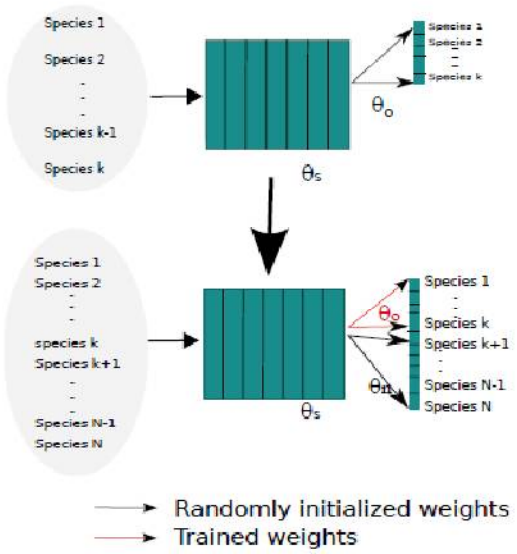
Classification of live fish with CNN in under water

Tamou et al. [12] classified live reef fish species in an unconstrained underwater environment with Deep-CNN using incremental learning strategy.

Incremental Learning in refining tuneable weights of NN: This training procedure starts by focusing at first on learning of the difficult species. It is followed by gradually learning the new species incrementally making use of knowledge distillation. At the same time, the high performances of the old species already learned is undisturbed. This model reaches an accuracy of 81.83% on the LifeClef 2015 Fish benchmark dataset.

12	Ben Tamou, A., Benzinou, A. and Nasreddine, K., Live Fish Species Classification in Underwater Images by Using Convolutional Neural Networks Based on Incremental Learning with Knowledge Distillation Loss, Machine Learning and Knowledge Extraction, **2022**, 4(3), 753-767. https://doi.org/10.3390/make4030036

12-



Operational view of the method based on incremental learning.

- It initializes weights corresponding to new species randomly
- keeps the trained weights unchanged

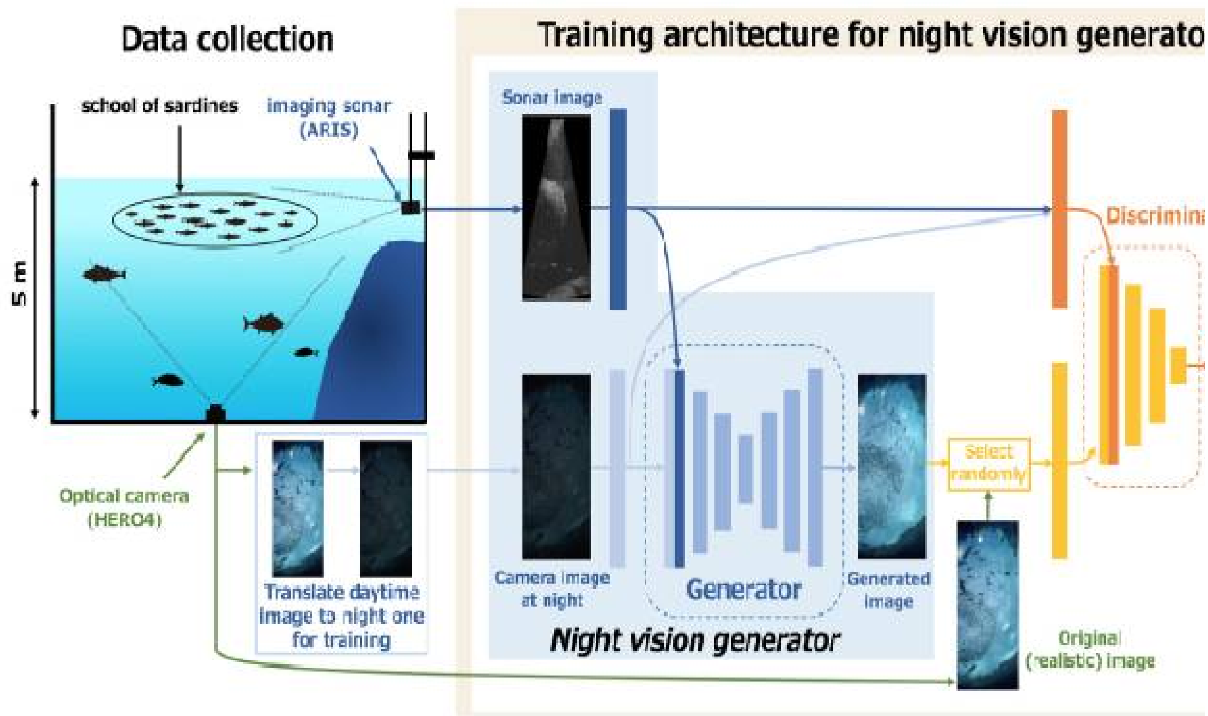
Sample images of 15 fish species in LCF-2015 dataset

Case Study

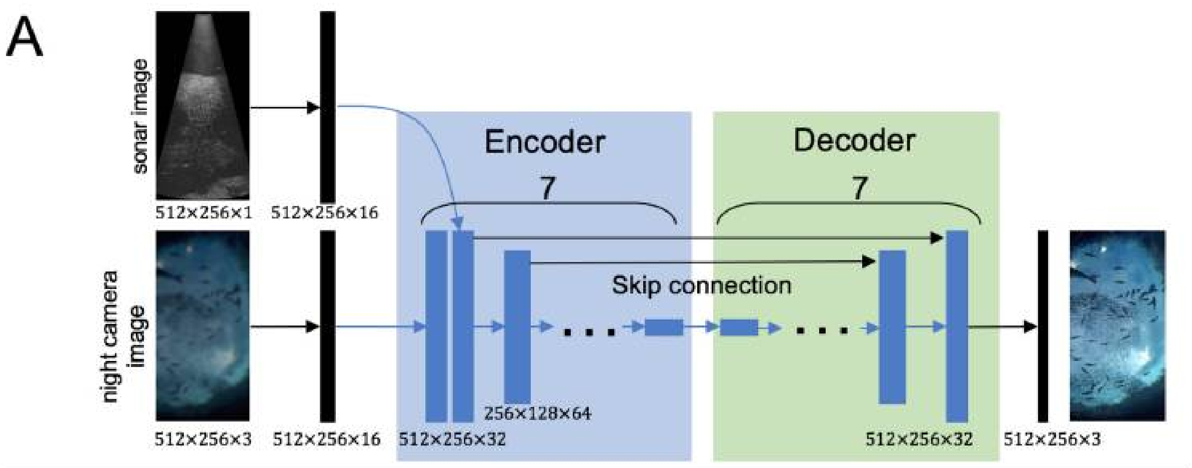
Synthesis of realistic day-light optical images of sardines by generative adversarial networks

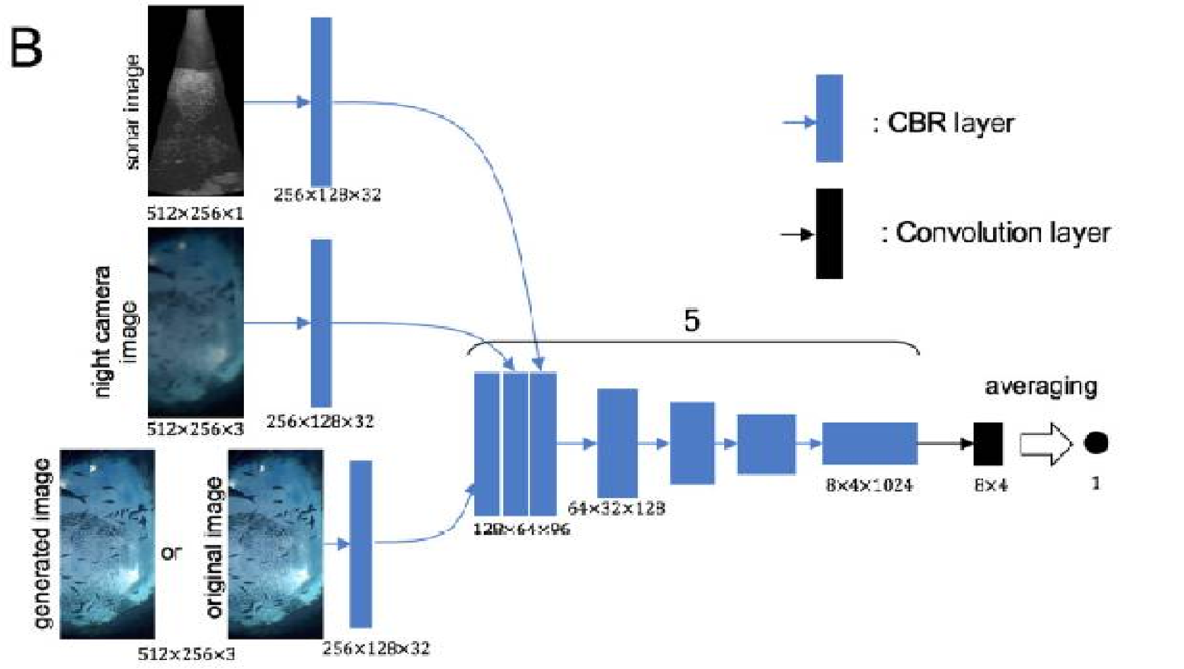
Terayama et al. [11] employed generative adversarial networks to synthesize realistic day-light optical images of sardines (Sardinops melanostictus). The input is high-precision sonar images and also optical images from an underwater camera from fish tank containing thousands of fishes. Even during near darkness, sonar images do the image-to-image translation task, of course, with limited accuracy. The results endorse night-time monitoring using sonar and an optical camera, leading to more efficient fish farming and environmental surveillance. It is contemplated to increase the accuracy of even 3D-entities by recording images from different angles and also to use advanced computer vision methods like RecNNs.

