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Review

Piscimetrics II$: Neural network models in fisheries research

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Dedicated to Dr (Emeritus Professor) Antonio Braibanti, Department of Food and Drug, University of Parma, Italy who lived 95years on the lap of Mother Earth

ABSTRACT

eXPisciMetrics (i.e. evolving + Xplanatory+ Pisci+metrics; or in general eX$$$Metrics) had been a sought after high-end-frame-of-tools(Heft) in computational science (CS) during past two decades in fisheries research. The studies are moving forward to shed more light with state-of-knowledge-of-instrumentation, large databases, output of knowledge/intelligence extraction tools, deep learning (with attention/self-attention) of I/O mapping with hierarchical/parallel/sequential neural nets, capsule (vector/ matrix) nets, GenerativeAdversarial Networks (GANs), transformer-NNs classical/ advanced machine learning tool-box of methods, functional (operator-valued kernel based) generalization of Nets, and nets in net (NiN), controlled by total quality assurance (TqA) with metro-metrics-measures(MCube) adhering to DARPA/NSF (USA) and European/Japanese agenda of target standards.

The application fields of research in fisheries covered in this review include recruitment/ settlement/distribution of fish species, their detection, re-identification and confirming micro-fossil fish teeth. The fore-casting of catches, classification (order, family/species) /discriminationof different varieties of live fish from dead-eggs, bio-mass, CPUE, and fish assessment index were studied with NN-architectures. The freshness, concentration of toxins, shelf-life, separation of healthy from unhealthy ones, segmentation of fish skin and mortality have been investigated. Fish appetite, feeding intensity, feed-in take was reported using advanced NN models. The fishing operations, closures, management paved way for planning potential economic fishery zones. The complex tasks like shrimp egg counting, arriving at day-light images of fish from those under various intensities and sonar signals are investigated with CNNs, DeepNNs etc. The design of futuristic fisheries research programs will be benefitted by rational/scientific xAI and Hierarchical-knowledge-based-machine learning as well as Deep-architectures with capsules-of -neurons as processing units making use of tensorial-fusion-data structures and ensemble-methods for robust output.

$Part 1: Neural network models in fisheries research (Review), Fisheries Research 92 (2008) 115–139, Iragavarapu Suryanarayana, Antonio Braibanti, Rupenaguntla Sambasiva Rao, Veluri Anantha Ramam, Duvvuri Sudarsan, Gollapalli Nageswara Rao.

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INTRODUCTION

A living species has internal environment wherein billions of processes proceed all through the life cycle. They culminate into functions at organ level and control the invasion by non-self-cells through immune system. The external environment also has a key role and adaptability in a slow process in one life time, but effective through generations. The specific chromosome pattern and subtle genetic code is responsible for integrity of a species through generations. The mutation, genetic variations, phenotype changes are a source of evolution, adaptability and even developing new strides in defense from poisons, drastic changes in the external environment. The science also evolved through centuries, starting from sensorial (visual, sound, touch etc.) observations to sophisticated hyphenated instruments (sources of indirect data and/or mathematically transformed result). This century reaped the benefits of artificial life, humanoid robots, partial mimicking of rat brain, IBM-blue chip being chess grandmaster, peta-/hexa-FLOP hardware and tiny robots playing soccer game, performing complicated surgical operations on humans. The expectations at this juncture are clean environment, health for all and 150 years of human life span in addition to transportation and habitability on other planets like moon and mars.

The human activity and intervention resulted in drastic changes in the earth (external) environment with significant perturbation of ecosystem. Even a panorama of the tip of ice-berg of life threatens the mathematical models from first principles. E-man (Evolution of Mimics of Algorithms of Nature), Ex.AI (Evolving explainable artificial intelligence) though superior to hitherto matured approaches, they are also quite far off from perceiving intoto what happens. It is a result of consequences on the dynamic processes in spacio-temporal frame (atto-second and nanometer size) and evolving of theoretical principles.

The effect of NN models in fisheries research is not only unignorable, but significant [**1-141**]. It is a well nurtured and trodden path, with available software for multiple-layer-perceptron (MLP-NN), self-organizing-map (SOM-NN), recurrent-neural-networks (Rec-NNs) etc. It is beyond doubt that NN models of any category of 1980s passed through renaissance, and hence worth to pursue indispensable tools. In other words, AI of 1950s (now called classical-AI or first-generation AI) given birth to AI-2 and multi-(sequential, parallel, hierarchical) hybrid methods AI-3 or HAI (hyper AI). At software level, (meta-) heuristics, algorithms for AIx are all but mappings of knowledge-based skills incorporating a large number of methods in complicated manner.

1.1 Data structure: Unsupervised_multi-variate_multi-dimensional_data is the start of any recording of observations. The explanatory variables(X) and responses (Y) are picked up based on a priori knowledge, data processing, wild guess or intuition in an iterative cycle. This results in supervised data set. Many a time, multiple responses or multiple-X are statistically/chemically correlated. But, they are rarely mathematically independent/ statistically uncorrelated/ orthogonal. PCA/PLSA, Orthogonalisation, independent component analysis (ICA) etc. are sure-to-fire methods in this context. The traditional, long cherished but yet indispensable gauze is visual inspection (with human eye) of 1D-, 2D-, 3D- display on a piece of graph sheet or CRT/LCD/LED/Plasma devices of computer/tablet/smart phone. The analysis of cause-effect model of supervised data paves way to understand/control/alter the causation and effective response.

1.2 Modeling: The clustering tendency for unsupervised data in multi-dimensional (m-D) space is calculated by k-means and its variants (c-means, Fuzzy-c-means etc.). It results in clusters of data only if one has a priori knowledge of number of clusters. Multi dimensional scaling (MDS) was a method of choice in 1960s. The dimension reduction techniques viz. PCA, PLSA (both linear and non-linear) have been good pre-processing procedures prominent from 1980s to arrive at obviating correlation with less/equal number of new variable vectors in a new mathematical space, of course at cost of loosing chemical/biological tinge. SOM, a brain child of Kohonen in late 1990s, surpassed almost all unsupervised clustering techniques and is a coveted tool in all disciplines. Not only more than 5000 publications during 1990 to 2000 endorses the virtues of the approach, but its modifications and hybrid versions rendered it as an indispensable computing/visual approach from simple tiny to mega systems. The supervised version LVQ, made a mark even for supervised data analysis and prediction. The competing paradigm, based on altogether different axiom, adaptive resonance theory (ART) proposed by Grossberg (1976) is another robust, classification/clustering/discrimination tool under the ARTx and ARTMAP and their clones.

2. Life cycle of fish

2.1 Recruitment: Chen [113] compared MLP-BP, Fuzzy logic, and Ricker stock-recruitment model for pacific halibut recruitment using environment information. Pacific Decadal Oscillation (PDO) index denoted as positive and negative régimes is modeled with fuzzy sets. The residuals of the series with these models exhibits first order auto correlations. When AR component was added fuzzy logic model outperformed. Later, Lee *et al.*, [39] made a comparison of NN, MLR and generalized additive models to predict recruitment of Gulf of Alaska walleye pollock (Theragra chalcogramma). A time series of 41 years for recruitment, spawner biomass and environmental covariates is used. Monte Carlo resampling was used to obtain more robust measure of forecast accuracy. Haxton and Findlay [24] studied growth, mortality, recruitment and relative abundance of 11 large bodied fish species in three water-management regimes viz. unimpounded run-of-the-river and winter reservoirs in large regulated Ottawa River, Canada.

Recruitment Forecast [39]		
Species	**Model**	**Comment**
ॐ Gulf of Alaska walleye pollock (Theragra chalcogramma)	🕮 Monte Carlo resampling 🕮 Generalised additive model 🕮 MLR 🕮 NN	Response • Recruitment • Spawner biomass • Environmental covariates → 41-year time series

The survival and growth of fishes vary with habitat due to spatial heterogeneity [140]. Behavior of a class of fish also depends upon how the information about food, temperature, light and predators not only passes through the sensory system of the fish, but also how it integrates a response at the current moments. Huse applied GA for migration of fish in Barents Sea capelin (Mallotus Villosus). He investigated (predator-prey model) for single/multi species of fisheries. The principles of theoretical ecology are incorporated in the models. Spatial movement of each fish species is modeled with NN and GA is employed for evolving (refining) weights.Buckley et al. [51]used NN and Bayesian models to assign Juveniles to larvae populations. There is no widespread movement of juveniles away from spawning grounds. Young-off-the-year-juveniles are collected in the same year as the larvae.

