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Article

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THE USE OF ARTIFICIAL INTELLIGENCE IN STURGEON AQUACULTURE

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Abstract
This paper presents the experience and lessons learned in a pilot project aimed at integrating artificial intelligence (AI) technologies in sturgeon aquaculture. The project used convolutional neural networks and visual intelligence for the evaluation of fish biomass and the optimisation of sturgeon rearing technologies in integrated multitrophic production systems. Similar solutions have been used before to determine the biomass of other fish species, but this is the first documentation of the application of such a solution for sturgeons. The application challenges were significant, which was determined by the special morphological peculiarities of the sturgeons (shape, way of swimming, their dimensions). Both YOLACT technology and a computer vision context were tested using LAB and HSV colour spaces to estimate fish biomass based on imaging data. It was found that the LAB colour space provided superior results in terms of precision and efficiency, but maximum accuracy was achieved using convolutional neural networks (YOLACT). The analysis of the project results confirms the significant advantages of using the AI system for biomass monitoring, advantages consisting of the reduction of unit costs with labour and feed, improvement of water quality, active optimisation of sturgeon growing conditions. In this way, conditions are created for the sustainable growth of sturgeon production, both for consumption and for the restocking of various aquatic ecosystems with brood. It also proves that the large-scale implementation of AI-based technologies in the fisheries industry can make an important contribution to the achievement of Romania's National Multiannual Aquaculture Strategic Plan 2022-2030, as well as to the implementation of the European Union's strategies on food security and biodiversity.

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JEL classification: Q22, Q01, O31

Introduction

In the context of the need for fish farms to ensure the medium- and long-term sustainable development of fishing and aquaculture in Romania, increasing the sustainability of production systems is absolutely necessary. Thus, aquaculture production systems fulfil a dual role in achieving the aforementioned goal, providing fish production for human consumption while actively contributing to the activities of populating and repopulating natural fish habitats. It is well known that production systems and technological facilities in aquaculture are classified according to a multitude of technical, technological, and ecological criteria. Among the various types of production systems, recirculating aquaculture systems offer the possibility of rigorous control of the technological process throughout the entire production cycle, with the aim of ensuring optimal growth conditions for various fish species. Consequently, considering the current concerns regarding the diversification and intensification of aquaculture technologies, as well as those related to the restoration of bio resources in natural aquatic ecosystems, significant investments are required to implement complex recirculating production systems. The high cost of fish produced in recirculating systems poses numerous technical and financial problems that must be addressed to ensure their competitiveness.

The present study aims to present how artificial intelligence-based techniques can be successfully used to increase fish biomass, with the goal of maximising profitability and supporting the sustainability of intensive sturgeon aquaculture. Thus, the main objective of the study is to integrate AI technologies into industrial sturgeon fishery systems to maximise profitability by reducing operational effort and increasing efficiency in fish feed utilisation through the optimisation of sturgeon feeding processes while maintaining production performance, thereby reducing operational costs by eliminating unconsumed feed quantities.

The paper demonstrates how technical improvements can be made to sturgeon recirculating systems by synergistically integrating AI-based imaging modules into an existing aquaponic system within a Romanian company specialising in this field. The aim of this integration is to estimate the real-time growth performance of the fish biomass involved in the production process, including a data acquisition and feed control module. This estimation contributes decisively to optimising nutrient utilisation in intensive aquaculture. Thus, the prototype intelligent system based on imaging data and convolutional networks implemented within the organisation can optimise fish biomass production, ensuring increased production, improved economic efficiency, and sustainability of sturgeon aquaculture industry. Maximising profitability, along with improving the sustainability of sturgeon aquaculture by connecting it to the ecosystem services system through the use of intelligent technologies, justifies such a study, which contributes to further aligning technological progress in Romania with the requirements of the national and international socioeconomic environment.

Thus, the use of artificial intelligence technologies, based on convolutional neural networks, within recirculating aquaculture industrial systems allows for the development of modern systems that can assess the growth performance of fish biomass in real time (total length of fish for biomass calculation), accurately regulate the amount of feed administered, and provide ecosystem services to support restocking actions of aquatic ecosystems with sustainably obtained sturgeon fry, limiting feed losses and the discharge of nutrients resulting from the decomposition of unconsumed feed into natural ecosystems.

From an economic standpoint, the IT solution presented in this paper contributes to the bioeconomic stimulation of the fishing sector in Romania by improving sustainability (involvement in restocking programmes and limiting nutrient discharge from the decomposition of unconsumed feed) and profitability of recirculating aquaculture systems, integrating an engineering approach based on multitrophic production techniques and technologies supported by intelligent visual recognition and Internet of Things (IoT) tools. In the context where sturgeons, a highly valuable fish species economically, grow and reproduce naturally in the Lower Danube, the only area in the European Union with this quality, the importance of conserving stocks of these species becomes paramount. By adopting a holistic and socially responsible approach, the fishery industry can contribute to creating a sustainable balance between economic, social, and environmental needs (Cristache et al., 2019). Consequently, recirculating aquaculture systems meet the requirements for the growth of various sturgeon species, particularly in the early development stages. Finding means to increase technological maturity, involving the growth of sturgeons within recirculating aquaculture systems, combined with the implementation of intelligent technical solutions aiming to maximise the profitability of the respective fish farms while maintaining or improving sustainability, are essential goals for transitioning from a blue economy to a green one, according to the European Green Deal.