11	Terayama, K., Shin, K., Mizuno, K. and Tsuda, K., Integration of sonar and optical camera images using deep neural network for fish monitoring, Aquacultural Engineering, **2019**, 86, 102000. https://doi.org/10.1016/j.aquaeng.2019.102000

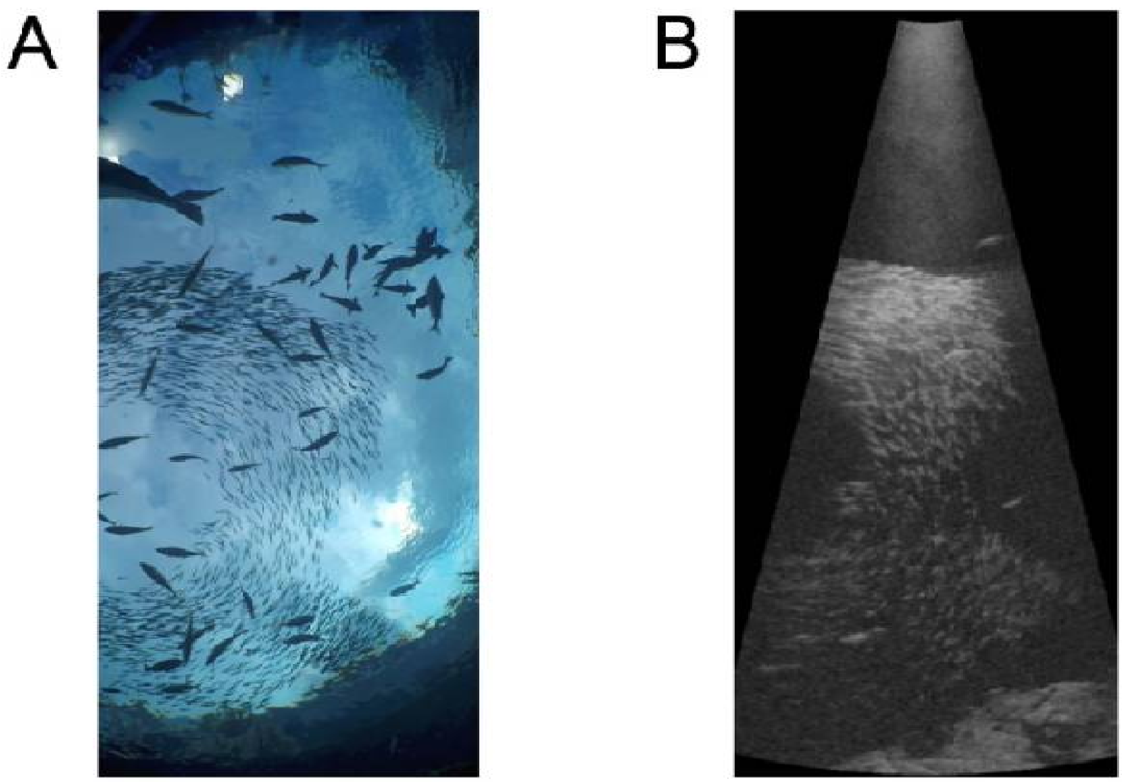


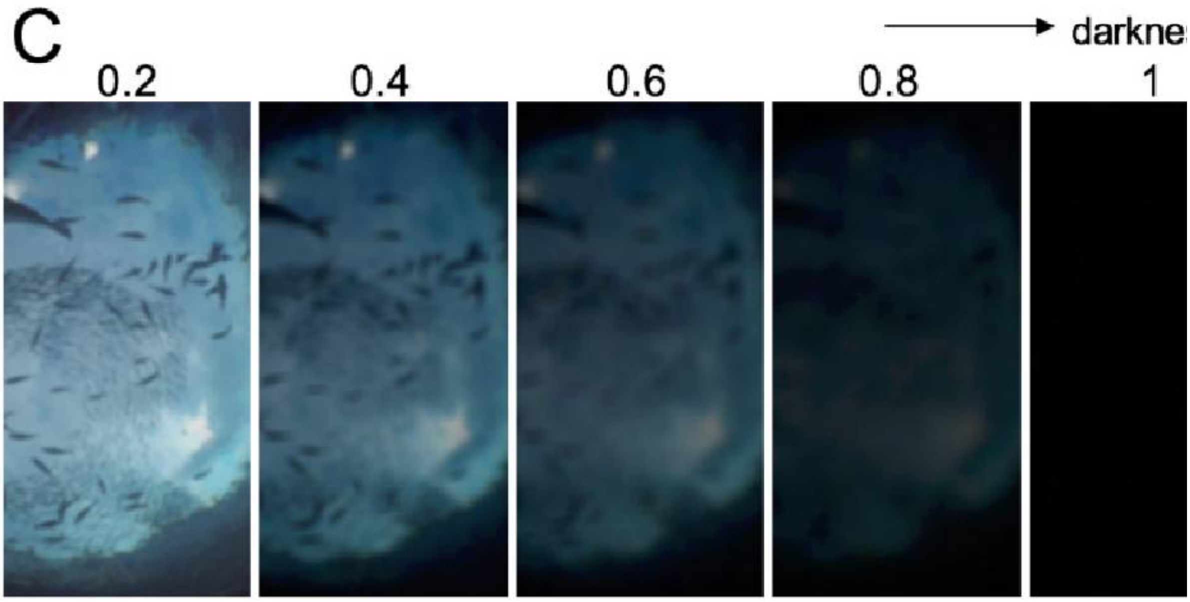
Overview of data-enabled night vision generation





Network structures for (A) generator. (B) discriminator
CBR (Convolution- BatchNorm-ReLu)





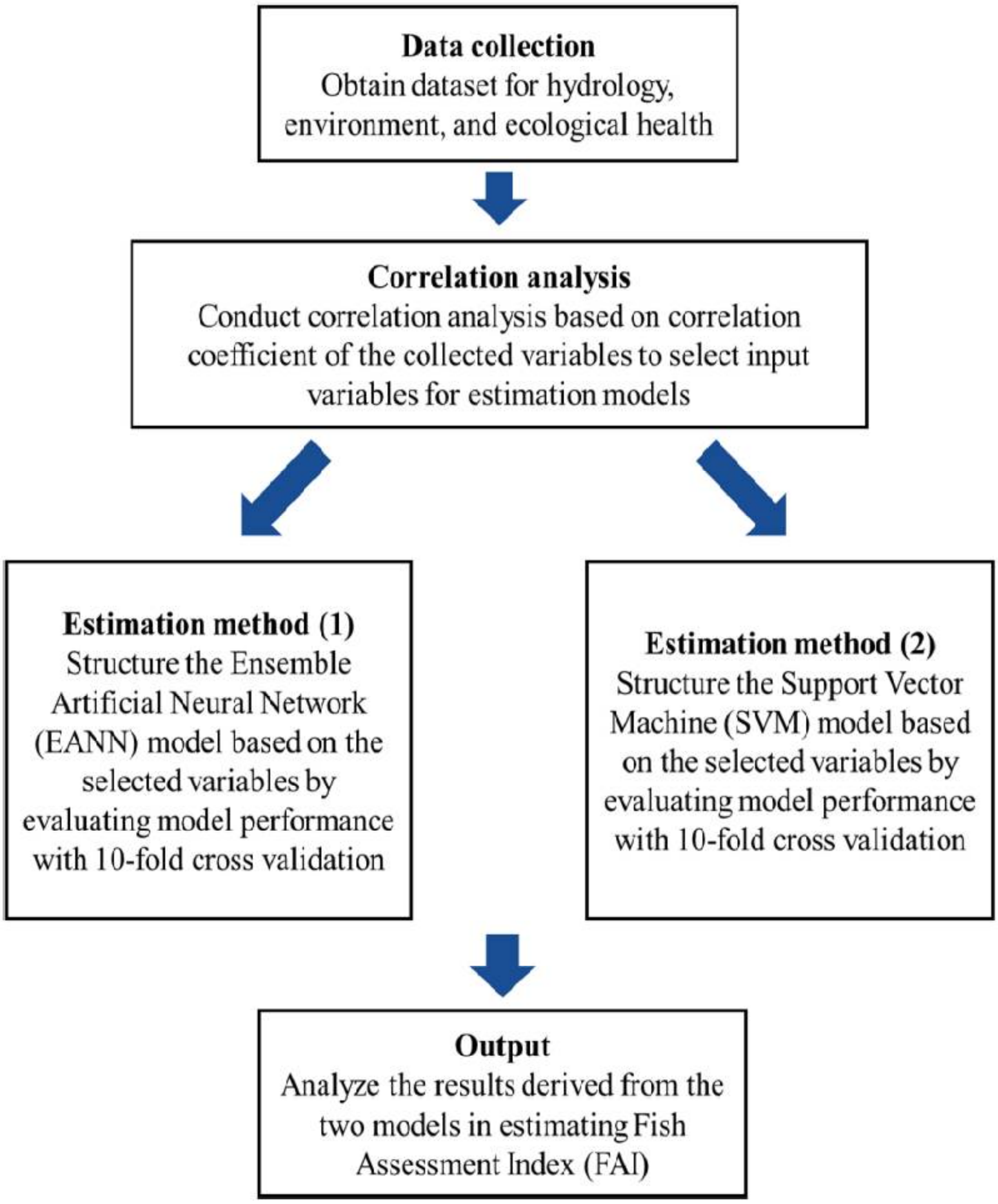
(A) Snapshot of a school of sardines recorded by an underwater camera in daytime. The sardines are the smaller fish that can be seen in their hundreds, along with mackerel, which are relatively large
(B) Snapshot of the same school, recorded by ARIS at the same time.
(C) Examples of night camera images created from (A). As the darkness coefficient d increases, the entire image becomes darker and noisier.
The values of d represent changes in natural light or the turbidity of the water