2.2 Spatial distribution: A database of 50,000+ lakes was compiled based on geography, lake morphology, water chemistry, climate and composition of fish community [72]. NN, logistic regression, classification tree and LDA methods are used to predict smallmouth bass distribution using winter and summer temperatures. By 2100, smallmouth bass community will be shifted to the north as the majority of Canadian lakes will have suitable thermal condition. It has negative impact on native lake trout populations. It is estimated that 9,700 lake trout populations are threatened by 2100 AD. A consequence is change in climate due to invasion of smallmouth bass.

The distribution and abundance of fish [98] in 808 km long Warta River, Poland, is studied for the period 1996 to 1998. The differences in pollution levels between the upper and middle sections of the river are significant based ground truth. The monitored data showed that concentrations of dissolved oxygen (DO), volatile phenols and nitrite nitrogen vary distinctly. Kohonen SOM showed largest differences between the two regions confirming the crucial role of the degradation of aquatic environment in shaping fish assemblages. The fish species like rheophilic burbot, stone loach, gudgeon, chub and dace etc. are most abundant in the upper region (X) and while they are almost absent in the middle regions (Y). The downstream section (Z) was moderately disturbed and the species were reoccurring although the numbers are less compared to the upper regions. Mud loach, tench, ide and silve bream were most abundant and in the degraded section (Y). The abundance of generalists viz. coach and pike were similar in all three sections. These species neither changed along downstream nor in the polluted region of the river.

Distribution Habitats prediction		
Species	**Model**	**Ref**
ॐ Bog turtles	🕮 GA - Rule-set Prediction	
in the Southeast.	🕮 Ecological niche model	
ॐ Fish population	🕮 SOM	**75**
	🕮 CCA	
	🕮 k-means clusters	
ॐ Japanese medaka	🕮 Fuzzy-NN	**54**
[Oryzias latipes]	🕮 Fuzzy habitat preference model	
ॐ Smallmouth bass	🕮 Logistic regression	**72**
	🕮 Classification tree	
	🕮 LDA	
	🕮 NN	

In Europe, reservoirs are common aquatic habitats [91]. However, there is little quantitative information on the spatial organization of fish assemblages inhabiting their littoral zone. The ontogenetic species-specific habitat changes influence the dynamics of the fish. Brosse *et al.*, [91] identified spatial distribution of seventeen fish species with SOM based on weekly data on fish assemblages' structure in the littoral zone of a reservoir (Lake Pareloup) in SW France. The display showed three distinct faunal structures within the littoral zone during the periods mid-May to mid-July, mid-July to late August and late August to mid-October.

Fukuda *et al*., [54] compared quality, sensitivity and portability of fuzzy habitat preference model (FHPM), patterns of preference level (PPL) and habitat suitability index (HSI) in prediction of spatial distribution of Japanese medaka (Oryzias latipes) dwelling in agricultural canals in Japan. Here, 50 different initial conditions are used in arriving at fuzzy_NN models.

FuzzyNN	(+) Best predictive power (-) High sensitivity to initial conditions
FHPM	(+) Best description in habitat preference
PPL	(+) Prediction less than FHPM (+) Good calibration
HSI	Qualitatively similar NNs (-) Quantitatively less preferable (-) Lacked transferability

In coral reef management ecosystems, accurate quantitative and spatial distribution of abundance of the species is needed. Pittman [82] reported predictive mapping of abundance of fish across shallow-water seascapes in Caribbean.

2.3 Migration: Fish are highly mobile organisms moving in large groups. In spite of concerted investigations in marine ecosystems, major gaps exist in the knowledge and modeling of their movements, selection of prey and responses of zooplankton to predators. Huse [168] modeled predator-prey interactions for Herring. The consideration of the interaction between mortality of zooplankton and fish renders the model more viable. Further, inclusion of horizontal migration of fish in the model enhances quality of model. Siira [22] reported NN models for migration of Atlantic salmon in the Gulf of Bothnia Baltic Sea. A mark–recapture experiment was performed and the catch data is from commercial trap-nets. NN model showed that the migration is non-linear on their way to northern-most Bothnian Bay before turning back South. This shows moving from one region to other does not progress linearly. The Salmon returning to different home sites showed no difference in runtime.

Dedecker [85] proposed migration models for macro-invertebrates in Zwalm river basin in Belgium as a tool for restoration of species and management of the river. Antropogenic activities polluted the river systems in Flanders with a consequence of deterioration of quality of drinking water and fish etc.

Task	Species		Model	Explanatory variables	Ref
Simulation	Japanese sardine	Western North Pacific	MLP +GA	Surface temperature Surface temperature change Current speed Day length Distance from land	33
Model	Atlantic salmon [Salmo salar L.]	Gulf of Bothnia [Northern Baltic Sea]	NN		22

The migration models for Baetis, Ephemera and Limnephilidae have been developed for Zwalm river basin. The three resistance layers considered are migration through air/over land and two for migration through the river in upstream and downstream directions. Dagorn [130] proposed models for movements of Tuna using sea surface temperature (SST). Ethological knowledge -- search of thermal fronts -- is used in the first model, which explains northern movements from Mozambique Channel. NN is used in second model to explain the behavior of Tuna, where in Ws are refined by GA. The daily local environment information sensed by fish school network is instrumental in choosing appropriate time to pass from the Mozambique Channel to Seychelles Island. A NN mimics Tuna movements based on variation in SST versus adaptive behavior. Huse [126] proposed an individual-based-NN-GA model for life history and behavior of fish. The adaptation process in fish is analysed considering state-dependent patch selection. It is a culmination of consequences of predator and prey outcome and a complicated-vertical migration-scenario of a planktivoros fish and the results are close to optimal solutions.

3. Fish identification

3.1 Detection: Sharma and Jackson [69] modeled the presence and absence of smallmouth Bass (Micropterus dolomieu) by NNs, discriminant analysis, logistic regression and classification tree using 4181 geo-referenced data along with climate profile. NNs performed best in prediction where winter air temperature was found to be the most important predictor. Logistic regression and classification tree exhibited very low sensitivity.Steen [67] analysed the absence/presence of Brook trout with MLR, NN, classification trees and logistic regression. Classification trees enable one to arrive at interpretable models. They are applied to Michigan stream fish with asuccess of 72%. This study throws light on scenario of fish communities of Muskegon river in year 2100 system (Michigan,USA).

Task	Species	Model	Ref.
Detection	AB d Pungitius Pungitius Barbatula barbatula Gasterosteus aculeatus	SOM	34

<table>
<tr><th>Task</th><th>Species</th><th></th><th>Ref.</th></tr>
<tr><td>Detection Automatic</td><td>American eels</td><td>Anguilla rostrata canal of a small hydroelectric station
<table>
<tr><th rowspan="2">Method</th><th colspan="2">% Misclassification</th></tr>
<tr><th>Eels as debris</th><th>Debris as Eels</th></tr>
<tr><td>NN</td><td>7</td><td>5</td></tr>
<tr><td>Discriminant</td><td>12</td><td>4</td></tr>
<tr><td>k-NN</td><td>17</td><td>12</td></tr>
</table></td><td>47</td></tr>
<tr><td>Detection Remote</td><td>Endangered Shortnose</td><td>Tidal Delaware River</td><td>31</td></tr>
</table>

	Sturgeon	Discrimination sturgeon | river bottom sturgeon | non-sturgeon fish sturgeon | river bottom	

Penczak [34] used IndVal (indicator species index) to detect fish assemblages in Narew River containing 36 fish species using SOM-NN. The results are precise and accurate regarding habitat preferences of the fish.Kennard [100] reported multi scale influence of environmental landscape/hydrological factors, local habitat features and their interaction terms on spatial and temporal variation of fish in eastern Australia. Multi response NNs predicted accurately the fish assemblages in Mary River with data on presence/ absence of the species. However, the model is less accurate when abundance of species is used. The most important factors are land scape/local scale habitat variables and long-term flow regime factors, while the short-term hydrological variables are not important.

Presence/absence			
Species		**Model**	**Ref.**
Telestes muticellus	Piedmont North-Western, Italy		15
Brook trout	Michigan stream fish	MLR Logistic regression NN Classification trees	67

3.2 Composition: Novotny [35] reported predictive models for composition of fish in clusters of sites based on biotic fish community using the factors viz. influence of environment and in-stream habitat stress. The data used in this study was monitored by state agencies in north-central and northeastern US. The modeling techniques applied are NN, PCA, Canonical Component Analysis, MLR and ANOVA. Steen et al. [115] proposed conservation of fish models explaining habitat characteristics at a land scape scale. The performance of presence/absence models for brook trout Salvelinus fontinalis with the help of Michigan Fish Atlas is in the order LogistReg > MLR > ClassTrees > NN.