1. State-of-the-art

The objectives of this work are in line with the "National Multi-Annual Strategic Plan for Aquaculture 2022 – 2030", which, through objective 2 - Participation in the green transition - specific objective 2.1. environmental performance - aims to modernise traditional aquaculture units by promoting integrated, innovative multitrophic technologies. This objective was also present in action 2 of the previous strategy ("National Strategy for the Fisheries Sector 2014 – 2020"), which encourages the stimulation of sustainable aquaculture in a competitive, innovative, knowledge-based manner that protects the environment and efficiently uses resources. The strategic plan for 2022-2030 emphasises that modern aquaculture is an essential subdomain for the sustainable development of the fisheries sector, which is why specific activities carried out in the traditional system must undergo a process of technical and technological modernisation through investments and innovation, as well as through more efficient management of material resources. Thus, sustainable aquaculture and biodiversity conservation are imperative, especially in the area of sturgeon stocks, linking their existence in the natural environment with the contribution of aquaculture, particularly through the implementation of programs supporting/restocking natural aquatic ecosystems.

Modern aquaculture is an essential subdomain for the sustainable development of the fisheries sector, which is why specific activities carried out in the traditional and archaic system must undergo a process of technical and technological modernisation through investments and innovation, and more efficient management of material resources. In this context, integrated multitrophic systems represent an optimal solution to ensure the sustainability and profitability of the intensive aquaculture industry. The integration of these technologies can not only contribute to increasing profitability, but also to the responsible management of resources and the environment (Gruia et al., 2020; Țarțavulea et al., 2020).

The National Multi-Annual Strategic Plan for Aquaculture 2022 - 2030 aims to increase the ability of fish farms to improve water quality and contribute, through nutrient recycling, to the circular economy, thereby becoming a net provider of environmental services to society. The national strategy for sustainable development within the aforementioned strategic plan aims to create a competitive and sustainable food industry, considered a key foundation for accelerating economic growth and achieving the multiple sustainable development goals outlined in the Agenda 2030. In this regard, in line with the EU Industrial Policy Strategy, support is required for strengthening value chains (Roja et al., 2012; Cristache et al., 2021), implementing the most advanced technologies, and promoting circular and competitive economies associated with recirculating systems that use multitrophic production technologies and techniques. The concept of multitrophic aquaculture is also associated with point 3.1.1.7 within the aforementioned strategic plan, which encourages diversification of production and the creation of added value at the level of existing fish farms.

Thus, in the context of the recommendations from the "National Multi-Annual Strategic Plan for Aquaculture 2022 – 2030" aiming to increase the profitability of aquaculture operators by expanding activities into complementary domains and the necessity of enhancing aquaculture sustainability, the intelligent technological solution presented in this paper offers a financially accessible solution, utilising new, interdisciplinary approaches in current international research. Multiple studies attest to the contribution of integrating aquaponic techniques into aquaculture systems in terms of maximisation of profitability and profitability (Bosma et al., 2017). To date, researchers (Petrea et al., 2016) have conducted a cost-benefit analysis of several intensive multitrophic technologies, using various combinations of fish-plant species, such as rainbow trout - spinach, perch - spinach, perch - basil, perch - mint, and perch - tarragon. They concluded the usefulness of integrating aquaponic techniques to maximise the profitability of the existing sturgeon recirculating system and recommended further studies to develop solutions to minimise or better utilising nutrients from intensive aquaculture.

In another study, Engle (2015) highlights the increase in fish farm profitability through the integration of aquaponic growth technologies for tomatoes, lettuce, and basil, recommending the latter plant species for economic reasons. From the same perspective, Xie and Rosentrater (2015) studied the economic and sustainability aspects of basil biomass growth in aquaponic systems, recommending this species for cultivation within multitrophic systems based on aquaponic production techniques.

To increase profitability, reducing investment costs regarding the realisation and implementation of the aquaponic module is absolutely necessary (Geambașu et al., 2011). To achieve the desired level of sustainability and profitability, multitrophic aquaculture systems based on aquaponic techniques require optimisation of both growth technologies (for fish and plant biomass). Therefore, the present work proposes the use of visual intelligence techniques for real-time determination of sturgeon biomass growth, aiming to optimise the quantity of feed administered during the production cycle.