Case Study

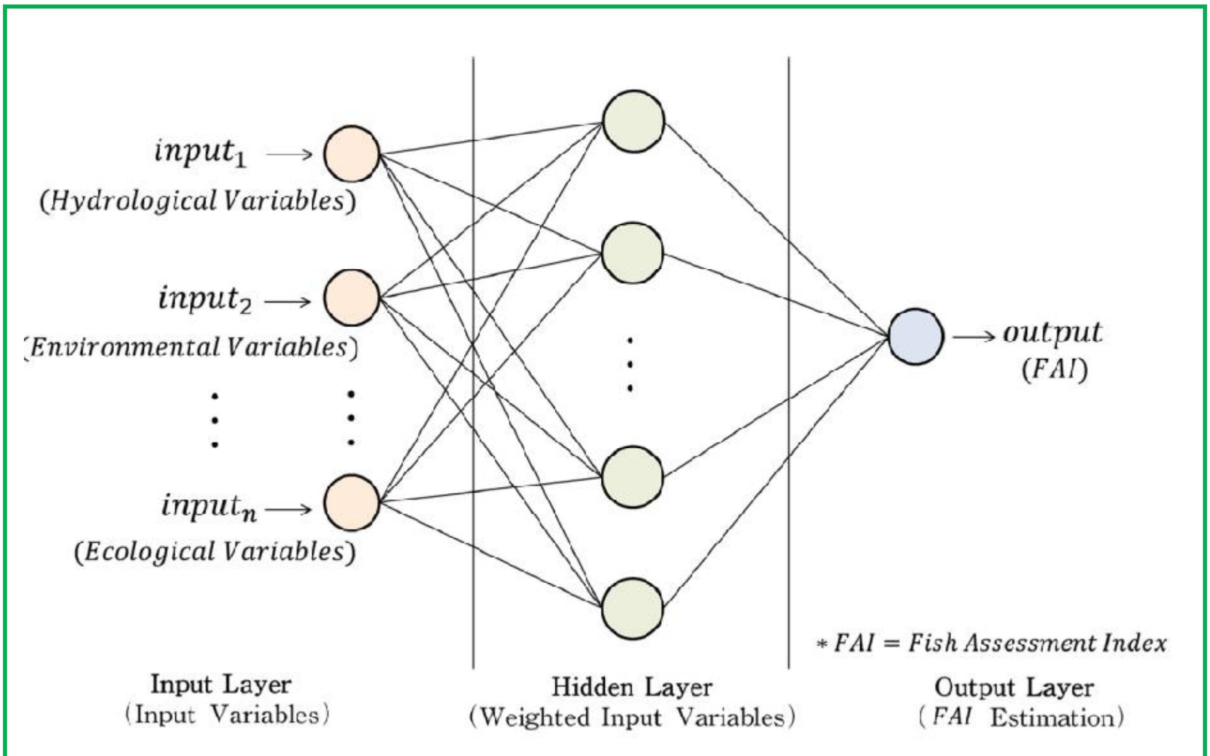
Fish assessment index estimation with ensemble-NN

Kang et al. [12] estimated fish assessment index (FAI) employing an ensemble artificial neural network (EANN) and compared the results with SVM. The hydrological, aquatic ecosystem and environmental causative factors were used in this study. Four hidden neurons and 11 members in the ensemble set showed EANN is more accurate and has high generalisation capacity compared to a single MLP or SVM (a machine learning method). The performance measures checked are NASH, rRMSE, and rBIAS indices for monitoring 143 sites across Han, Nakdong, Geum, Yeongsan, and Seomjin rivers in South Korea.

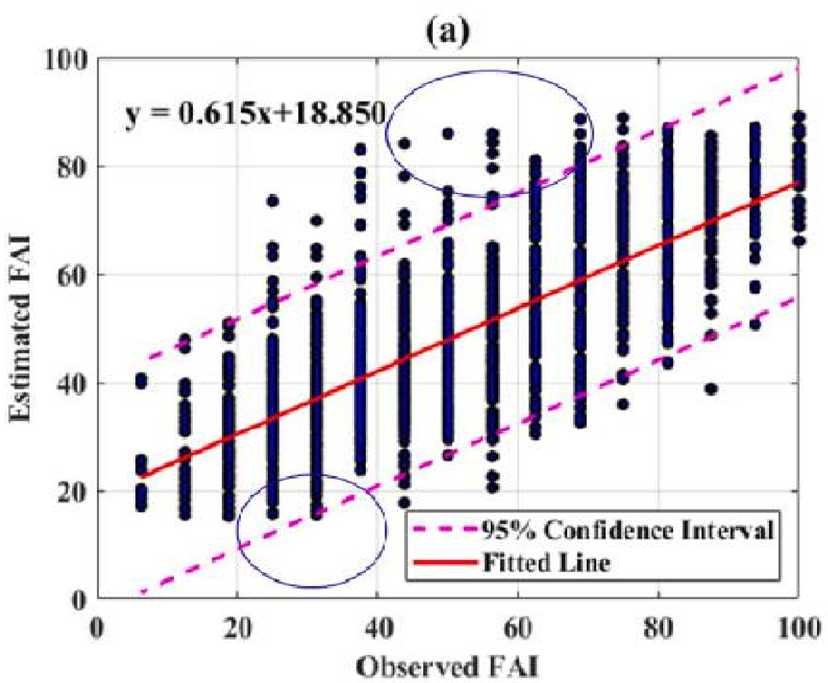
12	Kang, H., Jeon, D.J., Kim, S. and Jung, K., Estimation of fish assessment index based on ensemble artificial neural network for aquatic ecosystem in South Korea, Ecological Indicators, **2022**, 136, 108708. https://doi.org/10.1016/j.ecolind.2022.108708

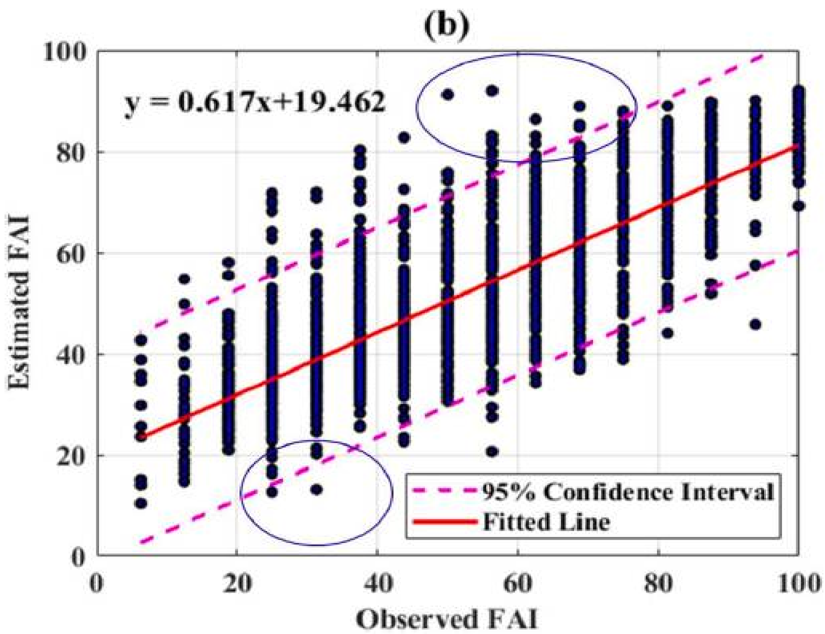


Fish Assessment Index (FAI) estimation –Methods flow chart
Ensemble-NN; Support Vector Machine; Corr.Analysis