3.3 Automation: Mueller *et al*., [47] conducted a feasibility study of automatic detection of adult American eels Anguilla rostrata in the intake canal of a small hydroelectric station by sonar images. The images were obtained by a hydro acoustic monitoring system with dual-frequency sonar of high resolution. This model distinguishes distinct shape and swimming motion of eels.

Model	**% Misclassification**	
	eels as debris	**Debris as eels**
NN	7	5
Discrimination fucntion analysis	12	4
K-nn	17	12

Partial automation is the start of high-end application of any task. An intricate human supervision brings down the false positives and false negatives. Full automation after an iterative cycle of partial automations is sought after goal. This of course should be under a continuous expert supervision, validation with more complex datasets, fixing bugs, adding heuristics, meta rules, modifications/ advanced algorithms with feedback from β versions.

4. Fish stock

4.1 Classification: Park *et al.* [108] used SOM-NN to determine the types of fish assemblages from samples in 191 sites in Adour-Garonne basin containing 34 species. SOM distinguished three types of fish assemblages according to the changes in composition of the species. The prediction of the types of fish assemblages is modeled with MLP-NN using landscape features (altitude, distance from source and surface area of drainage basin) and land cover types (agricultural/ forest/urbanized/artificial surface). Rezzi *et al*., [99] reported classification of fish with PCA, LDA and probabilistic NN (Prob_NN) using ^{1}H NMR finger print region of lipids. Gilthead sea bream (Sparus aurata) is monitored to classify farmed specimen in Mediterranean basin. PC_scores of ^{1}H NMR amply distinguishes wild from farmed samples and the variables in PCA are selected by forward selection procedure. Prob NN provided complementary information here. In fish stock assessments of many species, hydro acoustic techniques are prominent but they do not result in identification of species. Robotham *et al*., [8] found the performance of models in the order [MLP = SVM] > Prob NN in the classification of anchovy, common sardine and Jack Mackerel. The input vector is the descriptors extracted from acoustic records.

4.2 Discrimination: Discrimination between fish populations using parasites as biological tags is difficult due to complicated of host-parasite relationships. Perdiguero-Alonso *et al*., [49] reported random forests in population assignment of fish. The dataset comprising 763 parasite infracommunities of Atlantic cod, Gadus morhua from five regions in North East Atlantic, which are spawning/feeding areas (Baltic, Celtic, Irish and North seas and Icelandic waters). Random Forests outperformed LDA and NN to predict the assignment of fish to their regions of sampling using parasite community. It is worth to analyze the data with ensemble NNs and with state-of-the-art NN architectures. Bayesian analysis distinguished 14 genetic populations of winter flounder larvae, which are collected from 20 stations within Narragansett Bay and one station outside Bay [51]. Analysis was done for six microsatellite loci and the geographic distribution also overlapped with genetic populations. Haxton and Findlay [24] used holographic NNs to discriminate fish species caught in the nets. The correct classification rate is 78.8% and 76% for trap nets and gillnets respectively. Littoral zone benthivores are significantly lower in abundance in winter reservoirs.

Task	Species		Model	Ref.
Model	ॐ Cestoda ॐ Ephinephelus marginatus ॐ Isopoda ॐ Nematoda ॐ dusky groupers (Ephinephelus marginatus) ॐ Lowe 1834	🕭 Iskenderun Bay, Turkey	• SOM • **Explanatory variables** Current speed • Relationship between length weight and infestation (with Nematoda 🕮 Cestoda, Isopoda) of seasonally	
Model	ॐ Oil sardine mackerel.			137
Prediction	ॐ Smallmouth bass (Micropterus dolomieu)	North America	🕮 NN 🕮 Logistic reg. 🕮 Classification tree 🕮 DA NN >> other methods • 4181 records	69
Prediction	ॐ Smallmouth bass (Micropterus dolomieu)	🕭 Canada USA	🕮 MLR 🕮 Bayesian-MLR 🕮 NN	72
Model	ॐ Winter Flounder	🕭 Narragansett Bay	🕮 NN 🕮 Bayesian-	51
Habitat Diversity fish community short-medium term time-scale		Tagus estuary (Portugal): 🕭	🕮 NN 🕮 MLR	70
Habitat Prediction	ॐ Bog Turtle	Glyptemys muhlenbergii	🕮	157

Habitat preference	Japanese medaka	Oryzias latipes Dwelling in agricultural canals in Japan	Water depth Current velocity Lateral cover ratio % vegetation coverage	**127**
Habitat Analyze fish		data on	NN PCA Canonical component analysis o Linear Non-linear	**41**

4.3 Diversity: Vasconcelos and Costa [**70**] reported NN and MLR models to predict the diversity of fish communities in Tagus estuary on short-medium time-scale. NN model revealed nonlinear dependence of DO, temperature depth and nitrate concentration with the diversity, while nitrite, silicate, transparency etc. impart a less influence.

5. Food products from fish

5.1 Freshness of fish: Freshness is one of the significant parameters of quality of fish for sale. It can also be determined based on concentration of certain bio-molecules with time after the death of fish. It is assessed by various indicators which are costly, time consuming and lack aptness for in-situ or on site. The potentials at Au and Ag electrodes are correlated (for seven days) with variation of ATP metabolites viz., inosine 5'-phosphate (IMP), inosine (Ino) and hypoxanthine (Hx) [56]. K_1 index reflects the simultaneous variation of INO, IMP and Hx. The gold and silver wires were used in a potentiometric measurement to analyze the evolution of sea (Sparus aurata) bream fish. PCA and NN models determine post-mortem time elapsed in minced gilthead sea bream.

5.2 Optimum cooking conditions: A single screw extruder is used to cook fish muscle-rice flour blend [**90**]. The extrudate properties like expansion ratio, bulk density and hardness at different combinations of operating variables like barrel temperature, feed content and feed moisture are modeled with MLP-BP using MATLAB toolbox. NN predicted extrudates properties better than RSM.

5.3 Quality of fish oil: The discrimination in connection with the nature composition refinement and/or adulteration or authentication of commercial fish oil-related health food products is studied with ^{13}C NMR spectra [**80**]. Prob-NN, SOM NNs, PCA generative topographic mapping are used. SOM and GTM visualizations are better than PCA score plots. There are ambiguities in PCA. PNN gave greater than 95% accuracy in the prediction of class of trout, salmon and cod-oils. However, there are misclassifications in salmon and cod-oils.

6. Forecast/prediction Models in fisheries

6.1 Fish landing: The prediction of landings of fish improved over decades due to continuous progress in modeling techniques and with use of more and more relevant environmental factors. Gutierrez-Estrada *et al*., [**17**] reported computational NNs, MLR, generalized additive models for Pacific sardine landings in north area off Chile. The independent variables consist of local and global environmental factors. The calibration and validation of CNNs was performed with anchovy (Engraulis ringens) landings in the same area and this NN captured the trend of the historical data. This model explained more than 86% of variance and NN is far better than MLR and GAM. The local and global variables separately resulted in models with low prediction error. Gutierrez- Estrada *et al*., [**78**] compared Rec-NN, Elman NN and hybrid seasonal NN+ARIMA model for one month ahead forecast of catch of anchovy Engraulis, Ringens in the north area of Chile. In ARIMA (2,0,0) the data of six previous months of monthly catches of anchovy resulted in very accurate monthly forecast. The variance explained is 84 to 87% and the catch is 18,000 tones.

Task	Species	Location	Model	Ref.
Catch Decline	ॐ Eulachon (Thaleichthys Pacificus)	Fraser River	o NN **Explanatory variables** - Monthly mean temperature - Discharge of the Fraser River, the Pacific Decadal Oscillation - Index, the El Nino Southern Oscillation index, a spawning biomass - Index derived from the eulachon commercial catch in the Fraser River - Offshore shrimp trawl fishing effort	97
Catch Monthly Forecasting stock	ॐ Anchovy Engraulis ringens	North area of Chile:	- NN - ARIMA - CNN +ARIMA	78
			- NN - Tree regression	68

Hanson [106] found MLR and NNs are similar in modeling landings versus affords data for Atlantic purse-seine (1942–2002) fishery and forGulf menhaden B. Patronus (1946–2002). ARIMA (1,0,0) is inferior to NN. The accuracy of one year ahead prediction between 1993 – 2002 is used as a test of performance of the model. The forecast errors are 19-21% in the Atlantic and 15-20% in the Gulf.Georgakarakos *et al*., [122] used NNs and ARIMA forecast annual landings of loliginid and ommastrephid based on time series data (1984–1999) from fishing ports in the Northern Aegean Sea. The environmental information like temperature and SST are used. In ARMA, the trend and system parameters remain same across the observation and forecasting periods.