Studies using similar technologies have been conducted by Mathiassen et al. (2011) for automating the grading and sorting process of fish material, using computer vision techniques based on VIS/NIR spectroscopy, computed tomography (CT), X-rays, and MRI (magnetic resonance imaging). Additionally, Zion (2012) highlights the use of imaging techniques for fish counting within a system developed by AquaScan AS, Norway. Hufschmied et al. (2011) used a transit tunnel positioned outside the growth unit to determine fish biomass based on length-weight regressions. Odone et al. (2001) designed a device shaped like a transparent tube used for transferring fish biomass to other growth units, equipped with an automated device for evaluating the shape of specimens based on machine learning algorithms (SVM - Support Vector Machines) that can learn the relationship between fish weight and shape.

Hao et al. (2016) designed a visual identification system for transporting fish material using conveyor belts, consisting of sonars, cameras, and algorithms based on convolutional neural networks (R-CNN) for precise identification of specimen length. Furthermore, Álvarez-Ellacuría et al. (2020), using intelligent technologies based on deep learning, specifically the Mask R-CNN neural model, highlights that the dynamics of fish length distribution are a key element for understanding fish population dynamics and making informed decisions regarding exploited stock management.

Although new technologies now make it possible to change the way aquaculture biomass is determined, in most fisheries, the measurement of fish length is still done manually. As a result, length estimation is accurate at the individual fish level, but due to the inherently high costs of manual sampling, the sample size tends to be small. Consequently, the precision of population-level estimates is often suboptimal and prone to errors when appropriate stratified sampling programmes are not accessible.

Recent applications of artificial intelligence in fisheries science open up a promising opportunity for massive sampling of fish catches. For example, Yu et al. (2023) emphasise that precise measurement of fish size in spawning areas is crucial for the fishing industry. Unlike acoustic methods, which involve high equipment costs and low measurement accuracy, current imaging-based methods offer promising alternatives. In this regard, the authors have introduced an automated method for measuring fish size based on key point detection using convolutional neural networks (DLAT neural network transformed into a prototype network CenterFishNet). The rapid emergence of deep learning technology has been analysed in Yang et al. (2021), where the authors successfully demonstrated its use in the fishing industry for live fish identification, species classification, behavioural analysis, feeding decisions, size or biomass estimation, and water quality prediction using simple convolutional networks and recurrent neural networks.

The development and implementation of AI technologies should be guided by ethical and human principles. The global community must collaborate to establish standards and rules to ensure responsible AI development, taking into account its impact on individuals and society as a whole (Vrabie, 2022, 2023; Petrariu et al., 2023).

Thus, building on a level of technological maturity associated with the use of intelligent digital imaging techniques, validated in various experimental studies aimed at developing an assisted optimisation system in the fishing domain (Abinaya et al., 2022; Duhayyim et al., 2022; Muñoz-Benavent et al., 2022), the present study puts into practice, at a micro-production level, a new integrated imaging technology capable of adding value to existing aquaculture recirculation systems.

2. Materials and methods

2.1. General experimental framework

The experimental part of the present study was conducted within a system of intensive microproduction of sturgeons, located in the southern development region of Romania. A physical upgrade was integrated into the existing system to capture image data with high fidelity. This involved the use of Intel Real-Sense 455 cameras and Raspberry-Pi microcontrollers for data storage and transmission, as well as the delineation of an imaging study area at each sturgeon growth unit.

2.2. Techniques used for image content processing

The prototype of the intelligent system developed for real-time measurement of aquaculture biomass utilises two computational approaches, namely: a) Deep Learning techniques (specific to the field of Artificial Intelligence), b) Computer Vision. Within the Computer Vision category, colour spaces were explored to create object masks as presented in (Lu et al., 2022). Thus, a series of colour spaces (RGB, HSV, LAB, CMYK, YCrCb, XYZ) were identified, these being the most commonly used in image processing systems (Figure no. 1). The specific channels of each colour space were analysed, and ultimately only the processes that aid in mask extraction were retained. Among the previously mentioned colour spaces, two provided acceptable results: a) the HSV space presented in Hamuda et al. (2017), an approach involving the extraction of all pixels from the image that fall within a range of values (Figure no. 1), and b) the LAB colour space presented in Umam et al. (2020) and Kang et al. (2021), from which the L (Length) dimension of the fish was extracted (El Abbadi and Saleem, 2020).