$input_1$
(Hydrological Variables)
$input_2$
(Environmental Variables)
$input_n$
(Ecological Variables)
output
(FAI)
* FAI = Fish Assessment Index
Input Layer
(Input Variables)
Hidden Layer
(Weighted Input Variables)
Output Layer
(FAI Estimation)

SLP-NN


(a)
y = 0.615x+18.850
Estimated FAI
Observed FAI
95% Confidence Interval
Fitted Line
0
20
40
60
80
100



95% confidence intervals for estimated vs observed FAI
(a) Ensemble-NN (b) Support Vector Machine

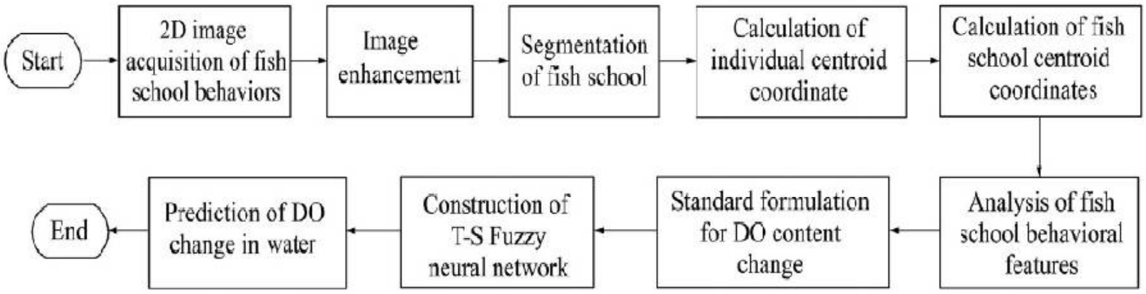
13	Yilmaz, M., Çakir, M., Oral, M.A., Kazanci, H.Ö. and Oral, O., Evaluation of disease outbreak in terms of physico-chemical characteristics and heavy metal load of water in a fish farm with machine learning techniques, Saudi Journal of Biological Sciences, **2023**, 30(4), 103625. https://doi.org/10.1016/j.sjbs.2023.103625

Case Study

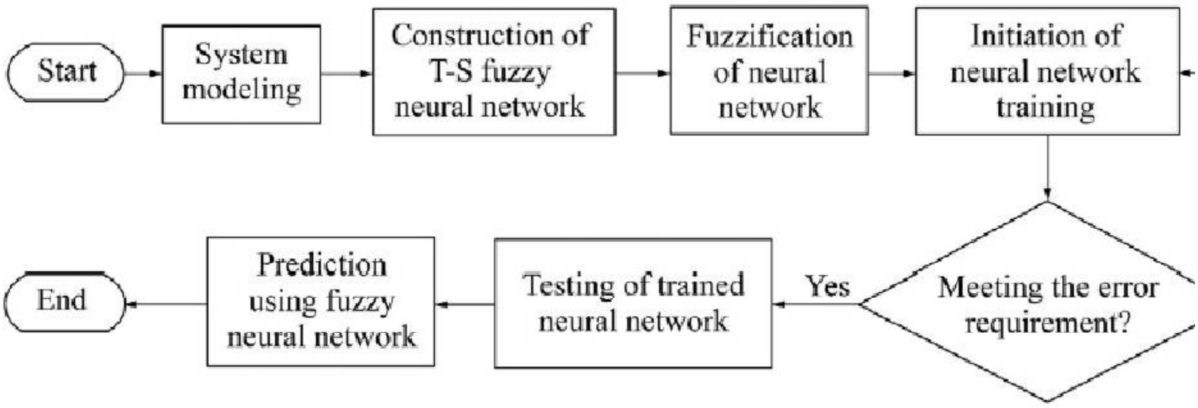
DissolvOxyg prediction with Takagie Sugeno FuzNN from 2D-fish school images

Bao et al. [14] used TakagieSugeno (TeS) fuzzy neural network (FuzNN) to predict DO in water using cluster features obtained from two-dimensional images of Carassius auratus fish school.

14	Bao, Y.J., Ji, C.Y. and Zhang, B., Prediction of dissolved oxygen content changes based on two-dimensional behavior features of fish school and T–S fuzzy neural network, Water Science and Engineering, **2022**, 15(3), 210-217. https://doi.org/10.1016/j.wse.2022.06.001



Methods-flow for prediction of change in DO content based on features of fish school



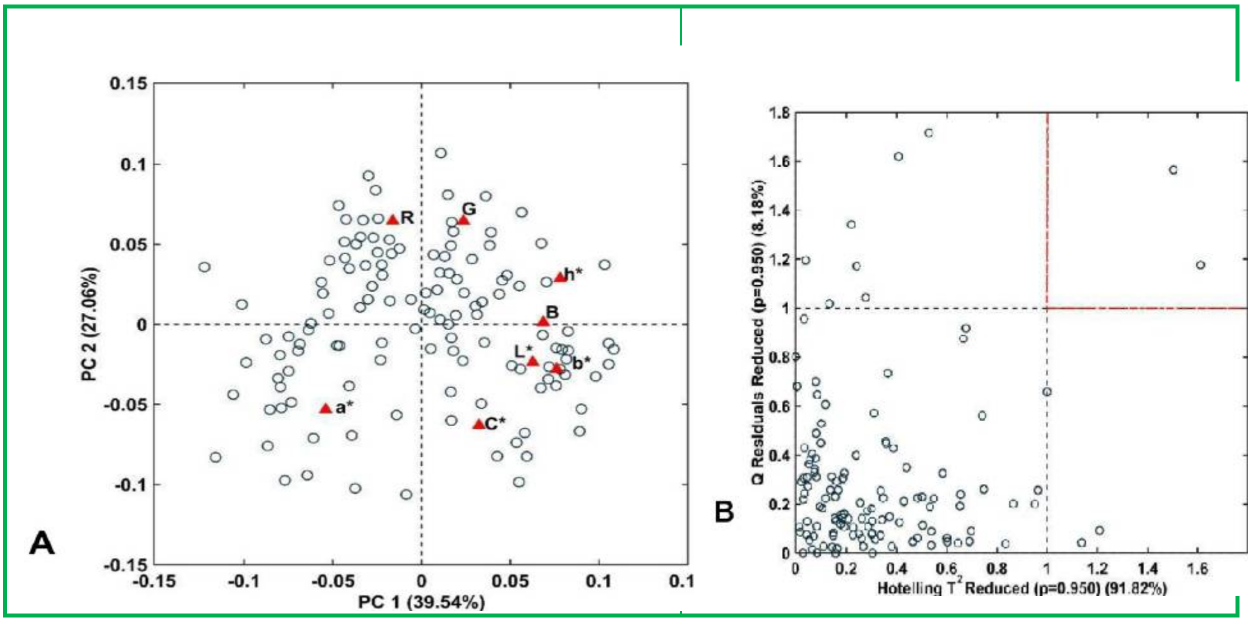
Methods-flow for prediction of DO content change using TeS fuzzy-NN