6.2 Abundance: Kruk [96] compared abundance and dominance of fish between two sampling periods (1963-66 and 2002-04) and in two lowlands rivers Widawka and Grabia from Warta/Odra (Poland) system. From 1970 onwards, Widawka was under strong influence of a brown coal strip mine and some of long stretches of upper Widawka and some tributaries were changed into concrete canals. Grabia, the tributary of Widawka, however, maintains its natural character. Kohonen-SOM separated the fish samples in the 2 periods from abundance data. Although, there are drastic spatial differences, the variations in the different time periods are more pronounced, for ichthyofauna. But, 70% of the total fish number corresponds to roach, gudgeon, bleak and dace.

US-Caribbean marine habitat types of complicated mosaic are studied using remote sensing data, field observations and GIS. The purpose is to predict abundance of different types of fish species. NN, regression trees and MLR are compared [82] for the data from south-western Puerto Rico. Regression trees outperform MLR and NNs. The accuracy is 75%, when three classes for richness i.e., high, medium and low are used. It increased to 83.4% if high and low species richness areas alone are analyzed.

Garcia *et al*. [79] reported FFNN to predict one month and three months ahead population of shrimp in Charleston Harbor. The accuracy is 92% for one month and 79% for three months ahead forecast. SST and salinity have influence on shrimp population. The data is from Atlantic white shrimp during 1986 Jan to 2004 Dec. Although mechanistic models are used in earlier days, environmental conditions were not considered.

6.3 CPUE: CPUE (Catch Per Unit Effort) depends on the tactics employed in longline fisheries. For example, large Pelagic fish fisherman deploy different tactics based on fishing ground and also season [116]. Maximum fishing depth (MFD) and hooks per basket (HPB) were considered as indicators. The mean depth appears as a better proxy indicator for MFD. The inadequacy of this type of information in the input cannot be compensated by habitat-based model, GLM, GAM, GLMM or NNs [68]. CPUE is a relative abundance index. It includes spatiotemporal and environmental effects. The trend in annual variation of the stock needs removal of these contributions and generally, analysis of covariance (ANCOVA) models is used to estimate the factorial effect of the year. Catch is used as a discrete response variable and Poisson or negative binomial distribution was assumed in Catch-Poisson and Catch-negative-Binomial-models. These methods are called CPUE standardization approaches [127]. Here, logarithm of CPUE is taken as response variable and assumed factorial effects are incorporated into the model as explanatory variables and generalized linear model is applied. Southern bluefin tuna data was analysed by NNs. Czerwinski *et al.*, [77] used ARIMA and NNs to forecast CPUE for Pacific halibut, Hippoglossus stenolepis (Pleuronectidae) for short term intervals. ARIMA seasonal model indicated that one non-seasonal autoregressive term combined with non-seasonal moving average term and a seasonal moving average term explains 32.6% variance. Although, it is statistically acceptable, the next step is to develop a model with larger explainability. NN (3-5-1) using 3 autoregressive terms as input explain 91% of variance. It is a clear indication of the presence of a non-linear relationship.

7.0 Factors affecting fish stock

7.1. Habitat preference: Cho et al. [12] used SOM to make out habitat preferences of otters (Lutra lutra) in Eurasian river otters. Neira et al. [105] employed multi response NN to classify fish classes using 24 environmental variables based habitat preferences.

7.2 Fishing tactics: Czerwinski *et al*. [7] studied experimental fishing trials with NN and logistic models. Four sizes of the hooks were used in the black spot seabream (Pagellus bogaraveo) fishery in the Strait of Gibraltar. Logistic model was adequate only for one of the two time periods. Acceptable results are obtained even with small data samples. Bottom trawlers are multi-specific and different fishing tactics are used even during same fishing trip in Mediterranean Sea. Plamer *et al*. [37] compared NNs with discriminant analysis to predict fishing tactics from multi specific fisheries. The information is obtained from skippers about the landings of the vessel from daily sale bills. The tactics used on boat are employed. The prediction percentage was high for FTs with more than 25 cases, and increases with increasing dissimilarities between corresponding species. However, the success rate decreases for smaller sample sizes.

Task	Species	Location	Model	Ref.
Fishing tactics Prediction	Multi specific fisheries	Mediterranean	🕮 NN 🕮 LDA	
Fishing vessel Control of rudder roll system. Yaw controller			🕮 LDA 🕮 MLP-BP	76

Alarcin and Gulez [76] proposed a controller using NN with BP. The controller makes use of Rudder to regulate both the Yaw and roll motion of fishing vessel. The functioning is compared with linear quadratic regulator. Rolling angle, Rubber angle, Rudder angle are used in this study.

7.3 Selection of sampling sites: Manolakos *et al*. [75] used SOM to find patterns in the sampling sites in Ohio state based on similarity in IBI's[Index of Biotic Integrity] and fish metrics. Complex inter relationships in aquatic system are explored by inspecting super imposition of different visualization in SOM clusters. This helps the managers of watershed to understand the effects of environment on the fish. Latitude, longitude and metrics of intensities are input to SOM. Although, local models help fishery management, multi-species predictive models in time and space are still complex. This is partially due to manmade activities and natural calamities.

IBI [Index of Biotic Integrity]: A single biological metrics is developed along gradients of environmental degradation. Multiple metrics are combined using best professional judgment to find stressor – response relationship. These indices of biological integrity are widely used. The simultaneous effects of anthropogenic stressors and corresponding IBI on population of the fish are used.

The impact of Human activity in Piedmont of Italy disturbed fresh waters and their inhabitants [15]. There is an immediate need to probe into ecological assessment of fresh water system. As far as fishery management is concerned, the endangered Cyprinidae found in Western Alps. With ten environmental variables the classification of the sites for the species as positive (+ve) or negative (–ve) with NN is better than decision tree model. The inputs of NN are analysed by sensitivity technique to sort-out the influential variables. The unpruned decision tree models classified a high percentage of cases correctly and also the predictions were accurate. The post-pruned tree models are simpler and are easily interpretable, but there is no increase in accuracy.

7.4 Effect of weather: Abdullah [38] compared DF, QDF, MLR, MLR-BP-NN, RBF-NN to forecast possible shifts in the prediction of ozone in Houston for a 12 year period (1990 to 2002 daily date) air quality data from Texas Environmental Quality Commission. This is an extensive comparative study while the earlier studies used ARIMA.

7.4.1 Water quality for fisheries: Zhu *et al*. [2] reported an online water quality monitoring system, which is used in intensive fish culture in China. It combined mobile telecommunication technology with web-server-embedded technology. NN is used to model and forecast water quality based on historical database. Another half an hour to one-hour-ahead forecast model for dissolved oxygen is based on earlier experimental data.

Task	Model	Ref.
Ozone Daily data	🕮 LDA 🕮 QDA 🕮 MLR 🕮 RBF 🕮 MLP-BP	38
Air quality Monitoring12-year period (from 1990 to 2002) Management Forecast	🕮 LDA 🕮 QDA 🕮 MLR 🕮 RBF 🕮 MLP-BP	38
Optimal operational strategies of a multi-purpose reservoir	🕮 GA 🕮 SDP	132
Management reservoir with six hydrologic indicators	🕮 GA-NDS	136

7.4.2 Dissolved oxygen (DO): DO is an influential factor on growth of cultured organisms including fish in ponds. The variables influencing DO in pond are not completely enumerated. Further their relation with DO is complicated. NNs are proposed as they are adequate data driven methods for incompletely known cause effect relationships and when there is a noteworthy inter-explanatory factor correlation.Dissolved oxygen (D.O) in fish pond differs with seasons, measuring time, the position, depth, wind speed, surface area of the pond and depth of measuring point [129]. The prediction of DO is multivariate non-linear time lag task.Guo and Deng [120] in the year 2006 reported Fuzzy NN with PSO training algorithm to predict DO in fish pond using water temperature, nitrite, ammonia and total nitrogen as inputs. It is faster and better than using BP training method. PSO is used to train NN and it is faster than B.P. The authors report that it is one of the attempts for intelligent computational methods applicable in industrialized Mari culture.

7.4.3 Temperature of water: In aquatic ecosystem, temperature of water is one of the most important environmental variables and it has a positive or negative effect on organisms, sometimes to a very drastic extent. For instance, high temperatures increase the mortality rate in salmonid fishes. Sivri et al. [94] predicted stream temperature of Firtina Creek in Black Sea region. The variables used are local water Temperature, DO, pH, air temperature and rainfall. This model enables one to arrive at suitable habitat for native Sea Trout (Salmo trutta Labrax, Pallas 1811) under past drought or other adverse environmental conditions.

