FishWise AI

Tackling Fish Mortality, Pursuing Sustainability

IN COLLABORATION WITH

Final Report

Team 3 Meitner

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Executive Summary

A silent problem plagues the global aquaculture industry, causing up to 30% of farmed fish to die annually. This translates to over $70 billion in losses and threatens the livelihoods of millions, especially in developing regions. The cause: unidentified mass fish mortalities outpacing current diagnostic capabilities.

Our collaborative ATTRACT-EU program with CERN and fundamental physics researchers pursued innovations that can be scaled to solve real-world problems. Relying on two of these ATTRACT-EU technologies, our team proposes a solution to this massive unsolved problem in the aquaculture industry globally, which is hindering productivity and sustainability, particularly for small-medium scale farmers in the developing world.

We reveal our solution, FishWise AI - an integrated precision platform combining underwater AI behavioral monitoring, automated microscopy scanning surface abnormalities, and on-site hyperspectral imaging to rapidly confirm the presence of disease. The system identifies evolving risks pre-symptomatically, isolates subjects exhibiting concerning indicators for validation while guiding recommended care regimens for targeted interventions minimizing antimicrobial needs.
Economic viability assessments indicate initial subscription pricing tethered to inventory planning costs offer farmers attractive propositions given estimated mortality reductions possible. We detail a modular rollout strategy easing assimilation while still delivering standalone surveillance utility immediately through retrofit integrations before adding advanced diagnostics increments.

FishWise AI, our conceptual solution detailed here, integrates an intelligent platform combining continuous underwater monitoring, automated isolation mechanisms and multimodal diagnostics advancing early, precise disease detection minimizing required interventions. We model hypothetical service pricing demonstrating viability for small-medium sized aquaculture operators. The impact of FishWise AI solution to promote sustainable aquaculture, which promises greater stability, advancing local prosperity goals while nourishing growing populations.

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Introduction

Aquaculture has emerged as a critical component in meeting rapidly rising global protein demand sustainably. It accounts for over 50% of all consumed seafood globally (U.S. Food & Drug Administration, 2023). Small-medium sized aquaculture farms account for about 30% percent of global production, and developing countries account for as much as 60% of all seafood production. Farmed seafood production has boomed—expected to surpass wild-sourced fish as the primary supply within the decade. However, systemic risks plague this growing aquaculture sector, the most pressing of which are sporadic, unexpected mass mortality incidents. Episodic disease outbreaks are crippling, particularly for small to medium land-based farms in the developing world, triggering economic hardship, food insecurity, and environmental damage on an immense scale during significant losses.

Emerging technology proliferation through cross-domain partnerships holds promise to curb such risks. ATTRACT-EU innovative technologies offer monumental upside for agriculture. This paper outlines a collaborative project between university students, academic facilitators, CERN–Idea Square, and physics researchers sponsored by ATTRACT-EU to conceptualize a pragmatic solution leveraging emerging detection capabilities. We employed design thinking combined with systemic and exponential considerations during the evaluation process to deeply understand stakeholder needs first. Our solution, FishWise AI, aims to make continuous monitoring and adaptive rapid diagnostics accessible to small farms most vulnerable, curbing antibiotic misuse while slashing mortality through early intervention.

Transformative positive potential propelling FishWise AI lies at the intersection of increased food production resilience, secured smallholder livelihoods, preserved environmental integrity, and technological spillovers locally. We detail this high-precision, integrated platform with end-to-end disease tracking from behavior analytics to spectral biomarker analysis, contrasted against conventional diagnostics.

Exploring the Problem

We worked on SDG 14 "Life Under Water", and started to look into different problems. The one that caught our attention was that the was high unexplained fish mortality across aquaculture farms globally due to various reasons.

A. Understanding the Challenge

Mass aquatic livestock mortality events have intensified, surprising producers with up to 30% stock devastation annually. A mix of bacterial, viral, fungal, or parasitic outbreaks proves difficult to anticipate as aquaculture density has increased. Limited monitoring makes containing outbreaks more difficult once they emerge. Losses already exceed $70 billion yearly, disproportionately sinking family-run small operations in developing countries like the Philippines that lack diagnostics access or antibiotic alternatives when issues arise. Such volatility deters agricultural livelihood pursuit despite ballooning global seafood demand, while environmental biodiversity suffers from huge contamination spikes from contaminated discharge water from aquaculture farms.

The current method for detecting sick fish is cumbersome, hence farmers accept these mass-mortality events as part of doing business.

Typical method for sick fish detection

Aqua Farmers are not able to efficiently detect sick fishes and they lose a huge part of these undiagnosed fishes as there is a huge response time of around 10 days from the day the disease is detected since a medicine is deployed. This process consists of:

1. Sample Collection:
- Obtain fish samples from the target area, such as aquaculture farms, natural water bodies, or markets.
- Ensure proper handling and storage of the fish samples to prevent contamination and degradation of antibiotic residues.

2. Sample Preparation:
- Clean and prepare the fish samples by removing scales, skin, and bones as necessary.
- Homogenize or finely grind the fish tissue to create a representative sample for analysis.

3. Extraction of Antibiotics:
- Use an appropriate solvent or extraction method to isolate antibiotics from the fish tissue. Common solvents include acetonitrile or methanol.
- Different methods, such as solid-phase extraction (SPE) or liquid-liquid extraction (LLE), can be used for this purpose.

4. Purification and Concentration:

- After extraction, the sample may undergo purification steps to remove impurities that could interfere with the analysis.
- The purified extract may be concentrated to increase the detectability of antibiotics.

5. Instrumental Analysis:

Employ analytical techniques to identify and quantify the antibiotics. Common methods include:

- High-Performance Liquid Chromatography (HPLC): Separates and quantifies antibiotics based on their chemical properties and retention times.
- Liquid Chromatography-Mass Spectrometry (LC-MS): Combines liquid chromatography with mass spectrometry for high sensitivity and specificity in detecting and quantifying antibiotics.
- Gas Chromatography-Mass Spectrometry (GC-MS): Used for certain antibiotics that are amenable to gas-phase separation.
- Enzyme-Linked Immunosorbent Assay (ELISA): A specific immunological method that uses antibodies to detect antibiotics in fish samples.

6. Calibration and Standards:

- Develop a calibration curve using known concentrations of standard antibiotic solutions to quantify the antibiotics in the fish samples accurately.

7. Data Analysis:

- Analyze the data obtained from the instrumental analysis to determine the presence and concentration of antibiotics in the fish samples.

8. Reporting and Interpretation:

- Present the results in a clear and standardized format.
- Compare the measured antibiotic levels to regulatory limits or guidelines to assess if the fish samples are safe for consumption.

10. Quality Control:

- Implement quality control measures, including the use of blanks and standards, to ensure the accuracy and reliability of the analysis.