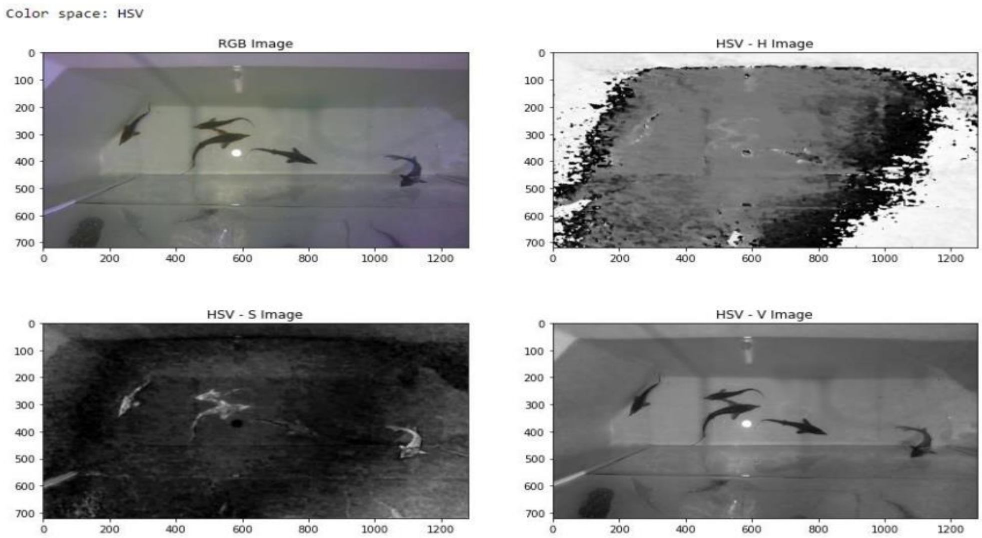


Figure no. 1. Example of image analysis using HSV color space

Deep learning, also known as structured deep learning or hierarchical learning, is part of a family of machine learning methods based on artificial neural networks (Janiesch et al., 2021). In the context of the intelligent system for automatic quantification of aquaculture biomass, deep learning provides the main models for computational inference. Learning can be supervised (applied in this study), semi-supervised, or unsupervised. Deep learning models are applied in a multitude of domains, such as image recognition, speech recognition, natural language processing, audio recognition, social network filtering, automatic translation, bioinformatics, drug design, medical image analysis, material inspection, and entertainment, achieving comparable and, in some cases, superior results to human experts (Ganaie et al., 2022). Deep learning is based on neural networks, flexible and complex systems that extract patterns from input data to subsequently recognise different objects or make numerical predictions. The concept of a neural network is similar to the human brain, with such networks designed on a similar structure. The network can be viewed as an ensemble of interconnected neurons, similar to a directed graph structure, and training such a learning model to identify new objects often requires a significant volume of data and computing resources.

Transfer learning is a concept in the field of artificial intelligence that is used in machine learning and neural networks. This approach involves taking a model that has been trained for a specific task and adapting or fine-tuning it to perform a different or similar task (Lauguico et al., 2020). Therefore, transfer learning is a deep learning technique in which a previously developed neural network is trained for a new task when training a neural network to recognise certain objects, but there are no algorithms available for such a task. In such situations, neural networks trained to recognise similar objects can be considered and later trained to recognise the specific object. As an approach, the last layer called the “loss output” layer, which is the final layer making predictions, is removed. This layer will be replaced by a new output layer that will identify the new class. Then, the annotated dataset is introduced, and the network is recalibrated to identify the desired class. This technique is not only intended for image recognition, but also for speech recognition or sound recognition, as well as for use in other types of neural networks such as recurrent neural networks (RNNs) (Zhuang et al., 2021). The main advantages of using transfer learning, compared to training a neural network from scratch, include significantly reducing training time and the ability to use deep learning models when the data volume is not large.

PyTorch is an open-source machine learning library developed by Meta AI Research Lab, which provides flexibility and superior speeds in developing neural network-based models, thanks to its intuitive interface and extensive support for Python. The library contains a rich set of tools and libraries, such as Torchvision for image processing, Torchaudio for sound, and Torchtext for natural language processing. It integrates with the NumPy library, allowing for easy manipulation of numerical data, and is compatible with CUDA, enabling fast training of models on graphics processing units (GPUs), which is essential for working with large datasets, such as deep learning models (Novac et al., 2022).

The development of the prototype intelligent system applicable in the fishing industry involved the use of MMDetection, an object detection library based on PyTorch, which provides an efficient and flexible platform for the rapid implementation and testing of a wide range of state-of-the-art object detection models (Wang et al., 2021). MMDetection is an open-source toolbox for both academic research and industrial applications based on PyTorch. It is provided by OpenMMLab and can cover a wide range of computer vision research topics, such as classification, object detection, segmentation, and image super-resolution. In the context of the current project, MMDetection was useful due to its support for multiple network architectures (RCNN, Mask RCNN, RetinaNet, etc.) and the efficiency of GPU utilisation in bbox (bounding box) or mask detection tasks. Thus, the training speed of AI inference models was superior to other inference modules such as Detectron2, maskrcnn-benchmark, and SimpleDet, whose characteristics are presented in Chen et al. (2019). From the MMDetection toolkit, the YOLACT algorithm was selected and used based on the specifications of the intelligent system to measure aquaculture biomass. The YOLACT algorithm performs instance segmentation and returns the bounding box and mask of the detected objects in an image (Figure no. 2).