7.4.4 Tides in Sea: Long term sea level data is needed for accurate tidal predictions. Lee et al. [84] reported a combined harmonic analysis and NNs to predict the tides in Sea. The prediction of tides by harmonic analysis uses superimposition of many sinusoidal components. The amplitudes and frequencies are determined from an analysis of locally measured sea levels. The data on sea level from Hillarys Boat Harbour tide gauge in Western Australia is used to test the original methodology proposed. The results show that short-term sea-level data also accurately predicts the sea tides. Kisi *et al*. [45] modeled suspended sediment of rivers in Turkey with MLR, GRNN, neuro-fuzzy-NN, sediment rating curve etc. The data is from the daily stream flow and suspended sediment at four stations in the Black Sea regions of Turkey.

7.5 Addictive behavior of opioid compounds on fish: Natural rewards and addictive opiates are responsible to reinforce behavior in fish. However, it is not clear whether identical pathways mediate both actions. Further, a little is known about this behavior and corresponding neural mechanisms in zebrafish Danio rerio.Lau *et al.* [104] reported wildtype zebrafish has robust preference for food and morphine and this addiction can be blocked by the opioid receptor antagonist naloxone. A mutant which exhibits a reduction of selective groups of dopaminergic and serotonergic neurons in the basal diencephalon. It has no preference for morphine, but preference only for normal food. Here, a conserved zinc-finger containing gene is disrupted. In the wild type pretreatment with dopamine receptor, antagonist removes preference for morphine. Further genetic analysis clears molecular and cellular mechanisms responsible for the formation and function of neural circuitry that regulate opiate and food preference.

Transparent larval zebrafish having previous experience with morphine spend more time in a compartment containing morphine [81] when given a choice of water or morphine-containing compartment. If the fish is pretreated with an antagonist of the opioid receptor or dopamine receptor, in a few mutant species still there is a decrease in getting attracted by morphine. In mutant species there is a genetic deficiency in the production of specific groups of dopaminergic and serotonergic neurons in the ventral forebrain. This uncovers a choice behavior for an addictive substance in larval zebrafish, which is mediated through central opioid and monoaminergic neurotransmitter systems. They offer a base to probe into genetic and NNs underlying behavior in a developing system. The behavior versus genetic code is determined with NN for planktivorous fish. Mueller's Perliside (Maurolicus Muelleri) is used as a model organism [128]. This species is chosen both for training and testing because of broad knowledge of its behavior and history of life.

7.6 Toxic algae: The redtide is one of the Harmful algal blooms (HABs) [119]. It has negative impacts on aquatic life and human health too. HABs grow explosively and lead to closure of beach loss of Mari culture due to depletion of oxygen. The other toxic algae are poisonous to cell fish. In 1998 April, redtide explosions resulted in a devastating incident of distribution of 3,400 tonnes of cultured fish stock (80% of stock) amounting to a colossal loss of HK$ 312 million. The ill effects on environment and fisheries necessitated the prediction with reasonable accuracy and lead time. One-week-ahead prediction of redtide and chlorophyll algae was performed with NN and genetic programming (GP). The coastal algal blooms were studied at Tolo harbor. GP parse tree is used and 80 runs of GP are performed.

Exotic brown trout Salmo trutta and native galaxiids demonstrated that there is native extirpation except where major waterfalls prevented upstream migration of trout. Some native fish species in New Zealand do not coexist with introduced salmonids. Leprieur *et al*. [103] predicted that spatial distribution of both the invader and a native fish depend upon water abstraction. Multiple discriminant function analysis was used to infer the differences in environmental conditions (catchment and instream scales).

The presence/absence of G. anomalous and brown trout at 135 sites was predicted with NNs. The factors responsible for spatial distribution are extracted from the trained NN model. In Manuherikia River hydrological disturbances due to human activities benefit a native fish at the expense of an exotic one [103]. There is a negative impact on native galaxiids when water is abstracted. The authors recommend a natural low flow to maintain sustainable habitats for native galaxiids. This is possible by constructing artificial barriers in selected tributaries to limit trout predation on native fish and also to remove trout in the upstream.

7.7 Threats for fish

7.7.1. Skeletalanomalies: The global study shows that the quality can be inferred based on the distance between aquaculture products and wild-like phenotype. The presence of high skeletal anomalies (SAs) in reared fish reduces commercial value. Russo [1] used SOM in analyzing skeletal anomalies in reared fish. The trend SOMs classifies the fish lots based on extent of SAs. The correlation between presence of SAs and rearing parameters in Gilthad Seabream (Sparus aurata L), a highly commercial valued reared fish. The input to SOM is from extensive, semi-intensive and intensive rearing approaches. Mesocosms resulted the best rearing approach to produce wild-like fish. On the other hand, intensive rearing resulted in large SAs.

7.7.2 Predators: In spite of concerted investigations in marine ecosystems, major gaps are detected in the knowledge and modeling capabilities of movements of fish at different scales, selection of prey and responses of zooplankton to predators [132]. It has an added advantage to consider the interaction between mortality of zooplankton and fish. Further, fish are highly mobile organisms moving in large groups. Thus, inclusion of their horizontal migration in the model will give a face lift in the end result. Huse [132] modeled predator-prey interactions for herring. Super-individuals also are considered. GA is employed resulting in versatile models reflecting realistic representation of interaction between fish and zooplankton.

Neira *et al*., [105] reported that a hybrid form of the eastern cordgrass Spartina alterniflora in San Francisco Bay, USA invades open mudflats in southern and central section of the Bay. The result altered habitat which reduces macro faunal densities and change in composition species. A significant reduction is in surface-feeding amphipods, bivalves and cirratulid. The subsurface feeding groups are not affected. Multiple physical, chemical, biotic and trophic factors of the Spartina invasion have a profound influence on bentheic communities. This leads to notable effects on the entire ecosystems. A multi response NN is used, to classify fish classes using 24 environmental variables.

7.8 Collapse of typical fisheries: The red grouper (Epinephelus morio) is one of the most dominant fisheries of Campeche Bank area of Gulf of Mexico [13]. The stock assessment studies showed that it has fallen to 30% of total in 1970s. In fact, federal government of Mexico declared that red grouper fishery has been over-exploited and there is a need to recover this species. Albanez-Lucero [13] analysed species distribution of red grouper with NN model. A relationship was found between coral substrates and the life cycle (juvenile, pre-adults and adults) of the fish. Juveniles and pre-adults are associated with coral substrates but distributed in shallow waters and at an intermediate depth respectively. Adults are found in deeper waters on sandy substrates. Further seasonal reproductive aggregation patterns were found [93].

Algal blooms (ABs) occur in urbanised coastal marine environments all over the world. They result in hypoxia and even fish kills. For protection of sensitive marine resources, an understanding of ABs and their prediction is the target of many studies. Lui applied vector ARX (VARX) and long memory filter to predict ABs. An alarming system was developed using VARX to warn the onset of AB to fisherman and regulatory authorities. It gives 83% correct prediction of AB occurrence with a lead time of 2.5 days. Here a daily forecasting performance is better than NN model. VARX model gives interpretable effects of specific lags of environmental factors and the importance of feedback effect of the variables. There is a serious decline in Bog Turtle population due to loss of wetland habitat and illegal (excessive) collection to meet pet trade demands. As a result, it is listed as "Threatened due to similarity of appearance" and declared in 1997 as under endangered species act of 1973[**131**].

8. Fishery management: The fishery management requires knowledge of fish, environment, fishermen, their skills/knowledge and market. It is indispensable for efficient allocation of tools in fisheries science/commerce. NNs are adaptable models for short term quantitative recommendations for fisheries management[77].Steen et al.[67] developed Models to test a hypothesis about the processes important to organisms, which are used to predict the abundance and distribution in management applications.

Closure of fisheries: Eulachon is an important on ecological ground and significant species from cultural stand point of view, in North America [**97**]. The commercial fishery activity of this species in Fraser River (British Columbia, Canada) has been closed since 1996. Fu [**97**] used NN model to find the reason for the closure using catch as dependent variable and six input factors. The effect of time of lags from one to four years and the number of hidden neurons from two to four was studied. This time series from 1941 to 1996, explained adequately the decline of the population. The fishery (Atlantic salmon in the Gulf of Bothnia, northern Baltic sea) is regulated by delayed opening of the fishery in consecutive regions Siira *et.al*. [**22**]. It is based on the assumption that the wild fish migrate before reared ones and the migration is unidirectional from south to north. The results with NN showed that there is a slight tendency towards earlier migration for wild salmon compared to reared fish.

The construction of dams has multifold effect in abundance of fish [**16**]. Electro-fishing samples were collected monthly in five tributaries of Corumba River before and after impoundment. The samples were randomly dispersed in SOM output making no separation in the two time periods. Although, pH, conductivity, DO, velocity of water, water temperature is related to pre-and post impoundment periods, the fish species clustered by SOM did not differ significantly. But biotic variables viz. species richness, equitability and log (total abundance) have noteworthy differences. Only one cluster was dominated by samples from the Furnas Stream. It was only channel that could be entered by fish the main river. This is because it is below the dam, which has no fish ladder.