11. Validation:

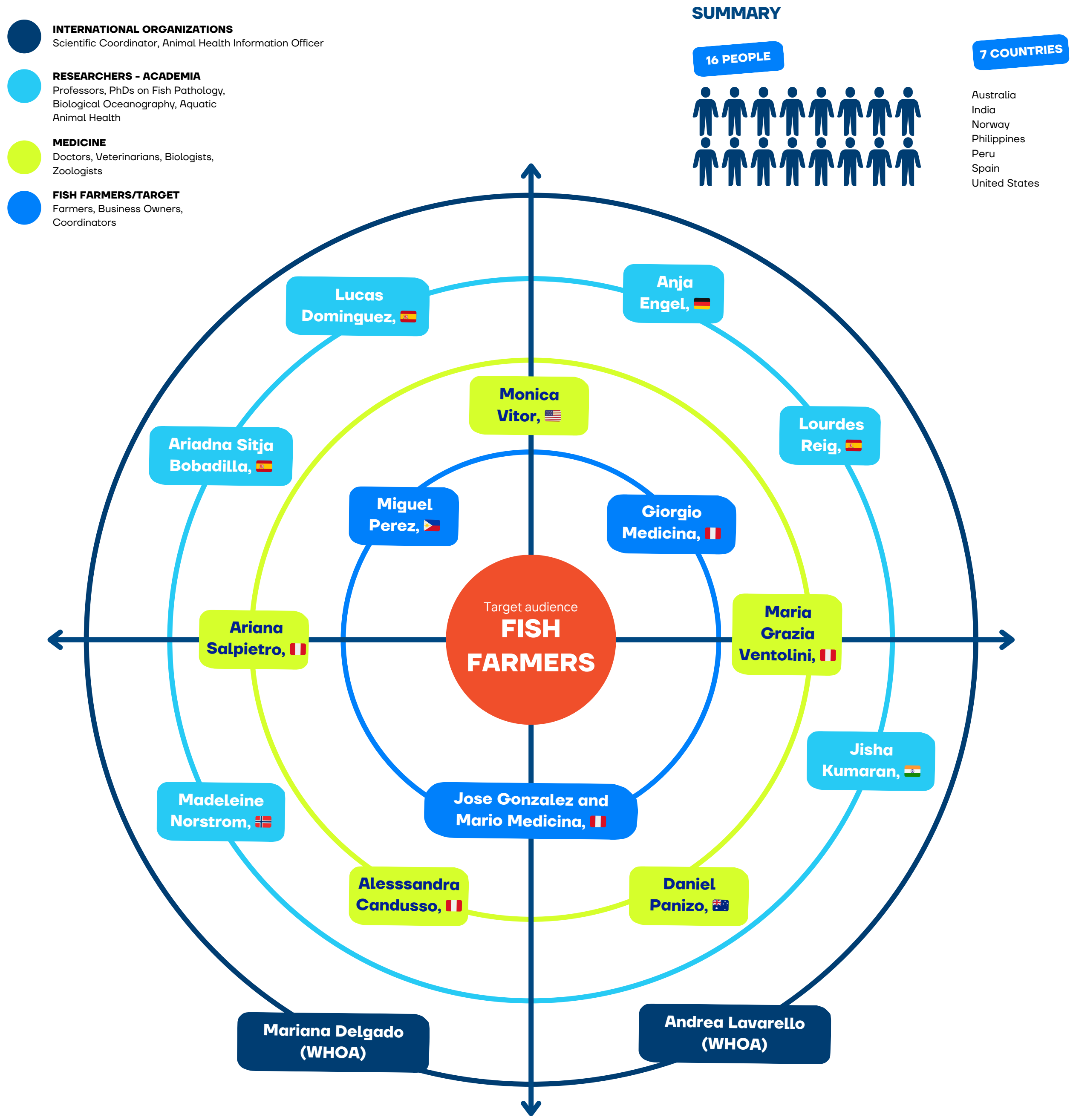
- Validate the analytical method to ensure its accuracy, precision, and reliability for detecting antibiotics in fish.

12. Interpretation of Results

B. Interview insights

Conversations with experts and various stakeholders highlighted the need for improved disease monitoring rather than antibiotics overuse, as the pressing priority now. Reduced treatment options increase outbreak prevention importance, and many interconnected farm variables constrain real-time monitoring currently. Farmers also can't determine causes of death easily without expensive off-site testing. They desired clear indicators identifiable on-location instead. Additionally, stakeholders noted opportunities to complement visual monitoring with new spectral imaging paired with an isolated examination workflow. The people and connections map shows the 9 stakeholders we interviewed during our project.

When we had done our own research through publications and papers, we wanted to speak with experts in the field as well as with aqua farmers as they are the final client of our solution. Because of this we did a people and connections map.



After many interviews, we obtained a huge amount of information and many important ideas that even determined the path of our project. These stakeholders interviews led us to focus our project in a different direction, instead of our initial inquiry into the overuse of antibiotics in the aquaculture industry. Our stakeholders interviews revealed that antibiotic overuse is not a problem as much as we initially assumed as it is highly regulated in the developed world. We were directed towards a more pressing matter in the aquaculture industry about unexplained mass-mortality of fish.

We even obtained some indicators that could be viable to differentiate sick and healthy fishes such as respiratory frequency, fin movement, fish jaw movement, irritability, color (fades with stress), fin integrity, fish length ratio (Fulton's condition factor), hemorrhages.

Another expert explained the procedure from the detection of sick fishes until the deployment of the medicine that is:

Dead fish appears -> Diagnosis -> Specific medicalized feed industry -> Deploying the medicine in the farm

C. Desk research

Industry analysis supported interview perspectives on rising small producer risk exposure amid double-digit future growth forecasts otherwise. Existing instability compounds hardships for small entities during mass mortality losses. Additionally, technology modernization has disproportionately benefited industrial operators up till now. Smaller players dealing in tight margins can struggle to adopt high-cost solutions without accessible financing. This means small farms can lag in implementing responsive measures as large-scale die-offs accelerate without contingency relief.

D. Research Tools and Frameworks

Our explorations leveraged core design thinking tenets of maintaining human needs centrality when problem finding before solutioning, structured iteration around uncertainty, and avoiding linearity assumptions by continually expanding concept scope. Additionally, we incorporated systemic perspectives linking mortality events to negative bi-directional socioeconomic consequences regionally. We also considered how new spectral diagnostics could exponentially improve outcomes if applied in a focused, phased manner despite current limitations.

E. Problem Statement

After exploratory research, we discovered a lack of field deployable diagnostics. And fish farmers wanted diagnostics that is:

- Quick
- Accessible
- Deployable
- Affordable
- Appropriate
- Accurate

After this in-depth analysis of the problem, we refined the problem statement as:

Aquaculture farmers lack field-deployable diagnostics and integrated continuous monitoring capabilities to identify sick fish early, which can lead to significant economic losses and environmental damage.

Defining a solution

A. Concept Generation

We started the visioning process exploring where current fish monitoring falls short and how farmers are impacted. This revealed key needs like speed, ease-of-use and affordability. We framed opportunity areas as "How might we..." questions, like "How might we detect sickness earlier?" and "How might we make diagnosis simpler?"