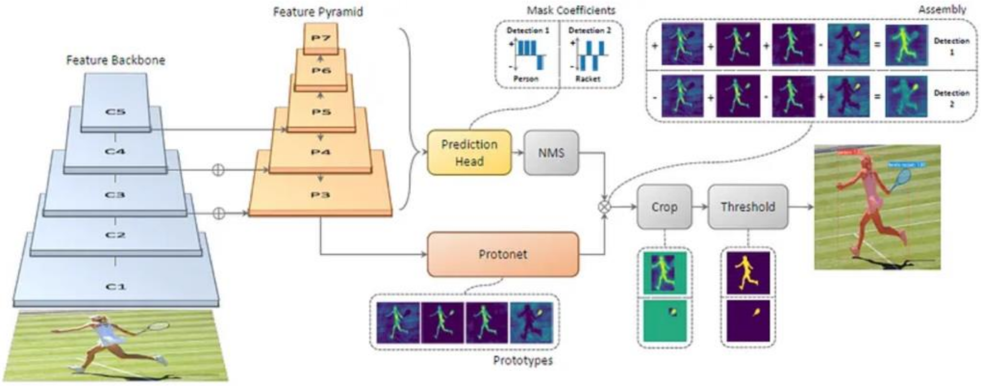


Figure no. 2. YOLACT architecture

Source: Bolya et al., 2021

Building upon the YOLACT model as the basis for implementing the AI inference module of the proposed system, an extension was made based on the concepts presented in Bolya et al. (2021), dividing the complex task of instance segmentation (images) into two simpler, parallel tasks, whose results can be assembled to form the final masks (Figure no. 3).

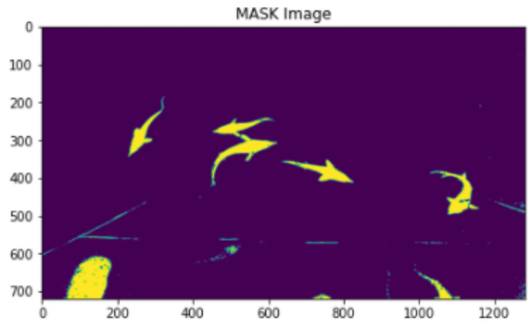


Figure no. 3. YOLACT final mask

Taking into account the specifications of the YOLACT networks presented in Bolya et al. (2022), the YOLACT network used in the development of the proposed intelligent system consists of the following components:

- Prototype Generation: The protonet branch provides the ability to predict a set of k prototype masks for the entire image.

- Mask Coefficients: The object detection branch is anchor-based and is used to predict the class confidence and 4 regression boxes.
- Mask Assembly: This component combines mask prototypes and coefficients using three types of loss functions: classification loss (Lcls), box regression loss (Lbox), and mask loss (Lmask).
- Cropping Masks: This component crops the masks using bounding boxes.

The results obtained from using the YOLACT model in the current project are presented in Table no. 1, demonstrating that the YOLACT model can be successfully used in the development of industrial systems for fish feature detection. The main motivation is represented by the processing time - accuracy tuple values compared to other tested algorithms, with this balance between accuracy and speed being important in real-time processing software applications.

Table no. 1. YOLACT results

Method	Backbone	FPS	Time (ms)	AP	APso	AP75	APS	APM	APL
PA – Net	R - 50 - FPN	4.7	212.8	36.6	58	39.3	16.3	38.1	53.1
RetinaMask	R - 101 - FPN	6	166.7	34.7	55.4	36.9	14.3	36.7	50.5
FCIS	R - 101 - C5	6.6	151.5	29.5	51.5	30.2	8	31	49.7
Mask R – CNN	R - 101 - FPN	8.6	116.3	35.7	58	37.8	15.5	38.1	52.4
MS R - CNN	R - 101 - FPN	8.6	116.3	38.3	58.8	41.5	17.8	40.4	54.4
YOLACT - 550	R - 101 - FPN	33.5	29.8	29.8	48.5	31.2	9.9	31.3	47.7
YOLACT - 400	R - 101 - FPN	45.3	22.1	24.9	42	25.4	5	25.3	45
YOLACT - 550	R - 50 - FPN	45	22.2	28.2	46.6	29.2	9.2	29.3	44.8
YOLACT - 550	D - 53 - FPN	40.7	24.6	28.7	46.8	30	9.5	29.6	45.5
YOLACT - 700	R - 101 - FPN	23.4	42.7	31.2	50.6	32.8	12.1	33.3	47.1

The image content database for sturgeon biomass required by artificial intelligence models was created by collecting images for a period of 1 month from the existing fish farming units within the recirculating aquaculture system of the profile company where the study was conducted. To create the dataset with sturgeon images, approximately 1,000 images were obtained daily from each basin, along with depth information. Initially (during the first two weeks), the photographs were collected both during the observation light period and during the growth light period, after which the collection was carried out only during the observation light period.

3. Results and discussions

The main outcome of the current study is the development, within a Romanian company specialising in fish farming, of an automated fish biomass calculation system using artificial intelligence and computer technologies. Based on the various solutions presented in the Literature Review section, the technologies and methods that provided the best results in the given organisational context were identified and aggregated into a prototype intelligent system developed within the Romanian company's domain. The solution presented herein can be adapted and implemented in other companies in the same field, with the Transfer Learning technique described in the Materials and Methods section allowing for incremental development through the integration of new fish species.