Model	Variables
CPE-Trout	Habitat features
IBI	Physical parameters, water quality
CPE-brook trout	Sineosity, % pool areaGradient, Cover
CPE-brown trout	Gradient, % fine sediments,
IBA coldwater	buffer width, width to depth ratio

In trout stream management biotic integrity and trout density are central measures [**50**]. The cause-and-effect relationship NN models are developed for 11 reach–scale habitat variables. The cold water fish index of biotic integrity scores (IBI) are also modeled.

09. High-tech experiments and Simulations in fish research: The size and shape of fish, especially sea-based ones which are submerged permanently, is monitored through remote systems. A dual optical camera collects images synchronically and transports to a portable waterproof PC equipped with two frame grabbers [**118**]. NN is used to correct the errors of measurement. The fish images are filtered by a geometric algorithm. Elliptic Fourier analysis of automatically collected fish out-line coordinates is used in shape analysis. For other fish orientations, landmarks (homologous points) are collected on fish outlines. The landmark configurations relative to fish are rotated. This automatic system reduces mortality and stress due to fish sampling.

9.1 Under Water Video Monitoring: A dual underwater camera system was connected to a computer through a water proof cables [20]. It is used for acquiring images of tuna under the water during transfer from fishing net to a floating cage. The frequency of recording of images is two per second. NN was trained to convert the distance between points in the real objects. The images of 1000 tunas are compared with conventional methods.

SELDI (surface-enhanced laser desorption/ionization)-TOF-MS is used to obtain proteomic profiles of plasma from 213 flat fish species, Dab(Limanda limanda) [109]. NNs are used to identify, the dabs from North and Irish Seas. It is also useful to detect macroscopic liver tumors, which are prevalent up to 10%. The data was collected in 2004 in UK NMMP. The accuracy is around 85%. The factors like age, gender and geographic origin have confounding influence and thus selection of samples plays a role. PCA and PLS analysis of the plasma proteome profile is performed.

Dehydration level: Mohebbi *et al.* [11] applied computer vision systems (CVS) to estimate the dehydration level of shrimp from the images at different drying temperatures (100 to 130°C) and several intervals of time (15 to 180 min). The factors through complete randomized block design (CRBD) are analyzed. The color features against moisture contents of dried shrimp are analysed by MLR and NN. NN model is highly correlated with the expensive and intrusive chemical method. NN procedure is fast non-invasive, inexpensive precise and above all, imbibing non-linear trends. It is free of subjective errors. The automated version is superior to subjected procedures.

	Sturgeon	
	Correct	Incorrect
Two class	96.6	3.4%

Brundage *et al*. [31] conducted broadband sonar echoes studies to detect and classify shortnose sturgeon in tidal Delaware River. NN-classification model is used for shortnose Sturgeon, three non-sturgeon fish species in river bottom. One classifier distinguishes Sturgeon from river bottom, the second classifier sturgeon against non-sturgeon fish and bottom. The training success is 100% for each class. Around 27% non-sturgeon and 5% bottom echos for incorrectly classified as sturgeon. This is equivalent to 16.5% false positive rate. It is explained based on large abundance of non-sturgeon fish.

	Correct	Incorrect	
	Sturgeon As Sturgeon	Sturgeon as non -Sturgeon	Sturgeon as bottom
Three class	89%	8.5	2.5

10. Simulation & emulation

10.1 (Spanning) migration of fish: Fish movement is as a result of passive transport along ocean currents. The other one is reactive movement or spawning movement. Okunishi *et al.* [95] proposed a two-dimensional individual based model of fish bioenergetics to simulate migration and growth of Japanese sardine in the western North Pacific. The spawning migration is modeled by MLP (5-H-8). The output neurons indicate directions of migration. The inputs are SST (sea surface temperature), change in temperature, speed of current, day length and distance from land. The NN is trained with BPand GA. The hybrid training reproduces realistic spawning migration of Japanese sardine. Okunishi *et al*. [33] reported a 2D simulation model using NNs for Japanese Sardine (Sardinops Melanostictus) migrations in the Western North Pacific. Using passive transport by simulated ocean current, fish movement is simulated by feeding and spawning migration. NN is used to model spawning migration with environmental variables. A feeding migration model is used to solve the moment of the fish based on its weight. NN is trained with BP and GA. Condition factor for sardines in the model is used as a factor of optimization with GA. The combination of GA with BP accurately reproduced the spawning migration.

10.2 Robotic-fish: Zhang [102] developed a Bionic-NN for Fish-Robot Locomotion. The inspiration of bionic-NN is from biological NN of fishes. A bionic-NN consists of a nonlinear neural Zhangoscillator, which is like a sine-cosine model. It is used in central pattern generators (CPGs). A chain of CPG and one high level controller forms a simulation model. This bionic-NN in fish robot performs various motions viz. startup, stop, forward swimming, backward swimming, turn right and turn left.Oral and Genc [71] reevaluated parasitism in dusky groupers in Iskenderun Bay (Turkey) using SOM_NN. The inter relationship between length, weight and infestation (with Nematoda, Cestoda, Isopoda) of Dusky groupers is visually displayed by 2D-SOM.

11 Futuristic Road map in fisheries research: Interdisciplinary research starts with well-trodden methods of mathematics/statistics in the model driven/data driven mode and physical/ chemical/ biological conceptual models prevalent in the specific discipline. To start with, many approximations in data/noise/error distributions are made. The data sets are small, undersigned in spatiotemporal frame with may compromises for real life tasks, low prediction accuracies etc. With time, momentum gains, the real fruits in information processing creep in. It results in more and more familiarity, experience and expertise in routine use higher order methods in data acquisition, noise filtering, pre-processing/transformation, dimension reduction, development of robust models, best set through ensemble, forest techniques, knowledge extraction, generation of intelligent sparkles in ever refining iterative research studies.

Case studies with advanced computational methods viz. CNNs, Deep- Learning- NNs, pretrained-Deep- NNs- architectures, Transformer- NNs, AI, Transformer-AI, xAI, Capsule (vector, matrix)-Nets, x-Capsule-NNs, x-Tensor-Processing object Nets with information useful for an expert to browse and researchers to probe interest in the up-to-date instances of success/failure/improvement in science and craft of the field.

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Appendix: Recent Case studies with state-of-knowledge NNs

Task.:	Gaussian Process (GP) generalization	Model	Residual neural networks (ResNets)
Method. Mod ResNN	Functions of the network are replaced by GPs		
Applicable to	Discretized solvers for a generalization of image registration/computational anatomy variational problems		
Theoretical understanding of this method	Deep learning from the perspectives of (1) shape analysis with images replaced by abstractions, (2) Lagrangian/Hamiltonian mechanics, (3) GP/Kernel regression with data-dependent warping kernels		
Publication type	Review		

Do ideas have shape? Idea registration as the continuous limit of artificial neural networks	Ti
Physica D: Nonlinear Phenomena, 444, 2023,133592	Ref-01
https://doi.org/10.1016/j.physd.2022.133592	doi
Owhadi, H.,	Au

Task.:	Fish feeding intensity	Goodness-of-fit	95 % Accuracy
Method	✓ Optical flow neural network → generates optical flow frames ✓ Inputted to a 3D convolution NN		
Data	o RGB water surface images from an aquaculture site during fish feeding activity		

Evaluating fish feeding intensity in aquaculture with convolutional neural networks	Ti
Aquacultural Engineering, 94, 2021, 102178	Ref-02
https://doi.org/10.1016/j.aquaeng.2021.102178	doi
Ubina, N., Cheng, S.C., Chang, C.C. and Chen, H.Y.	Au

Task.:	o Predictions of sensory drive Fish sexual signals	Species	Darter fish (etheostoma spp.)
Method	VGG19	Data	Images
Outcome	Role of camouflage in female		

Using deep neural networks to model similarity between visual patterns: Application to fish sexual signals	Ti
Ecological Informatics, 67, 2022, 101486	Ref-03
https://doi.org/10.1016/j.ecoinf.2021.101486	doi

Hulse, S.V., Renoult, J.P. and Mendelson, T.C.,	Au

Task.:	♘ Biomass estimates ♘ Classification	Species	Pelagic species schools
Method	MLP-NN	Data.probes	o Acoustic o Environmental
Features	! Morphological ! Bathymetric ! Energetic ! Positional	Dataset	2565 Fish Schools
Goodness-of-fit	Acc 95%		

Identifying small pelagic Mediterranean fish schools from acoustic and environmental data using optimized artificial neural networks	Ti
Ecological Informatics, 50, 2019, 149-161	Ref-04
https://doi.org/10.1016/j.ecoinf.2018.12.007	doi
Aronica, S., Fontana, I., Giacalone, G., Bosco, G.L., Rizzo, R., Mazzola, S., Basilone, G., Ferreri, R., Genovese, S., Barra, M. and Bonanno, A.,	Au

Task.:	Dynamic Fish mortality prediction	Species	American black bass
Method	LSTM-NN	Data	Static data with cumulative time-series dynamic data
Features	32		
Goodness-of-fit	o Coefficient of determination (R2) 0.81 o (95% Confidence interval (CI) 0.73–0.89) o Root-mean-square error (RMSE) of 0.30 (CI 0.21–0.39)		
xAI	Game theory + To visualise the effects of the features on prediction result + To improve interpretability of prediction model.		