We then brainstormed ideas individually and collectively without constraints, using techniques like listing wild possibilities or mixing and matching known concepts. Some ideas included continuous robotic monitoring, training fish to self-diagnose, and instruments identifying morphological anomalies.

We refined options by modeling low-fidelity prototypes, like a diagram showing an underwater camera tracking movement feeding images to an AI. This helped visualize configurations meeting needs like automation. We calculated hypothetical impact metrics for attributes like productivity.

B. The Iterative Process

With an initial direction identified from the ideation phase, we moved into conceptual prototyping to test, refine, and advance the most promising ideas through simulation and expert feedback.

1. RGB Underwater Video Analytics: We applied machine learning models (see Appendix A) on sample footage of healthy and compromised fish to have algorithms analyze fish motions, identify outliers indicative of sickness for continuous monitoring, and flag atypical behaviors.
2. Adaptive Focus Microscopy: We presented workflow models of our non-invasive underwater early diagnosis solution to researchers behind IALL technology to determine the feasibility of our proposed applications. Our discussion with the expert researchers explored tuning focus range extension paired with automated sample scanning to screen for external parasites, e.g., sea lice present on fish skin and gills, in a non-invasive manner. We also explored technical constraints, configuration requirements, and performance capabilities in the aquaculture environment.
3. Hyperspectral Biomarker Detection: We sought feedback from the researchers of H3DVISIOnAIR on our preposition to use the unique hyperspectral signatures of sick fish tissue to distinguish pathogens and infected fish tissue from healthy ones for an on-site invasive diagnosis of sick fish. Integrated Platform Modeling: Finally, we solicited feedback from aquaculture practitioners. We constructed concept interaction flow models depicting how farmers could leverage these capabilities as an integrated platform, spanning detection through confirmation. This helped shape our assumptions around risks, constraints, and delivery mechanisms, balancing automation with human oversight elements.
4. Integrated Platform Modeling: Finally, we solicited feedback from aquaculture practitioners. We constructed concept interaction flow models depicting how farmers could leverage these capabilities as an integrated platform, spanning detection through confirmation. This helped shape our assumptions around risks, constraints, and delivery mechanisms, balancing automation with human oversight elements.

C. Conceptual Tools and Frameworks

We continued applying conceptual models to frame the solution contextually. The Impact Model Canvas proved useful for projecting hypothetical economic, jobs, and environmental impacts from mass mortality reductions if technology adoption realizes forecasted potential. This enabled approximate quantifications that underscored the proposition's attractiveness.

IMPACT MODEL CANVAS

1. Who are our key partners?

- **CERN** (access to emerging detection and imaging technologies)
- **AQUACULTURE INDUSTRY GROUPS** (critical needs insights)
- **LOCAL GVT** (on-ground facilitation)

2. What activities are vital to deliver this solution?

- R&D to optimize technologies for aquaculture
- Design user-friendly and rugged diagnostic devices
- Provide ongoing maintenance and operation support
- Aggregate data to map disease spread

3. What resources do we need to make this solution work?

- Underwater RGB cameras, IALL, and H3D VisionAir hardware
- Cloud servers and analytics software
- Logistics infrastructure and field technicians
- Industry partnerships for distribution

4. What positive impacts will we have on fish farmers and communities?

- Reduce unexpected fish die-offs
- Minimize ecological damage
- Improve productivity and livelihoods
- Develop more sustainable practices

5. What customer relationships will we aim to develop?

- Direct sales model to foster close partnerships
- Ongoing maintenance contracts
- On-the-ground technical troubleshooting
- Co-design of new features

6. How will we reach target customers with this solution?

- Aquaculture trade conferences and industry events
- Academic partnerships and field studies
- Targeted digital marketing campaigns
- Leverage distribution alliances

7. Who are the key groups we aim to impact?

- Small to medium aquaculture farms
- Local fishing communities
- Environmental advocates

8. What will be our major costs?

- R&D of detection algorithms / ML algorithms
- Manufacturing diagnostic devices
- Data infrastructure maintenance
- Field technician network

9. Where will the funding come from to enable this solution?

- Government innovation grants
- Transaction fees for disease data access
- Licensing of detection algorithms

We also leverage the Business Model Canvas to evaluate prospective revenue, cost, and distribution considerations along with projected customer ecosystem interactions. This revealed where human touch points remain essential despite pursuing automation, clarifying implementation partnership imperatives like local technician training networks.

We constructed a detailed Customer Journey Map from the lens of a small-scale farmer in the Philippines, spanning awareness, purchase, onboarding, and daily use phases. This uncovered pain points around financing, integrations with existing systems, and continuity incentives integral to positioning correctly.
Overlaying the Impact Business Model, Journey Mapping, and Iceberg Model onto technology prototyping helped us identify constraints and adoption factors we could have easily missed if we had looked at our solution in isolation.

EVENTS

- Fish mortality incidents and disease outbreaks on farms
- Shortages and price fluctuations in seafood markets – *can lead to shortages of certain types of fish in the market, which can drive up prices; e.g., the 2015 outbreak of salmon anemia in Norway, killing over 10 million salmon, led to a 20% increase in global prices.*

TRENDS/PATTERNS

- Fish mortality seems to be increasing each year; e.g., *In Scottish salmon farms alone 2002 to 2-19 quadrupled (3% - 13.5%)*
- Increased production costs and consumer prices

UNDERLYING STRUCTURES

- Knowledge gaps around emerging diseases
- Insufficient health monitoring and diagnostic capabilities leading to unchecked disease
- Fragmented disease reporting allows localized issues to go unnoticed
- Focus on short-term productivity can compromise welfare and ecology

MENTAL MODELS

- Assuming healthy-looking fish equals healthy fish populations
- Prioritizing immediate harvest productivity over long-term sustainability
- Underestimating downstream impacts of small actions
- Valuing shareholder profits over welfare or ecosystems