Thus, figure no. 4 illustrates the architecture of the data acquisition system for fish biomass. As can be seen, this system consists of two components:

- a mechanical structure based on two components, namely a septum (element 2 in Figure no. 4) and a tunnel (element 1 in Figure no. 4). These components are located within the fish rearing unit, they are movable, and their position can be changed depending on the behaviour of the fish biomass. Their role is to assist in the accurate acquisition of data for fish biomass.
- the second component of this system is represented by the automatic data acquisition system consisting of cameras (CF) for acquiring photographs of fish biomass and ultrasonic sonars (SU) for detecting the presence of fish in the septum and tunnel area.

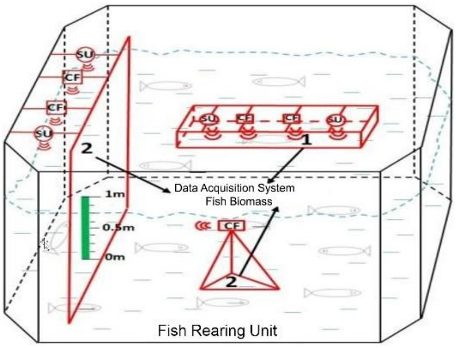


Figure no. 4. Architecture of the data acquisition system for fish biomass

The two components presented earlier and represented in figure no. 4 implement the following functionality: when a fish is present in the septum or tunnel areas, the ultrasonic sonar (SU) detects this, and the information is transmitted to the Raspberry-Pi microcontroller, which commands the cameras for image acquisition (figure no. 5).

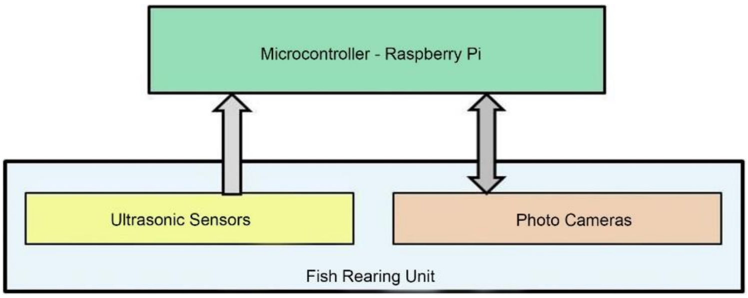


Figure no. 5. Fish Biomass Data Acquisition System

These images, through the Raspberry-Pi microcontroller, were transmitted to the AI processing and analysis modules for fish biomass, in order to determine a growth index. The cameras and ultrasonic sensors have the necessary mobility, along with the mechanical system, to obtain the best data acquisitions. It should also be mentioned that data acquisition was performed both underwater, as seen with the CF mounted on tunnel 1 and the tripod-mounted camera on 2, from figure no. 4, as well as from the water's surface, with cameras mounted above the fish farming unit between a wall of the fish farming unit and the septum wall. The motivation for implementing this architecture was to acquire the best image data on fish biomass, which, following AI inferences, could provide a growth index for aquaculture biomass as close to reality as possible. The calculation of the fish surface index was based on identifying each sturgeon specimen appearing in the region of interest in the basin (the basin wall and plexiglass). The formula for calculating the growth index took into account the pixel area of each sturgeon specimen correlated with the average distance to the fish, and the distance was being identified using an Intel RealSense camera. Thus, the first step in calculating the fish surface index was identifying each sturgeon in the image, a step performed using the YOLACT algorithm from the MMDetection framework. The network was trained for 600 epochs using transfer learning on a pre-trained network publicly provided by the PyTorch Python library. Following the training of the neural network on an annotated dataset (Figure no. 6), as seen in Figure no. 7, the YOLACT method segmented the supplied images, providing bounding boxes around the fish mass, with the results of fish identification being accurate.

Figure no. 6. Annotation of sturgeon images using the LabelMe software tool

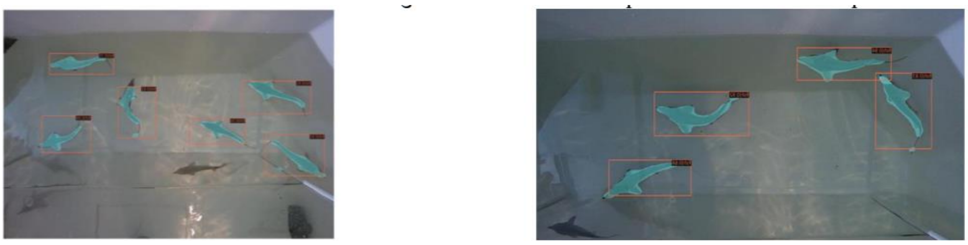
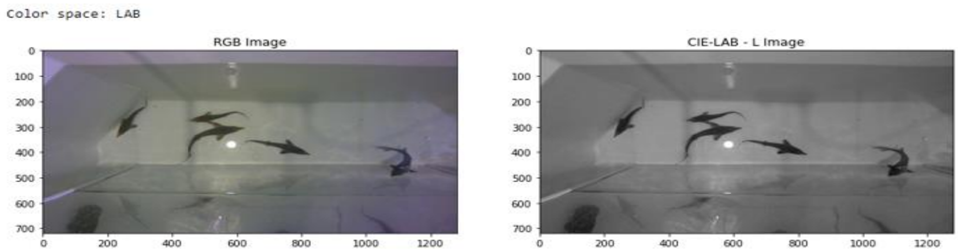