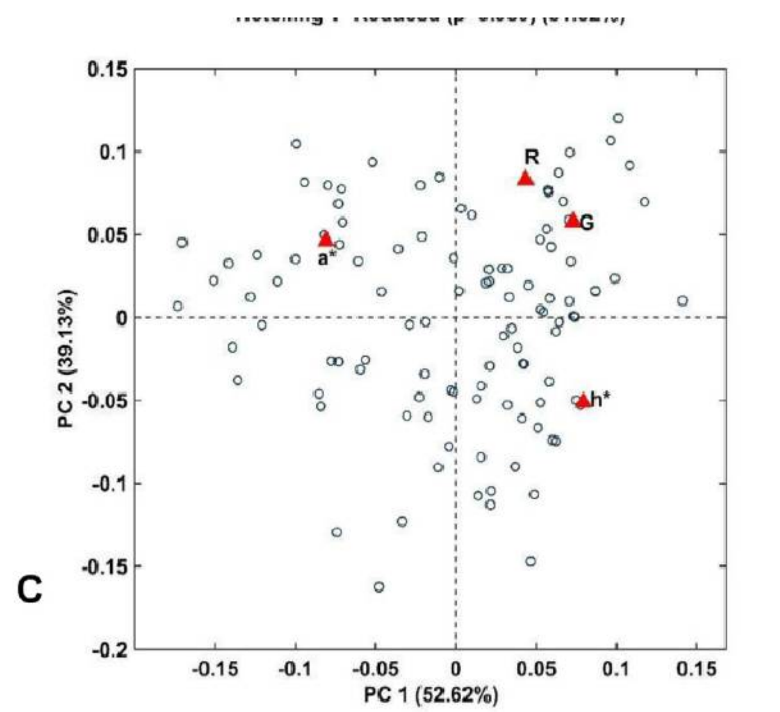
Case Study

Freshness in fish by NN-model

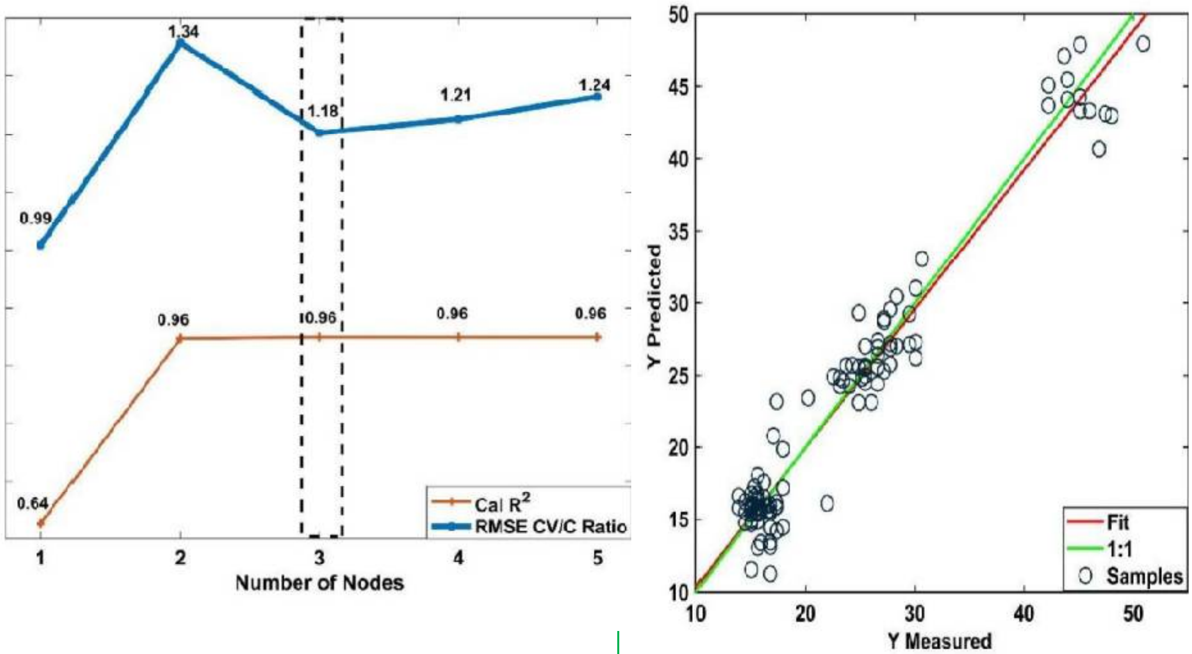
Rezende-de-Souza et al. [15] developed a NN-model using RGB spectral data for freshness in fish, based on Total Volatile Basic Nitrogen (TVB-N). This method is a fast, low-cost green tool which can easily be automated. Further, it is a sustainable alternative from environmental and economic stand point of views. The remarkable robust quality control of this chemometric-probe thus, falls within the acceptable requirement norms of the 4.0 food industry.

15	Rezende-de-Souza, J.H., de Moraes-Neto, V.F., Cassol, G.Z., dos Santos Camelo, M.C. and Savay-da-Silva, L.K., Use of colorimetric data and artificial neural networks for the determination of freshness in fish, Food Chemistry Advances, **2022**, 1, 100129. https://doi.org/10.1016/j.focha.2022.100129





A - PCA result of colorimetric data of fish;
B - Q residual and Hotteling T 2 scores of colorimetric data of fish;
C - PCA result of colorimetric data of fish after removing outliers and less influential variables



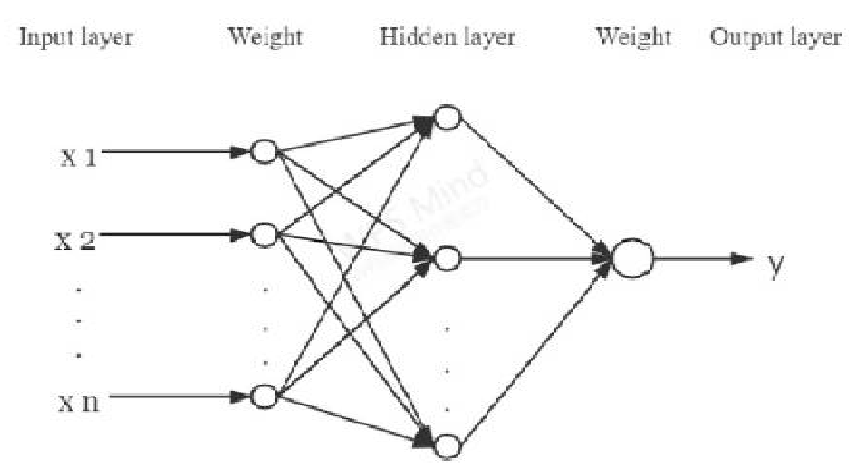
NN (with 3 hidden neurons) modeling of colorimetric data versus TVB-N measured with traditional method.

Case Study

Shelf life of Trachinotus ovatus using SLP-NN

Lan et al. [16] applied SLP-NN-with-BP to predict the shelf life of Trachinotus ovatus in frozen storage systems. The X variaables in the supervise-data considered were pH, total volatile basic nitrogen (TVB-N), thiobarbituric acid (TBA), water retention (water holding capacity, cooking loss) etc.

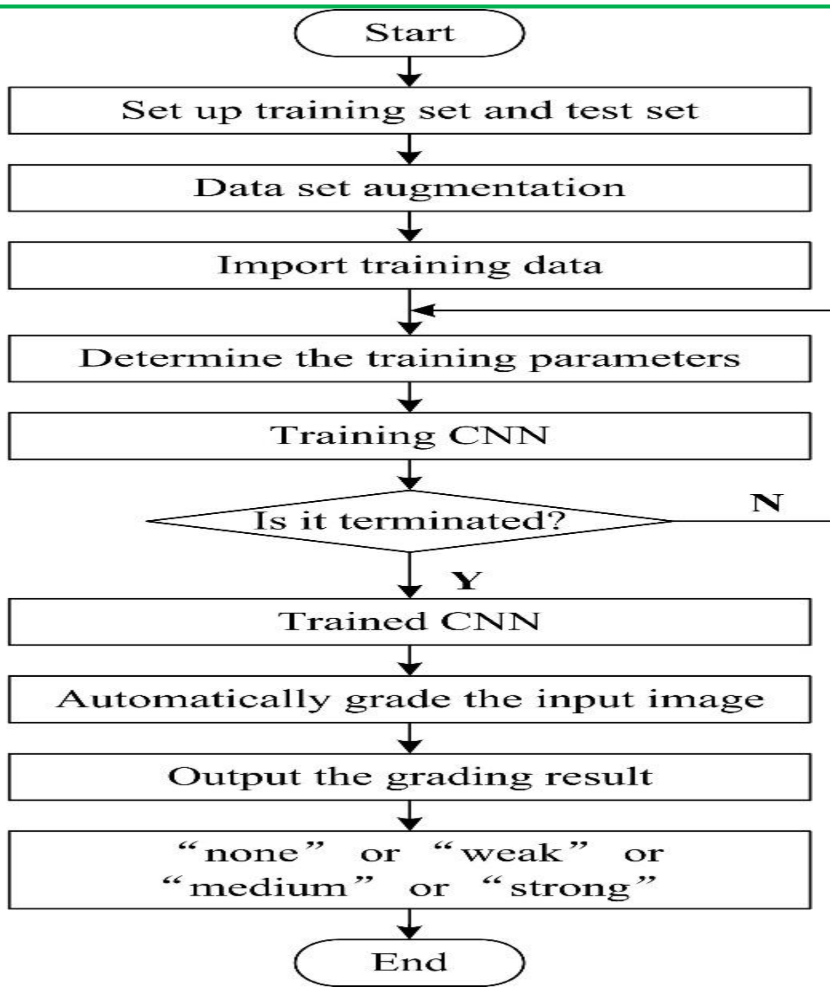
16	Lan, W., Yang, X., Gong, T. and Xie, J., Predicting the shelf life of Trachinotus ovatus during frozen storage using a back propagation (BP) neural network model, Aquaculture and Fisheries, **2023**, 8(5), 544-550. https://doi.org/10.1016/j.aaf.2021.12.016