D. Our Solution: FishWise AI

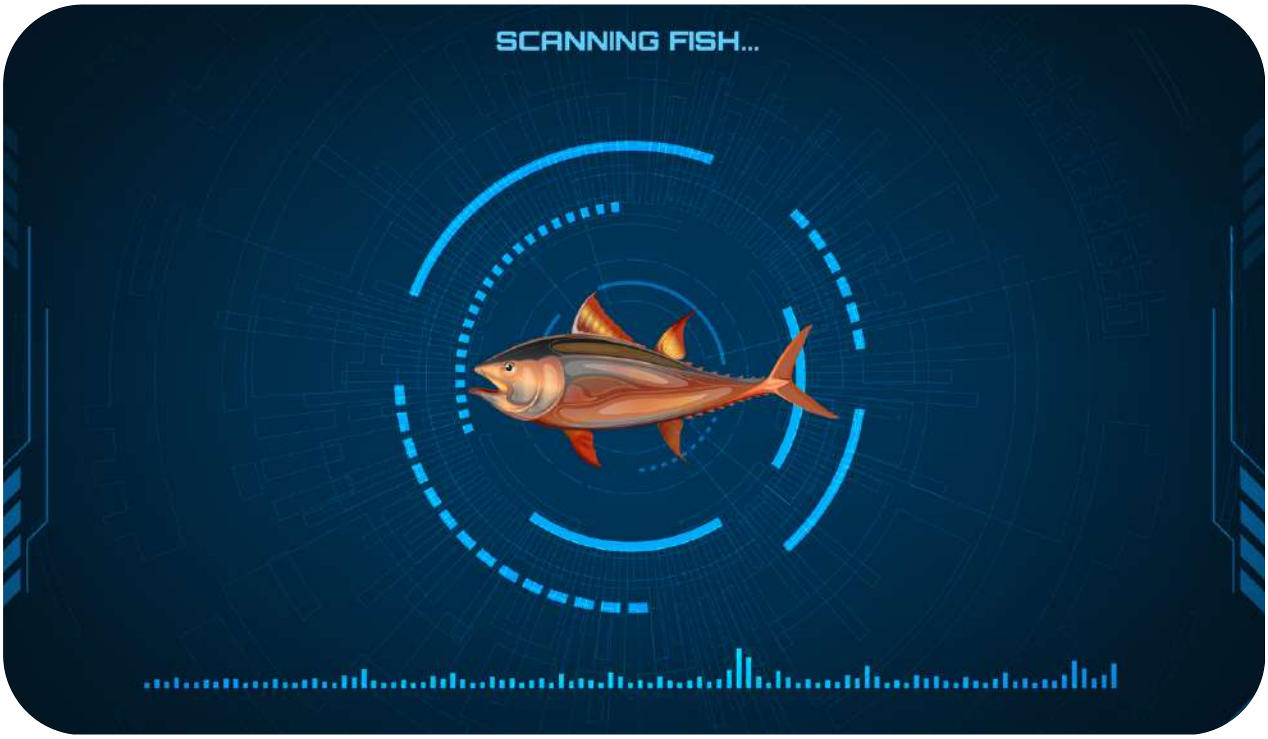
Our aquaculture solution, FishWise AI, is a continuous fish behavior monitoring system to identify early sick fish based on their movement combined with regular microscopic and spectral imaging to diagnose issues before they escalate into mass mortality events.
FishWise AI offers aquaculture farmers an integrated precision monitoring and diagnostic system combining specialized cameras, sensors, and analytical tools to mitigate losses from unexpected mass mortality incidents.

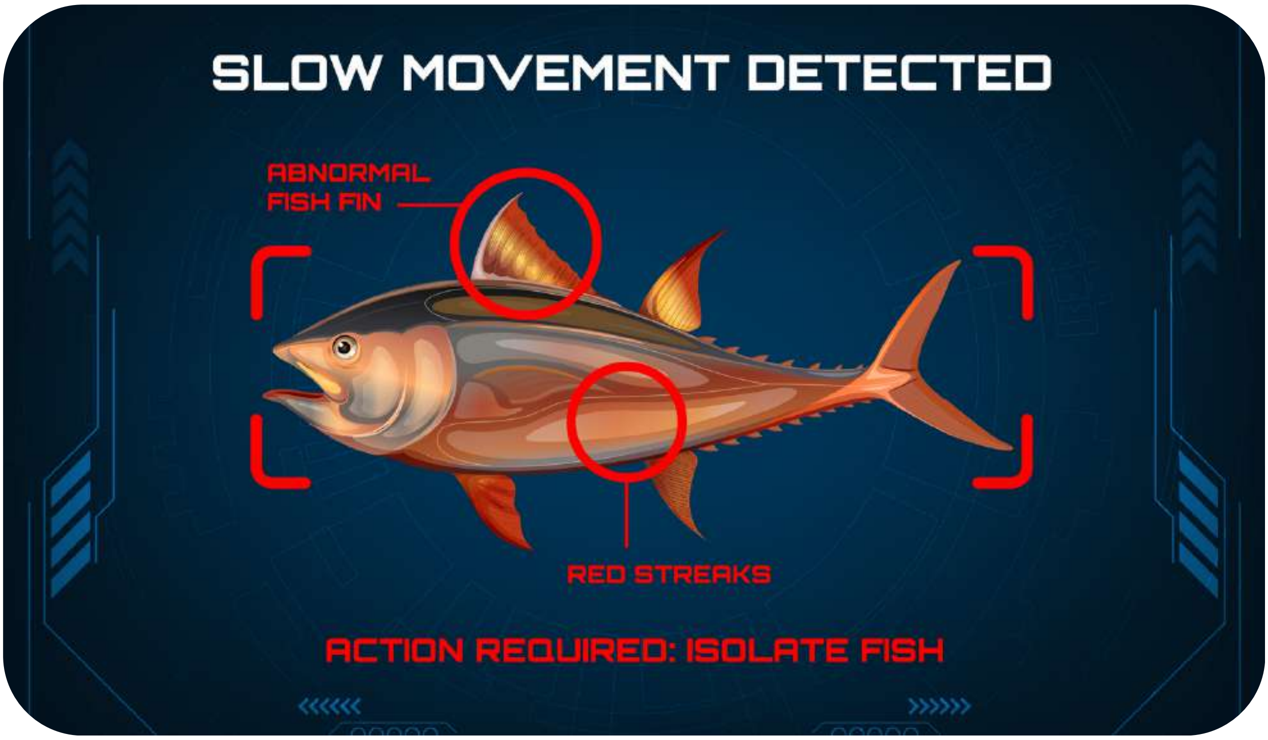
FishWise AI Features

1 Video Feed Analysis

Underwater video cameras provide video feed for analysis: First, high-resolution underwater cameras equipped with fish tracking algorithms continuously analyze video feeds to identify irregular motion patterns indicative of sickness.. The suspected sick fish are digitally tagged. This provides the first step of early detection of high-risk potential sick fish. For the underwater video cameras to provide continuous motion and behavior tracking of fish populations effectively, it is recommended that farmers maintain stocking densities between 10-20 kg (roughly 25 – 50 adult fish) of fish per cubic meter of pond to prevent visualization obstruction.