Dynamic and explainable fish mortality prediction under low-concentration ammonia nitrogen stress	Ti
Biosystems Engineering, 228, 2023, 178-192	Ref-05
https://doi.org/10.1016/j.biosystemseng.2023.03.003	doi
Wu, Y., Wang, X., Wang, L., Zhang, X., Shi, Y. and Jiang, Y.,	Au

Task.:	Fish feeding intensity quantification

Methods	Lightweight 3D ResNet-GloRe network	Functional Capability	Locates four levels of fish feeding intensities in video stream
	Lightweight 3D ResNet	Lightweight GloRe module is expanded in 3D space	
	GloRe network	Residual block in 3D ResNet network is modified to form the 3D GloRe module	
	Graph convolution in interactive space	To improve accuracy of discrimination	
	Sliding window andframe extraction processing of video data	Significantly reduces the model parameters and amount of calculation	
Goodness-of-fit	Classification accuracy for four types of feeding intensity was 92.68%, + It is 4.88% higher compared with that of classical 3D ResNet network + Parameters were decreased by 46.08% + GFLOPs decreased by 44.10%		

Fish feeding intensity quantification using machine vision and a lightweight 3D ResNet-GloRe network	Ti
Aquacultural Engineering, 98, 2022, 102244.	Ref-06
https://doi.org/10.1016/j.aquaeng.2022.102244	doi
Feng, S., Yang, X., Liu, Y., Zhao, Z., Liu, J., Yan, Y. and Zhou, C.,	Au

Task.:	Fishing operations CPUE distribution	Species	Short mackerel (Rastrelliger brachysoma)
Method	Random forest (RF)	Features/ Parameters	Twenty-five o Spatiotemporal o Environmental o Fisheries-related
Data	VMS (Surveillance systems like the Vessel Monitoring System) 3,237:trips ; 91 purse seiners		
Site and Time	✓ Thai waters of the Andaman Sea ✓ during 2020		
Best Model	o Eight algorithms were compared for model performance using cross-validation Most-relevant predictors o Calculated speed, operation time, instantaneous speed.		
Goodness-of-fit	86% accuracy for RF		
Applicable to	Stock assessments Fisheries management Prospective fishing operation of purse seiners→ better understanding of short mackerel distribution		

Estimation of the spatiotemporal distribution of fish and fishing grounds from surveillance information using machine learning: The case of short mackerel (Rastrelliger brachysoma) in the Andaman Sea, Thailand	Ti
Regional Studies in Marine Science, 62, 2023, 102914	Ref-07

https://doi.org/10.1016/j.rsma.2023.102914	doi
Meeanan, C., Noranarttragoon, P., Sinanun, P., Takahashi, Y., Kaewnern, M. and Matsuishi, T.F.,	Au

Task.:	To predict potential fishing zones	Species	✓ Indian mackerel (Rastrelliger brachysoma)
Method	✓ Random forest (RF) ✓ Spatial analysis with geographic information systems (hotspot analysis)	Site	R. kanagurta in the exclusive economic zone (EEZ) waters off the east coast of peninsular Malaysia.
Features	Sea surface height anomaly (SSHA) Eddy kinetic energy (EKE) Sea surface temperature (SST) Surface chlorophyll-a (CHL) concentration.		
Partial dependence	R. kanagurta prefers a habitat with parameters: SSHA -0.05–0.20 of predicted CPUE hotspots		
Goodness-of-fit	✓ Training dataset (n = 2535) ✓ Testing dataset (n = 1087) Model validation using lin's concordance correlation coefficient (CCC) ✓ (CCC = 0.811) good agreement between predicted and observed catch per unit effort (CPUE) of R. kanagurta		
Applicability	+ Cost-effective satellite-derived products + Useful to predict potential fishing zones of R. kanagurta + Toprovide useful information on relationship between environmental factors and CPUE of R. kanagurta		

Application of the random forest algorithm for mapping potential fishing zones of Rastrelliger kanagurta off the east coast of peninsular Malaysia	Ti
Regional Studies in Marine Science, 60, 2023, 102881	Ref-08
https://doi.org/10.1016/j.rsma.2023.102881	doi
Tan, M.K. and Mustapha, M.A.,	Au

Task.:	Formation control problem as a Markov decision process (MDP)	Method	✓ Leader–follower topology ✓ Deep reinforcement learning with non-expert imitation

Towards end-to-end formation control for robotic fish via deep reinforcement learning with non-expert imitation	Ti
Ocean Engineering, 271, 2023, 113811	Ref-09
https://doi.org/10.1016/j.oceaneng.2023.113811	doi
Sun, Y., Yan, C., Xiang, X., Zhou, H., Tang, D. and Zhu, Y.,	Au

Task.:	Detection of small molecular contaminants	Purpose	Food safety in aquaculture and fisheries
Species	Giant Pacific octopus *Enteroctopus dofleini*	Type of pub	Rev

Data.catch	TS : 1981 to 2019 Site: Southern coast of Tsugaru Strait	Output	Backcast for 2001–2019
Methods	o Seasonal Autoregressive Integrated Moving Average (SARIMA), o Light Gradient Boosting Machine (LightGBM), o Gradient Boosting Decision Tree (GBDT), o Recurrent Neural Network (RNN), o Long Short-Term Memory (LSTM) o Gated Recurrent Unit (GRU)		

Recent developments in biosensing strategies for the detection of small molecular contaminants to ensure food safety in aquaculture and fisheries	Ti
Trends in Food Science & Technology, 133, 2023, 15-27	Ref-10
https://doi.org/10.1016/j.tifs.2023.01.016	doi
Huang, L., Liu, G. and Fu, Y.,	Au

Task.:	Forecast of catches	Species	Giant Pacific octopus *Enteroctopus dofleini*
Models	Sarima-20 Sarima-5	Goodness-of-fit	MAE, MSE, RMSE, R, R^2
Data	1981 to 2019 TS Southern coast of Tsugaru Strait	Method.category	Mach.Lrn

Predicting catch of Giant Pacific octopus Enteroctopus dofleini in the Tsugaru Strait using a machine learning approach	Ti
Fisheries Research, 261, 2023, 106622	Ref-11
https://doi.org/10.1016/j.fishres.2023.106622	doi
Nagano, K. and Yamamura, O.,	Au

Task.:	To Predict shelf life	Species	Channel catfish fillets
Method	NN.BP Lin Mod	Data.Instrument	NIR
Model	Freshness prediction model :chemical analysis data (total volatile basic nitrogen (TVB-N), K value, thiobarbituric acid reactive substance (TBARS) and trimethylamine (TMA)) and NIT spectra (850–1050 nm). GOF: linear correlation coefficient (R2: 0.667–0.887)		
	Shelf-life prediction model Accuracy (above 90 %) Structure NN: 4–7–1.		