SLP-BP-NN

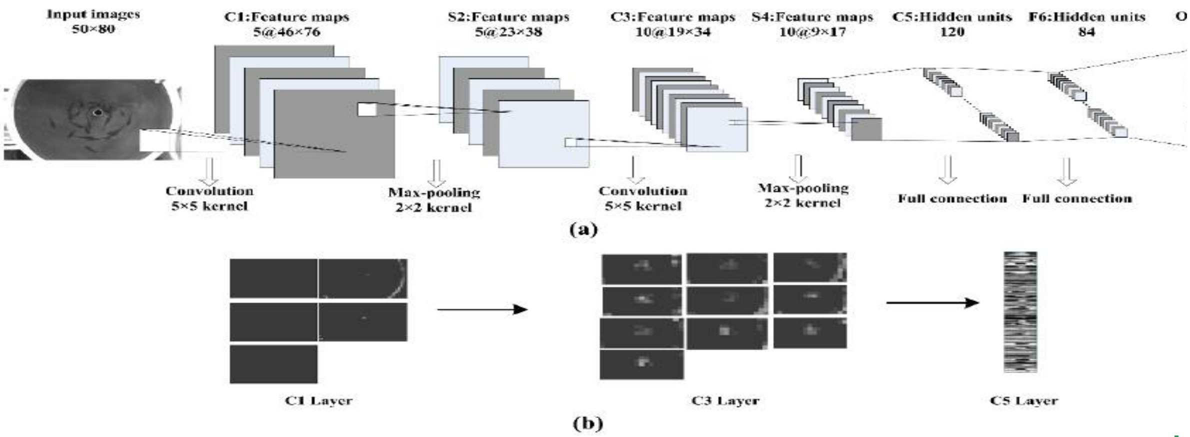
Case Study
Detection of fish appetite by CNN Zhou et al. [17] used CNN to detect fish appetite. This evaluation throws light on fish production practices. The augmentation of images was done through rotation, scale, translation and also by noise-invariant data expansion approach. The grading accuracy reached 90% in this study.

17	Zhou, C., Xu, D., Chen, L., Zhang, S., Sun, C., Yang, X. and Wang, Y., Evaluation of fish feeding intensity in aquaculture using a convolutional neural network and machine vision, Aquaculture, **2019**, 507, 457-465. https://doi.org/10.1016/j.aquaculture.2019.04.056



Flowchart of grading method for fish feeding intensity

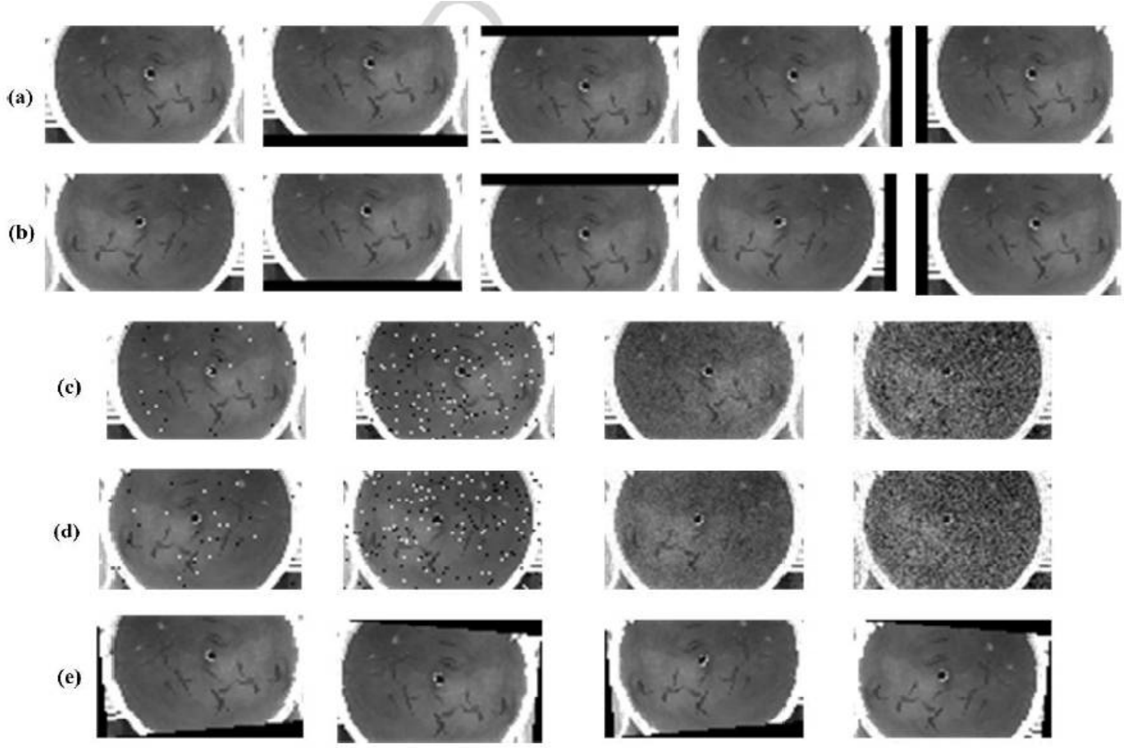
16-



CNN architecture
(a) LeNet structure; (b) example images from each stage

16-

Data augmentation



From left to right, the rows show the original image

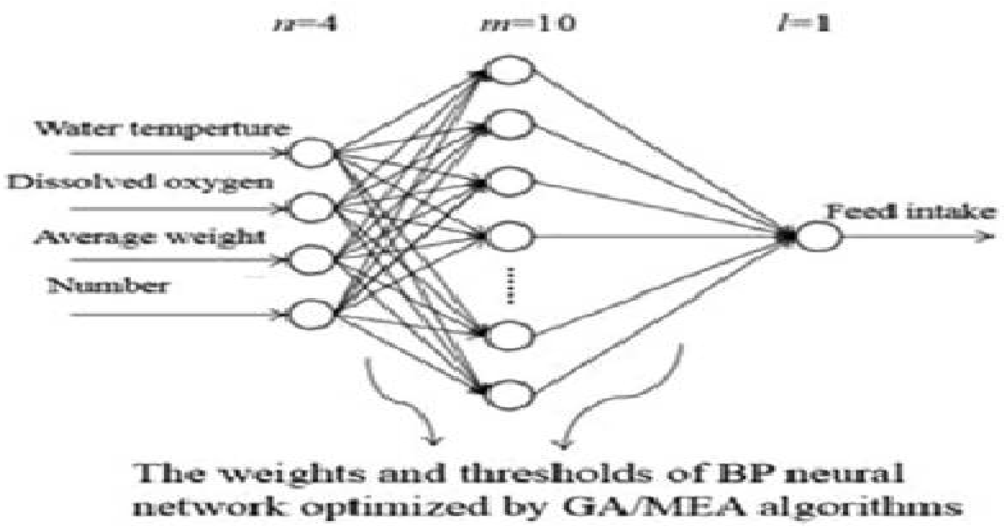
(a) That shifted up, down, left and right by 5 pixels
(b) Horizontally flipped original image and the horizontally flipped image shifted up, down, left and right by 5 pixels
(c) Original picture with added salt-and-pepper noise (density: 0.01; density: 0.04) and Gaussian noise (variance: 102/2552; variance: 0.01)
(d) Horizontally flipped image with added salt-and-pepper noise (density: 0.01; density: 0.04) and Gaussian noise (variance: 102/2552; variance: 0.01)
(e) Original image rotated 5 degrees to the left and right and the horizontally flipped image rotated 5 degrees to the left and right