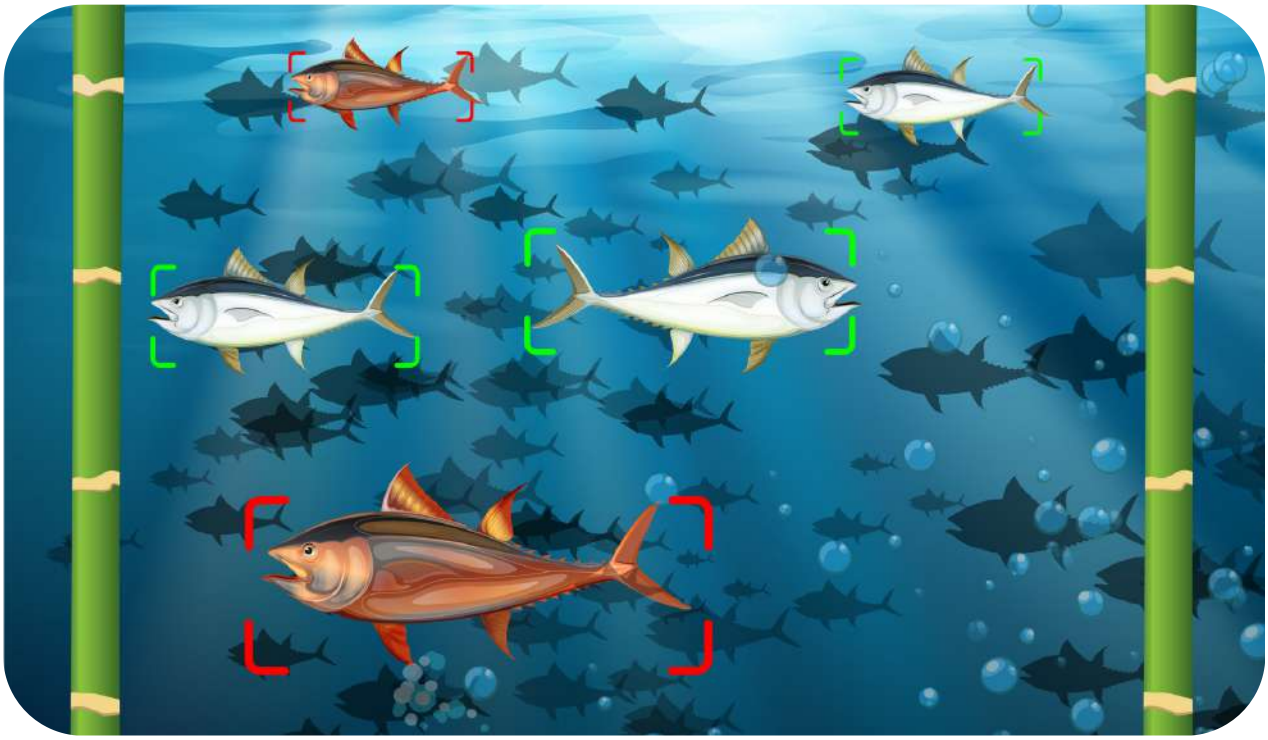
2 IALL Underwater Scanning





IALL Underwater scanning for non-invasive diagnosis: The IALL adaptive lens is tuned for underwater imaging to closely inspect fish skin and gills non-invasively in ponds. This allows for the early detection of parasites, lesions, and other abnormalities.

3 Automated Isolation Mechanism



Automated mechanism for isolation of suspected sick fish: The automated isolation mechanism uses a combination of air bubble curtains and slatted gates to segregate and make it easier for the farmer to net the suspected sick fish. The mechanism works as follows:

Digital Tagging for Isolation

Video algorithms digitally tag fish exhibiting abnormal behaviors, facilitating their isolation for further examination. Detecting fishes and tagging them is key in the work of our solution so we developed a code that detects performs this function. See Appendix A.