BP neural network to predict shelf life of channel catfish fillets based on near infrared transmittance (NIT) spectroscopy	Ti
Food Packaging and Shelf Life, 35, 2023, 101025	Ref-12
https://doi.org/10.1016/j.fpsl.2023.101025	doi
Mao, S., Zhou, J., Hao, M., Ding, A., Li, X., Wu, W., Qiao, Y., Wang, L., Xiong, G. and	Au

Shi, L.,	

Task.:	To model each fish individual as an artificial learning agent		
Method	Neural network trained with MFQ algorithm,	Output	Produce collective motion in groups of various sizes
Mapping	Each fish agent is represented as a multi-channel image each channel describes a different feature Ex: agent's position,agent's orientation		

Modeling collective motion for fish schooling via multi-agent reinforcement learning	Ti
Ecological Modelling, 477, 2023, 110259.	Ref-13
https://doi.org/10.1016/j.ecolmodel.2022.110259	doi
Wang, X., Liu, S., Yu, Y., Yue, S., Liu, Y., Zhang, F. and Lin, Y.,	Au

Task.:	Classification [unhealthy; healthy]	Species	Crayfish
Method	SVM	Method.category	Mach.Lrn
Kernel of SVM	o Polynomial o Radial basis o Pearson VII function	Expl.factors	Physiological characteristics
Data	Pontastacus leptodactylus Eschscholtz, 1823 samples were taken from national fishermen during the 2017 and 2018 fishing seasons from Eğirdir Lake, This study : 246 crayfish, 113 females and 133 males		
Features	Weight, length, sex, and total hemocyte count (THCs)		

Effect of polynomial, radial basis, and Pearson VII function kernels in support vector machine algorithm for classification of crayfish	Ti
Ecological Informatics, 72, 2022, 101911	Ref-14
https://doi.org/10.1016/j.ecoinf.2022.101911	doi
Garabaghi, F.H., Benzer, R., Benzer, S. and Günal, A.Ç.,	Au

Task.:	Detection of farmed fish	
Method	Integrated YOLOv5 with Deformable convolution module (DCM) adaptive threshold module (ATM)	
	DCM	o Offset the sampling locations o focuses more on fish so that the features of blurry fish are enhanced and the background is suppressed. .
	ATM	o Generating appropriate thresholds for different densities → Alleviates missed detections resulting from fixed thresholds, predicts thresholds dynamically + Improves robustness of proposed model

Method.Comp	DCM-ATM-YOLOv5 >> YOLOv5	Goodness-of-fit	Precision and recall of DCM-ATM-YOLOv5 were 97.53% and 98.09%,

Robust detection of farmed fish by fusing YOLOv5 with DCM and ATM	Ti
Aquacultural Engineering, 99, 2022, 102301.	Ref-15
https://doi.org/10.1016/j.aquaeng.2022.102301	doi
Li, H., Yu, H., Gao, H., Zhang, P., Wei, S., Xu, J., Cheng, S. and Wu, J.,	Au

Task.:	Detection	Species	Dense small-scale marine benthos
Method	Multiscale Feature Extraction and Attention Feature Fusion Reinforced YOLO (Multi Scal Attn , MAD-YOLO)		
	VOVDarkNet	▪ Designed as the feature extraction backbone ▪ It uses the intermediate features with different receptive fields to reinforce the ability to extract feature	
	AFC-PAN	Feature fusion network + Network learns correct feature information and location information of objects at various scales + Network ability improved to perceive small objects	
	Label assignment strategy SimOTA	+ Handles occlusion and dense distribution problems	
	Decoupled head	+ Helps to handle occlusion and dense distribution problems.	
DataSet	URPC2020	Goodness-of-fit	+ Detects blurred, dense, and small-scale objects

MAD-YOLO: A quantitative detection algorithm for dense small-scale marine benthos	Ti
Ecological Informatics, 75, 2023, 102022	Ref-16
https://doi.org/10.1016/j.ecoinf.2023.102022	doi
Xu, X., Liu, Y., Lyu, L., Yan, P. and Zhang, J.,	Au

Task.:	Identification	Fuel cells	Solid oxide
Method.Type	Black Box	Method	Hybrid Algs o Ridgelet NN + o Enhanced Fish Migration Optimizer

Blackbox-based model identification of solid oxide fuel cells by hybrid Ridgelet neural network and Enhanced Fish Migration Optimizer	Ti
Energy Reports, 8, 2022, 14820-14829	Ref-17
https://doi.org/10.1016/j.egyr.2022.11.020	doi
Yang, G., Ma, J., Deng, Y., Sun, S., Fu, B. and Fathi, G.,	Au

Task.:	Automatic detection of abnormal behavior of single fish	Image Processing	Image fusion
Method	**BCS-YOLOv5**	YOLOv5 +	Bidirectional feature pyramid network +
		Coordinate attention block +	Spatial pyramid pooling
Processing strategy	Image processing	o Outline information of moving object was extracted based on technology	
	Mosaic image fusion	o Position information of fish image was enhanced	

Advantage	Improves extraction of location information	Goodness-of-fit	Accuracy 96.69% + At 45 frames per second in four typical behavior datasets

A novel automatic detection method for abnormal behavior of single fish using image fusion	Ti
Computers and Electronics in Agriculture, 203, 2022, 107435	Ref-18
https://doi.org/10.1016/j.compag.2022.107435	doi
Li, X., Hao, Y., Akhter, M. and Li, D.,	Au

Task.:	o Fish image recognition o Classification		
Dataset	WildFish fish image dataset	# Classes	15
Method	MLFus.ConvNN **(**Tripmix-Net)	Multi-layer feature fusion	Convolutional network
		Multiscale parallel ResNet Improved residual networks	
Processing strategy	Network fusion	Used to integrate the information extracted from shallow and deep layers	
	Backbone network	Proposed model consists of multiscale parallel and improved residual networks that are connected in an alternate manner	

Advantage	New concept for fine-grained image classification of fish against complex backgrounds	Goodness-of-fit	Accuracy: 95.31%

Fish image recognition method based on multi-layer feature fusion convolutional network	Ti
Ecological Informatics, 72, 2022, 101873.	Ref-19
https://doi.org/10.1016/j.ecoinf.2022.101873	doi
Li, L., Shi, F. and Wang, C.,	Au

Task.:	To detect fish in realistic underwater environmen		
Environmental challenges fish images	- Low illumination - Complex background - High variation in luminosity - Free movement of fish - High diversity of fish species	Models.Fish.	YOLO-Fish-1 YOLO-Fish-2
YOLO-Fish-1	Enhances YOLOv3 by fixing the issue of upsampling step sizes → reduces misdetection of tiny fish		
YOLO-Fish-2	By adding Spatial Pyramid Pooling to the first model It adds capability to detect fish appearance in those dynamic environments Further improves the model		

DataSets	DeepFish	✓ 4505 Images ✓ 20 Different Fish Habitats ✓ Around 15k bounding box annotations across
	OzFish	✓ 1800 images ✓ 43k Bounding box annotations of wide varieties of fish across

Advantage	+ >>YOLOv3 + Lightweight compared to YOLOv4	Goodness-of-fit	o Average precisions of YOLO-Fish1 and YOLO-Fish2 are 76.56% and 75.70%,

YOLO-Fish: A robust fish detection model to detect fish in realistic underwater environment,	Ti
Ecological Informatics, 72, 2022, 101847	Ref-20
https://doi.org/10.1016/j.ecoinf.2022.101847	doi
Al Muksit, A., Hasan, F., Emon, M.F.H.B., Haque, M.R., Anwary, A.R. and Shatabda, S.,	Au

Task.:	Annotation on natural scene images	Data	Flicker Dataset
Tool	Exponential Sailfish Optimizer-based Generative Adversarial Networks ESFO-based GAN		
	ESFO	Newly created design used to train GAN classifier	

		Exponentially Weighted Moving Average (EWMA)	Sailfish Optimizer (SFO)

Method	Grabcut image annotation	Extracting the background and foreground images	
Advantage	+ Enhanced outcomes	Goodness-of-fit	o Maximum F-Measure is 98.37%, o Max precision is 97.02%, o Max recall is 96.64%, for tflicker dataset

Exponential Sailfish Optimizer-based generative adversarial network for image annotation on natural scene images	Ti
Gene Expression Patterns, 46, 2022, 119279.	Ref-21
https://doi.org/10.1016/j.gep.2022.119279	doi
Tripuraribhatla, R.,	Au

Task.:	Predict freshness	Species	Horse mackerel (Trachurus japonicus) during the 90-day frozen storage
Methods	✍ ANN ✍ Extreme gradient boosting ✍ Random forest regression ✍ Support vector regression	Methods.Type	Machine learning algorithms
Probes	o Electronic nose (E-nose) o Electronic tongue (E-tongue) o Colorimeter	Data combination	Data fusion of ! E-nose, E-tongue, colorimeter
	+ Contain more information (with a total variance contribution rate of 94.734 %) compared to individual probe information		

Goodness-of-fit	+ ANN, RFR and XGBoost showed good performance in predicting biochemical indexes with the R_P^2 (the square correlation coefficient of the Test set) $\geq$ 0.929, 0.936, 0.888 - SVR models showed a bad performance (RP2 $\leq$ 0.835)

Prediction of the freshness of horse mackerel (Trachurus japonicus) using E-nose, E-tongue, and colorimeter based on biochemical indexes analyzed during frozen storage of whole fish	Ti
Food Chemistry, 402, 2023, 134325	Ref-22
https://doi.org/10.1016/j.foodchem.2022.134325	doi
Li, H., Wang, Y., Zhang, J., Li, X., Wang, J., Yi, S., Zhu, W., Xu, Y. and Li, J.,	Au