Figure no. 7. Bounding boxes and masks at the level of sturgeon biomass using the transfer learning method

The second step in calculating the fish surface index involved creating a mask for each individual fish. Thus, the calculation of a fish's surface uses the mask of each specimen in the image, both masks obtained using neural networks and those obtained using the LAB colour space (L dimension) (Figure no. 8).



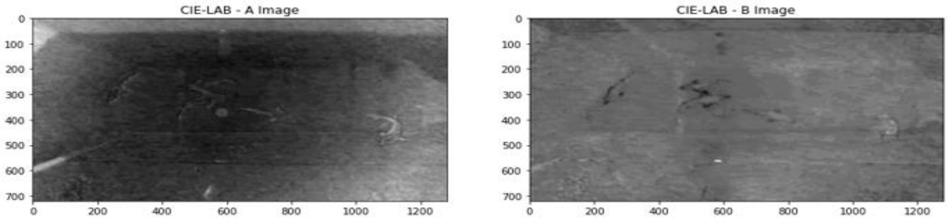


Figure no. 8. Analysis of the LAB colour space

As can be observed in figure no. 9, the colour space method aided in extracting a mask containing all objects in the image, similar to semantic segmentation methods (Figure no. 3). The main inconvenience in using this method was the possibility of noise appearing in the image, noise originating from factors such as brightness, reflection, or objects of similar colour.

Figure no. 9. Mask obtained using the LAB colour space

The representation of the masks (Figure no. 9) also involved the appearance of some image noise elements. To remove these, only the region where the fish is located was selected from each image, a region selected using the coordinates provided by the neural network. The formula to calculate the surface index of the sturgeon material was based on extracting the mask from each detected specimen and counting the pixels that appear in that mask. Using the depth information provided by the Intel RealSense camera and the obtained mask, a Bitwise AND operation was performed, and based on the depth information inside the mask, the average distance to the fish was extracted. The result of this operation is a surface index for each fish (Table no. 2).

Table no. 2. Surface Index of sturgeon exemplars

Date	Rearing unit			
	LAB		NN	
	Exemplars	AVG	Exemplars	AVG
2023.08.06	4552	5695.32	4552	4799.96
2023.08.17	3218	4066.09	3220	4570.89
2023.08.24	3700	4425.39	3699	5129.96
2023.08.31	3144	4712.21	3144	5465.89

The results obtained from using the prototype model to measure fish biomass were validated within the organisation, with the sturgeon biomass corresponding to the growth unit for which the surface index was calculated using LAB and NN (neural networks) techniques showing the following growth dynamics, identified through in situ weightings: 599g on 06.08.2023; 874g on 17.08.2023; 1043g on 24.08.2023; 1134g on 31.08.2023. Therefore, the following growth percentages were identified: 45.90%; 19.34%; 8.72%. It was observed that the index calculated through LAB and NN exhibited a negative trend in the first part of the experimental period (06-17.08.2023). This indicated both the need for calibration of the imaging system and the requirement for accommodating the sturgeon material to the new conditions within the growth unit, resulting from the positioning of the septum wall.

The sturgeon specimens needed to get accustomed to the presence of the separating wall and its traversal method, made possible by administering feed along the entire length of the delimited surface. Taking into account the periods 17-24.08.2023 and 24-31.08.2023, it was concluded that the sturgeon biomass surface index increased by 8.83% and 6.48%, respectively, using the LAB method, and by 12.23% and 6.54% using the NN method. The NN method proved to be the most accurate in this context, with the linear model for determining the biomass increase for the period 17-24.08.2023 being $y = x + 7.11$, where y is the corrected surface index and x is the real surface index. Similarly, for the period 24-31.08.2023, we have $y = x + 2.18$. The linear correction models in the case of LAB become $y = x + 10.51$ for the period 17-24.08.2023 and $y = x + 2.26$ for the same period. From an economic standpoint, the economic agent allocated an investment cost of 130.95 euros per sturgeon growth unit (9 kg of biological material per unit). However, the reduction in operational costs (feed costs, water exchange, and human resources) resulted in an investment return of 3.2%. Additionally, the development of the economic agent's capacity to offer ecosystem services should be considered. Consequently, the water quality improved (with a decrease of 12.4% in NH_4, 10.3% in NO_2, and 9.8% in NO_3 in the effluent, attributed to the reduction of feed losses), and the growth performance of fingerlings suitable for stocking programs increased (with an 18.3% increase in the administered feed conversion rate). Therefore, the tested imaging system managed to add value to intensive sturgeon aquaculture by reducing the amount of unconsumed feed and achieving superior utilisation of the administered feed, eliminating the need for classic biomass evaluation methods (physical manipulation-based weighing), activities that are frequently required in aquaculture due to the direct, proportional relationship between existing fish biomass and feeding rate (calculated as a percentage of the total fish biomass), improving production performance due to water quality enhancement (better water quality ensures better growth conditions for sturgeon), reducing water treatment costs, improving effluent quality and increasing the capacity to supply sturgeon fingerlings to the market, adaptable for use in restocking programmes.