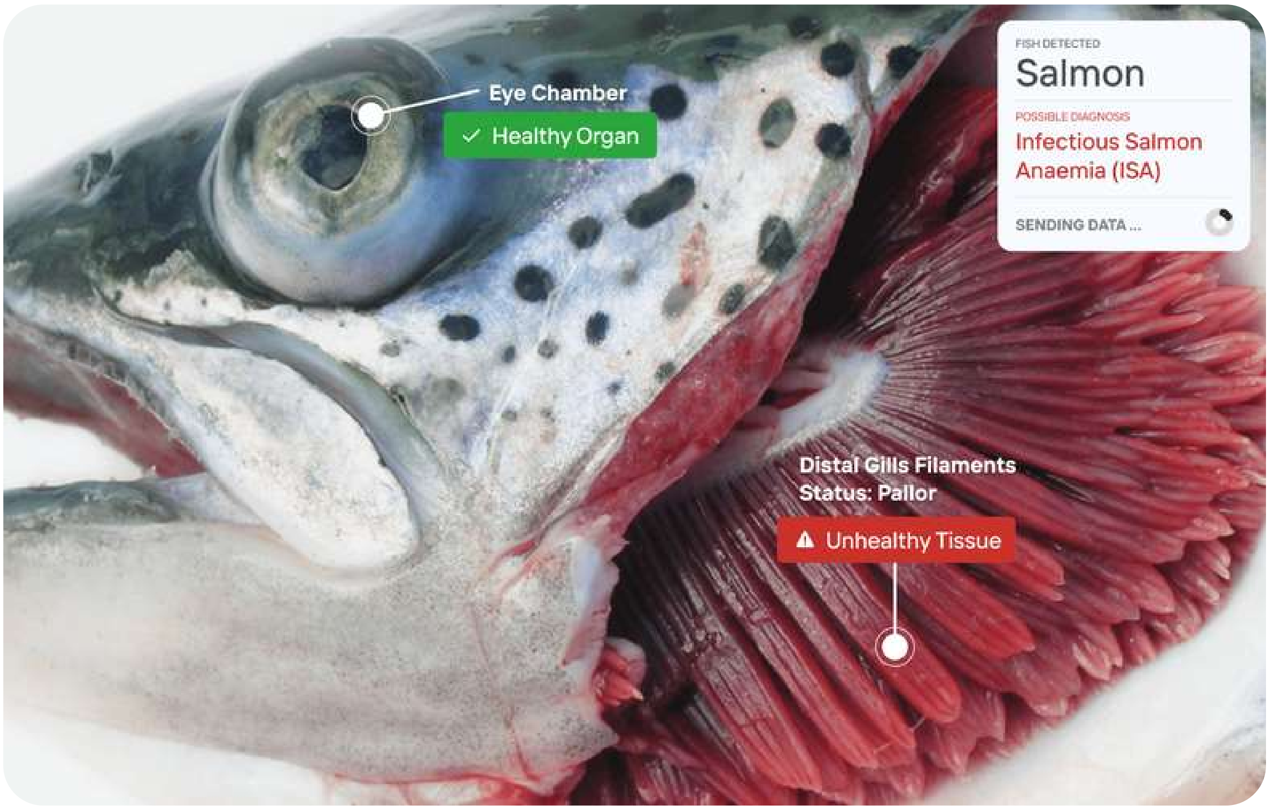
Gentle Herding Mechanism

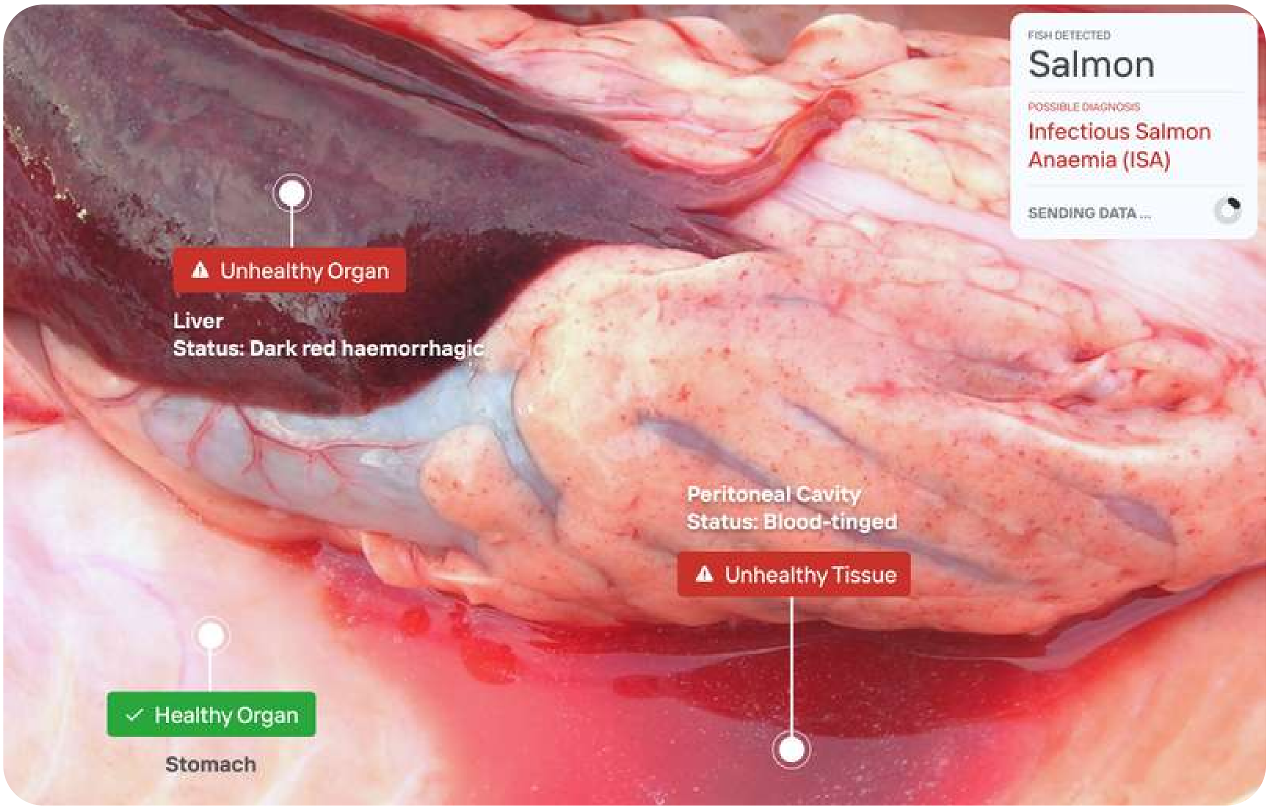
Once suspected sick fishes are identified, air bubble curtains are temporarily deployed to gently herd the flagged fish towards enclosed slated gates. The air-bubble curtains are emitted from perforated pipes placed around the pond perimeter, which is connected to an air compressor system. The bubble curtains are triggered by the monitoring system to provide gentle diversion routes that direct suspected sick fish to certain sections of the pond.

Precise Enclosure

To isolate the specific digitally tagged sick fishes from the school of other fishes, automated slated gates are deployed from the pond bottom to the surface, surrounding and isolating the area with flagged fish. The gates have a slatted design to allow water to continue flowing through the enclosed areas. The spacing between slats would be narrow enough to contain the fish while allowing the flow of water physically. The gates essentially form cages within the pond rather than solid underwater rooms. Within each Gate partition, farmers can net suspected sick fish that have been digitally tagged. See Appendix B.

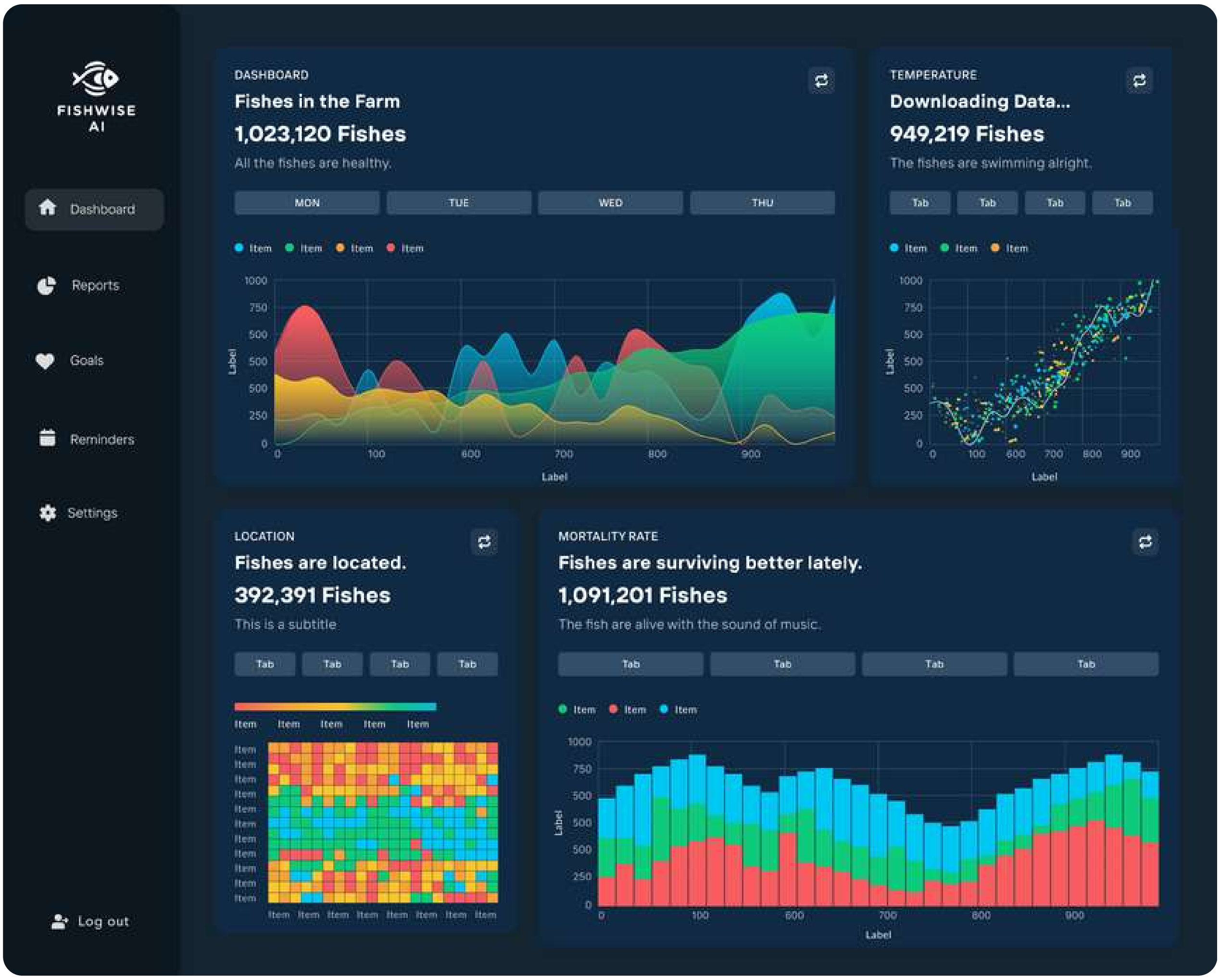
4 H3D VISIOnAIR Hyperspectral Imaging





H3D VISIOnAIR hyperspectral imaging capabilities would be used for invasive confirmation of pathogens or changes in tissue samples of suspected sick fishes. H3D VISIOnAIR can classify specific pathogens using fish tissue specimens by analyzing unique spectral signatures across frequencies. This advanced diagnostic technique enhances farmers' ability to identify and address disease outbreaks.