Case Study

Feed intake of fish model with BPNN

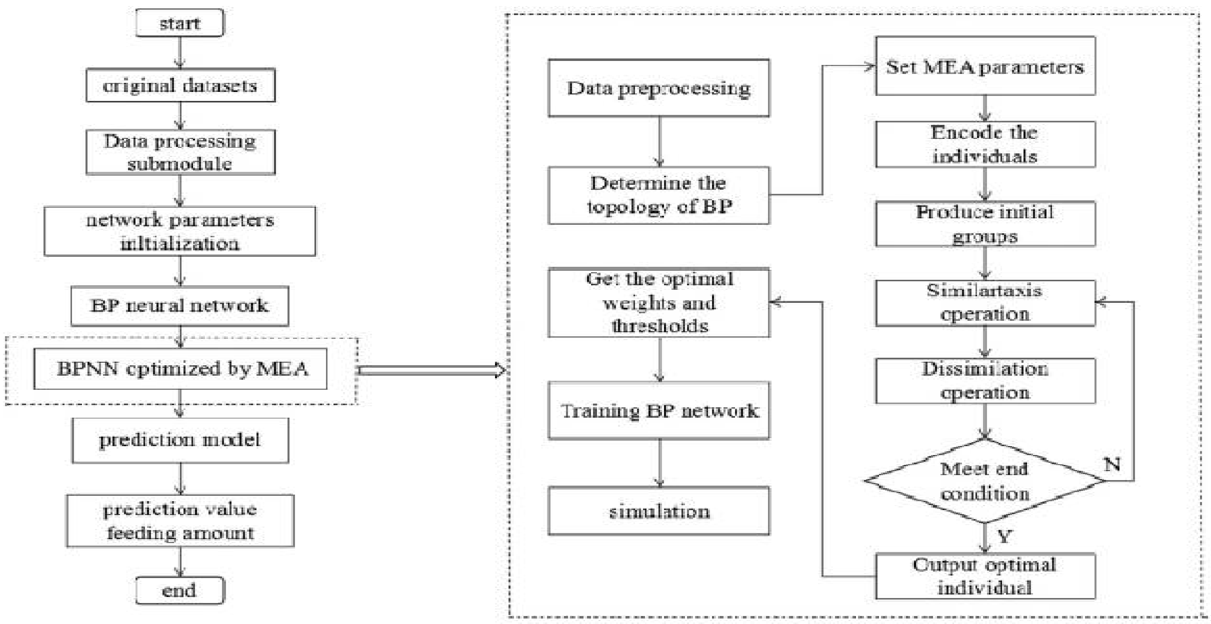
Chen et al. [18] developed an accurate prediction model of feed intake for group fish using back-propagation neural network (BPNN). The initial weight and threshold of model optimized with Mind evolutionary algorithm (Mind Evol Alg). The causative input factors chosen for NN model are water temperature, dissolved oxygen, average fish weight and number of fish. This research, thus a step forward smart fishery with an intelligent feeding procedure.

18	Chen, L., Yang, X., Sun, C., Wang, Y., Xu, D. and Zhou, C., Feed intake prediction model for group fish using the MEA-BP neural network in intensive aquaculture, Information Processing in Agriculture, **2020**, 7(2), 261-271. https://doi.org/10.1016/j.inpa.2019.09.001

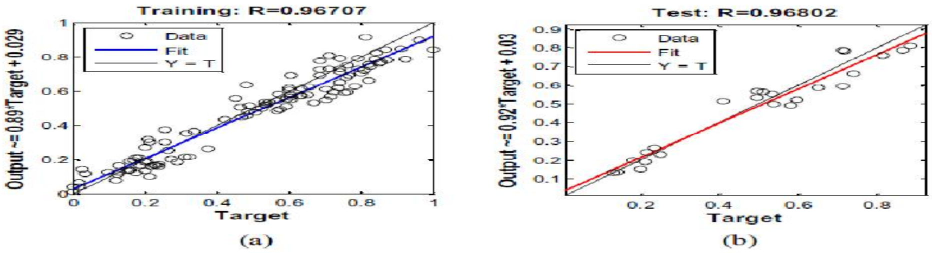


SLP-BP

1



Flow chart of the prediction model



Regression curve: (a) Training samples, (b) Testing samples

Case Study

Model of Non-linear processes by SOM-NN for settlement/recruitment of young fish

Alvarez et al. [19] put forward a Self-Organizing-Map (SOM)-NN-model for multivariate data acquired on larval fish and environmental factors at different depths. This study unveiled non-linear processes resulting in intricate patterns due to settlement/recruitment of young fish.

19	Álvarez, I., Font-Muñoz, J.S., Hernández-Carrasco, I., Díaz-Gil, C., Salgado-Hernanz, P.M. and Catalán, I.A., Using self-organizing maps to analyze larval fish assemblage vertical dynamics through environmental-ontogenetic gradients, Estuarine, Coastal and Shelf Science, **2021**, 258, 107410. https://doi.org/10.1016/j.ecss.2021.107410

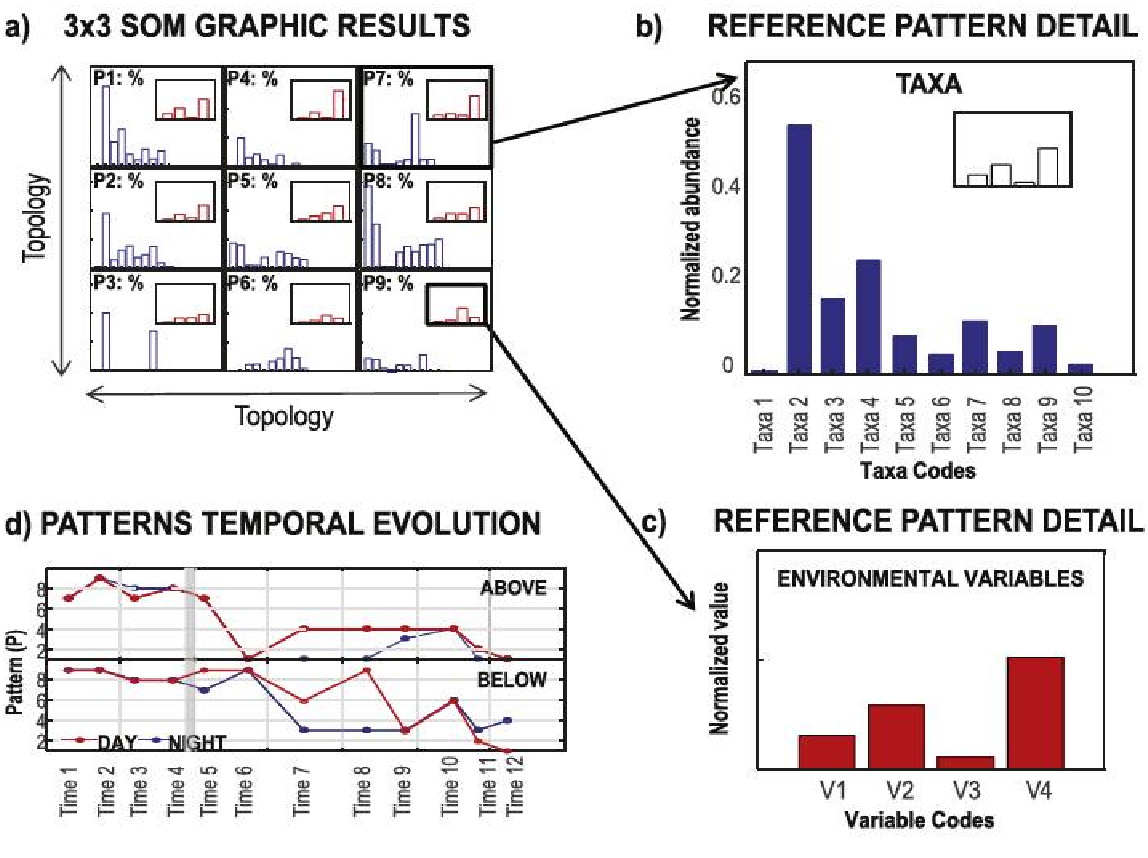


Diagram of the SOM output

a) Nine reference patterns extracted from a 3x3 coupled SOM analysis of taxa abundances (blue) and associated environmental parameters (red). Pn: probability of finding that particular pattern n in the data

Case Study

Prediction of toxin concentrations in bivalve shellfish using Generalized Additive Model (GAM) framework

Stoner et al. [20] adopted Generalized Additive Model (GAM) framework to predict Dinophysis toxin concentrations in
a range of bivalve shellfish species around Western Scotland, South-West England and Northern France. These spatio-temporal (2009-2020 years) modelling approaches quantify long-term HAB (Harmful algal bloom) risks in fish.

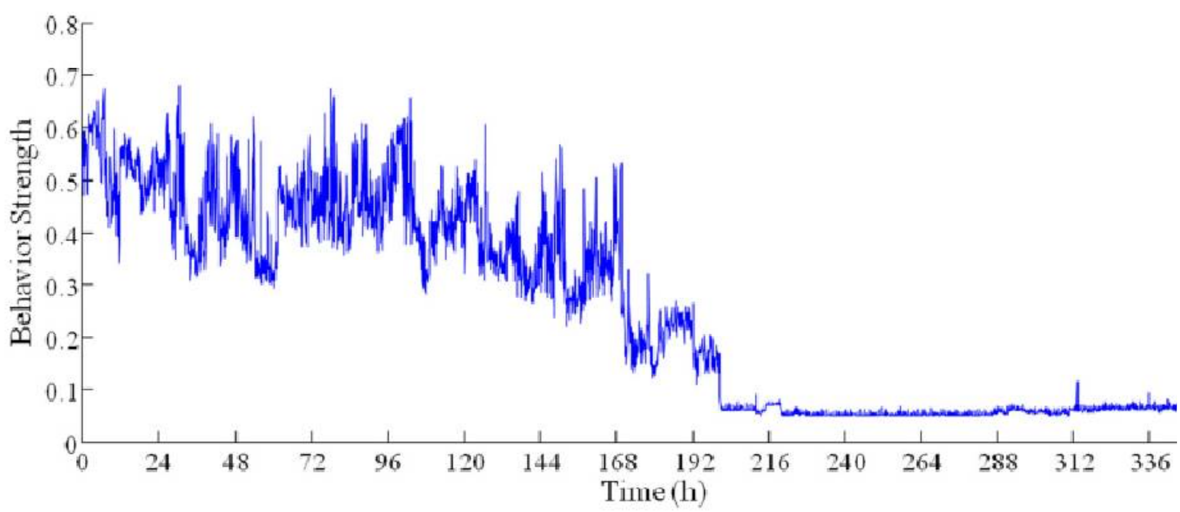
20	Stoner, O., Economou, T., Torres, R., Ashton, I. and Brown, A.R., Quantifying Spatio-temporal risk of Harmful Algal Blooms and their impacts on bivalve shellfish mariculture using a data-driven modelling approach, Harmful Algae, **2023**, 121, 102363. https://doi.org/10.1016/j.hal.2022.102363