Similar to other studies, the current study has limitations - among them is the lack of application of the study in macro-production systems. It is well-known that transitioning from micro-production systems to macro-production systems in bioeconomy can lead to considerable variations in indicators. Therefore, for future studies, it is recommended to test the scalability of the technology to replicate it in farms with different production capacities, in order to identify its elasticity in various industrial scenarios.

Conclusions

The involvement of artificial intelligence in the aquaculture sector implies sustained innovation activity that contributes to the economic sustainability of companies in the field. The use of artificial intelligence in the fish farming industry allows the optimisation of various biotechnologies or biotechnological sequences, efficient use of resources, especially those with limiting characteristics, reduction of operational costs, minimisation of environmental impact, increased fish biomass in accordance with European animal protection legislation, and efficient monitoring of inputs and outputs associated with the technological cycle.

The solution analysed in this paper is innovative, merging current intelligent technologies described in various profile studies into a prototype system. The innovation is also highlighted by the technical design of the imaging database sampling method (the creation of a septum parallel to the walls of the growth unit, transparent, which ensures the limitation of the overlap of sturgeon specimens within the imaging frames, as well as the variability of the specimens that are immortalised with the help of images), thus achieving a homogeneous distribution of them within the flow of images taken into account in the training and validation of the models developed using deep learning techniques.

The presented case study justifies and highlights how such a system can optimise feed usage (the most substantial component of fish farm operating costs), under the conditions of increased productivity performance of the system.

It is well-known that feeding in animal husbandry, especially in aquaculture, is based on optimal reporting of the administered quantity to the biomass of the biological material (in the current study, sturgeon biomass). Thus, real-time growth of sturgeon biomass requires adjusting the amount of feed to maintain a high production rate. Misalignment of these two essential components, namely the growth rate of sturgeons and the rate of administered feed growth, generates major dysfunctions in the production cycle. This negatively affects water quality, sturgeon growth rate, their well-being, susceptibility to diseases, feed costs, and consequently, reduces the economic sustainability of sturgeon aquaculture activities.

In a multitrophic integrated system, environmentally friendly, these dysfunctions will also affect plant biomass due to excess ammonia or nitrates, causing loss in it, food safety issues, and improving the efficiency of the technological water phytoremediation process. The prototype system presented integrates artificial intelligence techniques (deep learning) into multitrophic systems, automating real-time monitoring and control of feeding and sturgeon growth, respecting the environmental requirements (water quality) imposed by sturgeons.

Thus, it is concluded that the use of artificial intelligence techniques in the fish farming industry has a major socioeconomic impact. This is reflected, first of all, in the increase in fish biomass quality, as a result of improving water quality through the application of AI technologies that limit the quantity of unconsumed feed, feed that undergoes a degradation process that negatively affects water quality and the environmental sustainability of intensive fish farming systems. Second, the socioeconomic impact is reflected in the increase in economic sustainability of fish farming systems, as a result of optimising the feed administration rate and the quantity of administered feed, fish feed being a major cost element in aquaculture. Improving water quality, as a result of optimising the mode of administration and the quantity of feed administered, directly leads to ensuring food safety of products intended for human consumption. Fish will accumulate fewer nitrites and nitrates in their muscle tissue and, last but not least, ethical requirements related to the growth of biological material will be met. Like the majority of artificial intelligence technology-based contexts, this technology also presents a series of risks. However, both the occurrence rate associated with them, and the impact generated by their occurrence are reduced. Risks such as technical failures or risks associated with inappropriate fish behaviour associated with feed consumption can be countered in real-time, as the system consists of individual components that are easy to replace. Also, inappropriate fish behaviour (fish not consuming feed) can be an indicator of health status - thus, this risk can have a positive component integrated, as it can be used as an alert system (if unconsumed feed is observed) for a possible pathological problem existing at the level of the biological material. A possible barrier to adopting the system could be the additional cost generated by the initial investment associated with its integration at the fish farm level. However, the proposed solution has a low cost compared to the economic benefits it can provide over a production cycle, which is even more important in the case of sturgeons, a species with a long production cycle (minimum of 8 years) until obtaining the key product - caviar.

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