4 H3D VISIOnAIR Hyperspectral Imaging



Cloud Platform – Data Integration and Analytics: All sensor data is integrated with historical arrays on a cloud platform, allowing for the refinement of algorithms over time. This cloud analytics feature provides historical baselines and facilitates the mapping of disease spread.

E. Multiplicative Positive Impacts (Economic, social, and environmental)

Sustainable Development Goals (SDGs)

While our challenge was initially set out to tackle SDG 14 – Life Below Water directly, ripple effects also positively contribute across SDGs 2, 8, 9, and 12 through interlinkages.
Beyond SDG 14 our aquaculture disease diagnostic solution also aligns with these other Sustainable Development Goals:

- **SDG 2 (Zero Hunger)** - Our solution protects harvest yields and productivity by preventing massive unexplained fish mortality events This enhances domestic food security and economic sustainability.
- **SDG 8 (Decent Work and Economic Growth)** - Reducing production losses promotes continued growth, exports revenue, and employment for hundreds of thousands in small-medium scale aquaculture value chains.
- **SDG 9 (Industry, Innovation and Infrastructure)** - The application of breakthrough technologies like AI, advanced microscopy, and hyperspectral imaging drives innovation and builds technical capabilities locally.
- **SDG 12 (Responsible Consumption and Production)** - Better diagnostics and contaminated water management promote more sustainable natural resource consumption while curbing environmental releases in a responsible way.

Environmental Sustainability

Our solution contributes to environmental sustainability by preserving and improving environmental ecosystems. By reducing mass fish mortality events, we can help protect marine health and mitigate the negative impacts in two key ways:

- Algal Bloom - slow the accelerated spread of algal blooms, potentially preserving thousands of marine acres
- Lower Antibiotic Use - Reduces antibiotic residues in the environment that could enter food systems. Especially in regions of the world where regulations regarding antibiotic use in aquafarming are lax.

F. Cost Analysis (Pricing considerations)

Since the cost of producing the technologies for IALL and H3DVISIOnAIR are unknown, our pricing model assumes that entry-level packages to install our FishWise AI system would connect subscription fees to the inventory cost and size of the aquaculture farm. Start subscription would be priced at 10% of inventory costs today, reflecting only part of the 30% mortality we aim to cut. This conservative starting point establishes core value while providing visibility into bigger gains through overperformance over time, incentivizing users to upgrade.

Overall, our approach involved a combination of machine learning, software development, and integration with hardware components to create a comprehensive solution for the early detection and isolation of fish illness. The iterative nature of the development process ensured that we continually improved the accuracy and effectiveness of our solution over time.

Target User

Whose Livelihood are we improving by our solution? Our solution targets Small and medium-aquaculture farms (SMAs). SMAs play an important role in global fish production. According to a 2020 report by the World Bank, SMAs account for approximately 40% of total aquaculture production, or about 30 million tonnes. This production is worth an estimated US$50 billion annually.

There are approximately 4 million SMAs operating around the world, employing an estimated 10 million people. SMAs are typically family-run businesses and are located in rural areas. They produce a wide variety of fish species, including carp, tilapia, catfish, and salmon.
SMAs are important for a number of reasons. They provide food security for millions of people, especially in developing countries. They also create jobs and income in rural areas. And they can help to reduce poverty and improve livelihoods.

However, SMAs also face a number of challenges. They often lack access to capital, technology, and training. They also face competition from large-scale aquaculture farms. And they are increasingly vulnerable to the impacts of climate change, such as droughts and floods.
Despite these challenges, SMAs are an essential part of the global aquaculture industry. They are a source of food, jobs, and income for millions of people around the world. And they play an important role in ensuring food security for the planet.

Our solution to reduce unexpected fish mortality events in aquaculture is primarily improving the livelihoods of:

- Small to medium scale aquaculture farm owners and operators by:
  - Increasing productivity through lower stock losses
  - Reducing costs of replacements and treatments
  - Providing access to advanced technologies locally
- Local fishing communities by:
  - Preserving stock health of wild fisheries through less environmental impact
  - Protecting jobs dependent on intact ecosystems like processing plants
  - Making seafood more affordable and export market access more sustainable
- Regional economic development in aquaculture intensive geographies by:
  - Growing employment opportunities in allied industries
  - Increasing foreign reserves through stronger seafood exports
  - Enabling more aquaculture support services like equipment maintenance

The key beneficiaries are aquaculture farmers who directly see bottom line gains, as well as communities indirectly dependent on functioning aquatic ecosystems.

Conclusions

In conclusion, this collaborative project explored a persistent aquaculture industry issue – unexpected mass fish mortality events inflicting high economic and environmental costs, especially on small and medium-sized operators in developing countries. Our team employed design thinking and technology perspectives to conceptualize FishWise AI, an integrated precision monitoring and diagnostics solution promising early detection that would lead to faster intervention and reduced fish mortality before harvest.

Combining specialized detection and analytics innovations from ATTRACT-EU researchers, FishWise AI offers continuous tracking, non-invasive rapid testing, and hyperspectral on-site analysis capabilities, which are superior to the incumbent reactive manual approaches reliant on post-mortem sampling alone.

We detailed example pricing models improving accessibility for small farms unable to integrate sophisticated systems independently today due to high costs. We also outlined modular rollout phases delivering stand-alone value while easing ecosystem assimilation before adding advanced functionality.

Some areas of our solution still need further exploration as we continue developing an optimal integrated solution. This includes enhancing isolation approaches to completely contain identified suspected sick fishes and incorporating additional data for expanded ways to detect sick fish. detection.

Our vision is to scale up the adoption of our solutions across small and medium farms, transforming aquaculture into a more sustainable industry.
By applying enhanced bio-surveillance and diagnostics, we aim to preserve our vital natural resources and ensure the long-term viability of aquaculture.

Team 3 Meitner

Our team is composed of a multi-disciplinary team of five students. Emerald Bartolome and Camila Merino, Masters Design students from IED. Constanza Elfarkh and Joan Pané, engineering undergraudate students from UPC and Elorm Mensah, MBA student for Esade.

Together, human-centered design, engineering innovation and business impact formed the foundation framing our solution development process.