Case Study

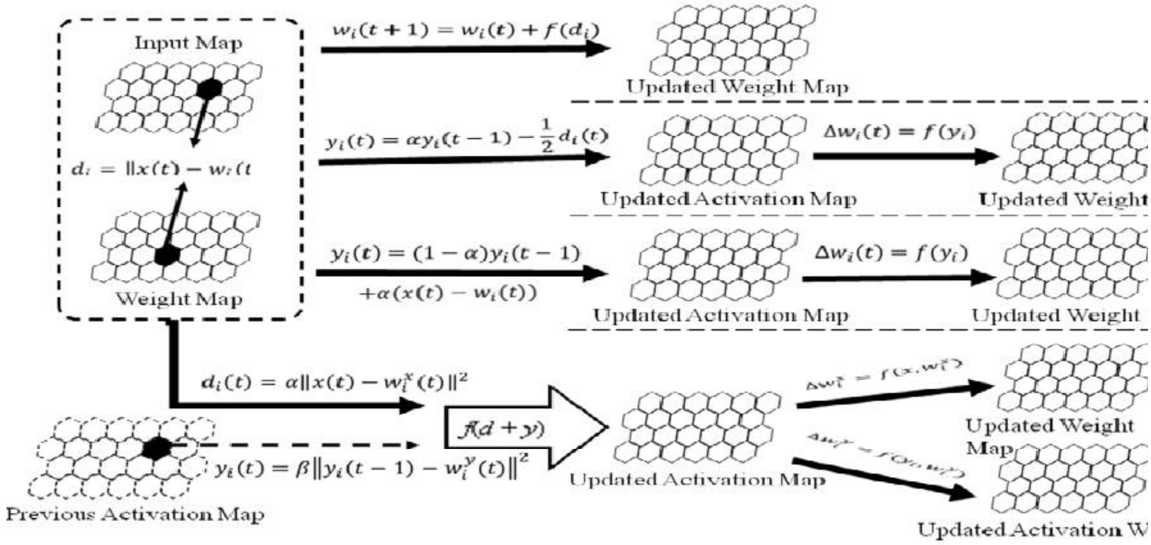
Behavior Response Model of fish under stress with variant NN of SOM

Li et al. [21] studied behavior response data of fish under chemical stress conditions induced by exposure to Atrazine (ATZ, 0.12 mg/L) for 15 days employing Stepwise Behavior Response Model (SBRM). The NNs made use in this venture are Temporal Kohonen Map (TKM), Recurrent Self-Organizing Map (RecSOM), and Recursive Self-Organizing Map (Recurs.SOM). Recurs.SOM was found to be most suitable for detecting behavior segments with both high and low
contrast response under toxic exposure.

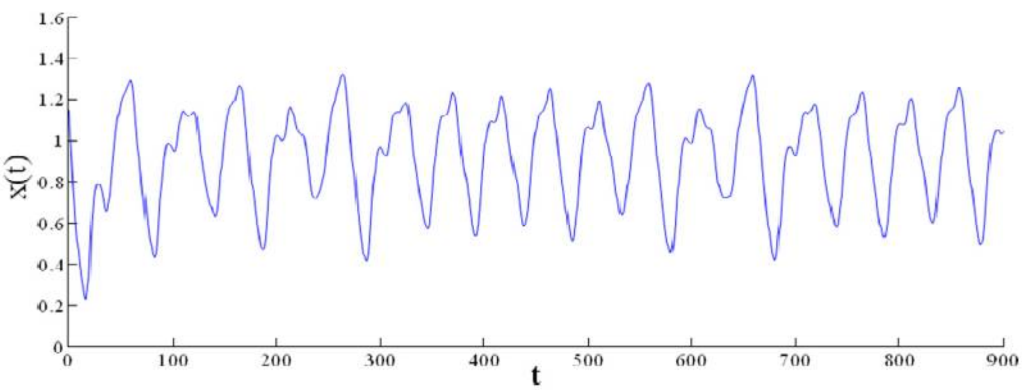
21	Li, S., Chon, T.S., Park, Y.S., Shi, X. and Ren, Z., Application of temporal self-organizing maps to patterning short-time series of fish behavior responding to environmental stress, **2020**, Ecological Modelling, 433, 109242. https://doi.org/10.1016/j.ecolmodel.2020.109242



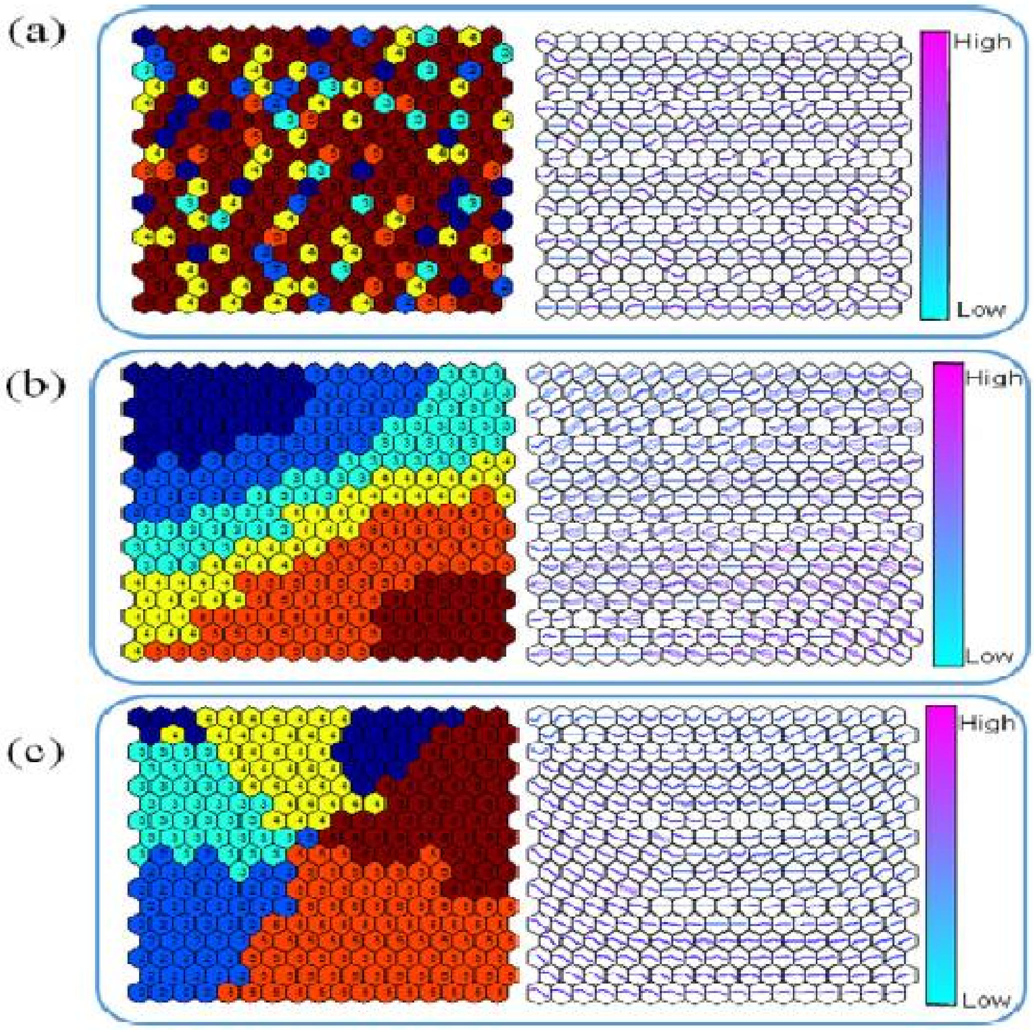
Time Profile of behaviour strengths for 15 days with intervals of 6 min



Time series model Flow charts with TKM, RSOM, RecSOM, and SOM



Mackey-Glass time series, the input data for testing the temporal SOMs



(a) TKM; (b) RSOM; (c) RecSOM.

Training Mackey-Glass time series with temporal SOMs.
The vertical bars indicate the degree of ‘x(0) ’.