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Joan Pané

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Appendices

Appendix A

Machine Learning Model /Digital tagging / Tracking system

A software to detect them must be developed and synchronized with the different cameras in the cage. Because of this, we developed this code that detects orange (in real case it should be fish characteristics, but we were detecting an orange fish), and generates a UI that shows the user, a tagged fish. It shows the fish areas surrounded by a green square so finally we can evaluate their positions in real time and analyze it with the machine learning model.

CODE:

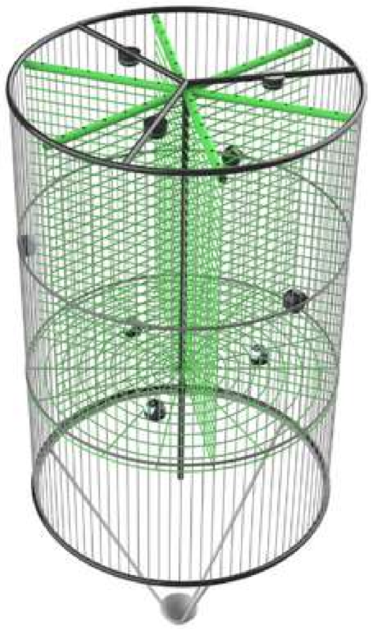
```
import cv2
import numpy as np

# Especificar el índice de la webcam externa (ajusta este valor según tu
configuración)
webcam_index = 1

# Umbral de área mínimo para considerar una forma como naranja (ajusta
según tu caso)
area_threshold = 500

# Inicializar la captura de la webcam externa
cap = cv2.VideoCapture(webcam_index)
print("Abriendo la cámara")

# Verificar si la captura se abrió correctamente
if not cap.isOpened():
    print("Error al abrir la cámara externa.")
    exit()

while True:x

    # Convertir la imagen de RGB a HSV
    hsv = cv2.cvtColor(frame, cv2.COLOR_BGR2HSV)
```

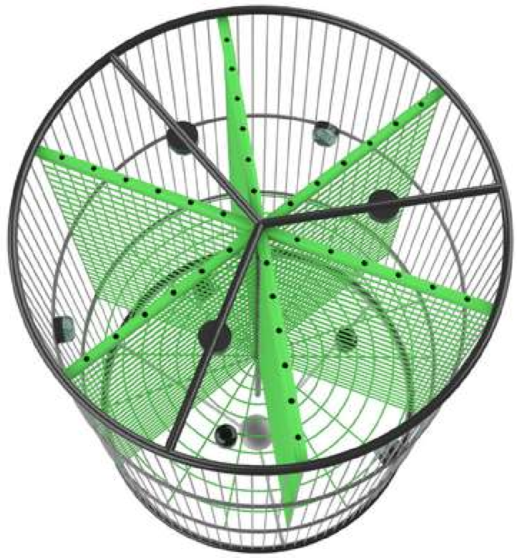
Appendix A

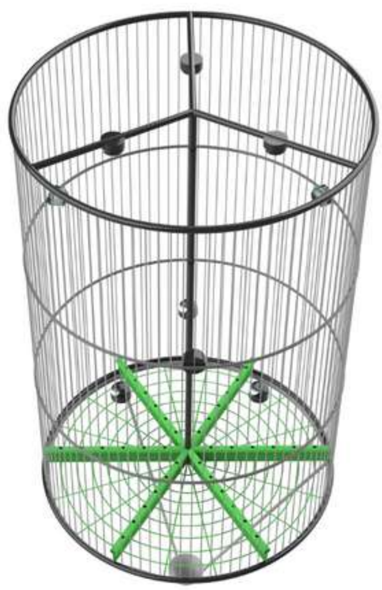
```
 # Definir el rango de colores naranja en HSV
   lower_orange = np.array([0, 100, 100])
   upper_orange = np.array([10, 255, 255])

   # Crear una máscara para el rango de colores naranja
   mask = cv2.inRange(hsv, lower_orange, upper_orange)

   # Encontrar contornos en la máscara
   contours, _ = cv2.findContours(mask, cv2.RETR_EXTERNAL,
cv2.CHAIN_APPROX_SIMPLE)
   print(len(contours))

   # Dibujar rectángulos alrededor de los contornos encontrados en la
imagen original
   for contour in contours:
      # Calcular el área del contorno
      area = cv2.contourArea(contour)

      # Ignorar contornos pequeños (menos que el umbral)
      if area > area_threshold:
         x, y, w, h = cv2.boundingRect(contour)
         cv2.rectangle(frame, (x, y), (x + w, y + h), (0, 255, 0), 2)

   # Agregar cuadro de texto arriba a la derecha
   #if len(contours) <50:
    # cv2.putText(frame, 'Detecting', (frame.shape[1] - 200, 30),
cv2.FONT_HERSHEY_SIMPLEX, 1, (0, 0, 255), 2)
   #else:
   #  cv2.putText(frame, 'Detected: Sea Lice', (frame.shape[1] - 300, 30),
cv2.FONT_HERSHEY_SIMPLEX, 1, (0, 255, 0), 2)

   # Mostrar la imagen resultante en una ventana
   cv2.imshow('Detección de objeto naranja', frame)

   # Romper el bucle si se presiona la tecla 'q'
   if cv2.waitKey(1) & 0xFF == ord('q'):
      break

# Liberar la captura y cerrar la ventana
cap.release()
cv2.destroyAllWindows()
```

Appendix B

RENDERS







Appendix C

MACHINE LEARNING MODEL CODE:

```
import sys
import os
import numpy as np

import cv2
import os
import numpy as np
from cv2 import resize
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score



input_dir = "/Users/constanzaelfarkh/Desktop/cern"
categories = ["sick_salmon", "healthy_salmon"]
data =[]
labels = []

#obtencion de valores de la imagen

for cat_indx, category in enumerate(categories):
  for file in os.listdir(os.path.join(input_dir,category)):
      image_path = os.path.join(input_dir,category,file)
      if not (image_path.endswith(".jpg") or image_path.endswith(".png") or
image_path.endswith(".jpeg"))or image_path.endswith(".webp"):
          continue
      #print(image_path)
      img = cv2.imread(image_path)
      if img is not None:
          #print(cat_indx)
          img = cv2.resize(img, (200,200))
          data.append(img.flatten())
          labels.append(cat_indx)
      else:
        print("error")
        print(image_path)
      #print(cat_indx)
```

Appendix C

MACHINE LEARNING MODEL CODE:

```
i
#entremamiento

(x_train, x_test, y_train, y_test) = train_test_split(data, labels, test_size=0.2, shuffle=True,
stratify=labels)

#classifier

classifier = SVC()
parameters = [{'gamma': [0.01, 0.001, 0.0001], 'C':[1, 10, 100, 1000, 10000]}]

grid_search = GridSearchCV(classifier, parameters)

grid_search.fit(x_train,y_train)

#test performance

best_estimator = grid_search.best_estimator_
y_prediction = best_estimator.predict(x_test)

score = accuracy_score(y_prediction, y_test)

print('{}% of samples were correctly classified'.format(str(score*100)))
```

DATABASE:

SICK

HEALTHY