Computer Vision Detects an Association Between Gross Gill Score and Ventilation Rates in Farmed Atlantic Salmon (Salmo salar)

Author

Vo, Quynh Le Khanh, Pitt, Kylie A, Johnston, Colin, Kennedy, Blair, Folkman, Lukas

Published

2025

Journal Title

Journal of Fish Diseases

Version

Version of Record (VoR)

DOI

10.1111/jfd.70055

Journal of Fish Diseases

WILEY

Journal of Fish Diseases

RESEARCH ARTICLE OPEN ACCESS

Computer Vision Detects an Association Between Gross Gill Score and Ventilation Rates in Farmed Atlantic Salmon (*Salmo salar*)

Quynh Le Khanh Vo[1,2] | Kylie A. Pitt[1] | Colin Johnston[3] | Blair Kennedy[3] | Lukas Folkman[1,2]

[1]School of Environment and Science, Australian Rivers Institute, Griffith University, Gold Coast, Queensland, Australia | [2]Blue Economy Cooperative Research Centre, Launceston, Tasmania, Australia | [3]Tassal Group, Hobart, Tasmania, Australia

Correspondence: Quynh Le Khanh Vo (quynh.vo@griffithuni.edu.au)

Received: 25 February 2025 | **Revised:** 15 August 2025 | **Accepted:** 20 August 2025

Funding: This research was funded by the Blue Economy Cooperative Research Centre, established and supported under the Australian Government's Cooperative Research Centres Program, grant number CRC20180101.

Keywords: AGD | amoebic gill disease | aquaculture | artificial intelligence | deep learning | fish | welfare

ABSTRACT

Poor gill health compromises the health and welfare of farmed Atlantic salmon (*Salmo salar*) by causing respiratory distress and increased ventilation frequency. Poor gill health is caused by numerous factors, including amoebic gill disease (AGD), jellyfish stings, and toxic algae, and is monitored by fish farmers by manual 'gill scoring'. Gill scoring involves visual inspection of gill surfaces for visible lesions, such as white mucoid patches. In commercial salmon farming, these patches are commonly associated with AGD, a major cause of poor gill health. Manual monitoring of gills is labour-intensive, costly, and stressful for fish. This study tested a non-invasive computer vision approach to detect the association between the gross gill score and fish ventilation rates in commercial farms. We hypothesised that increased ventilation rates of farmed Atlantic salmon were associated with a higher gross gill score. The computer vision model first detected fish heads and classified their mouth states (open or closed) using a convolutional neural network, followed by a tracking-by-detection method to estimate ventilation rates by calculating the frequency with which fish opened and closed their mouths. Ventilation rates were estimated from 240 videos recorded at Tasmanian salmon farms and analysed alongside gross gill score, water temperature, dissolved oxygen, and fish weight. Multiple linear regression analysis revealed a positive association between ventilation rates and gross gill score, although the observed change in ventilation rates was relatively small. As laboratory diagnostic methods did not confirm AGD in this study, the gross gill scores should be interpreted primarily as indicators of gill health, acknowledging that they may also reflect signs consistent with AGD. While the tested computer vision method cannot serve as a diagnostic tool, it may assist the industry in identifying health and welfare issues that require further examination. This approach provides a non-invasive way to oversee health and welfare, enhances management practices, and guides manual health assessments.

1 | Introduction

Computer vision has emerged as a powerful, non-invasive tool for monitoring fish health and welfare in aquaculture (Barreto et al. 2022). Computer vision enables precise detection and automated tracking of fish behaviours, such as breeding behaviours (Du et al. 2022). It can also monitor changes in physical appearance, including the detection of wounds and lice (Gupta et al. 2022). These capabilities reduce the need for physical handling of fish, thereby minimising stress and potential harm to stocks (Rushen et al. 2012; Li et al. 2022). These advanced computer vision and pattern recognition techniques provide consistent and automated assessments across aquaculture environments (Mandal and Ghosh 2024). However, most computer vision models have been developed and validated under controlled laboratory conditions (Tuckey et al. 2022; Lindberg et al. 2023; Huang et al. 2022), and their practical applications in commercial aquaculture settings remain largely unexplored. Many aquaculture farms already use underwater cameras to monitor fish manually. These cameras could be utilised for computer vision models and enable computer vision to be readily used at scale in commercial farms. Testing the application of a computer vision model in a commercial setting is essential to determine the usefulness of computer vision for the aquaculture industry.

The farmed Atlantic salmon (*Salmo salar*) industry is a major contributor to global food exports, with an export value of NOK 105.8 billion in Norway, GBP 578 million in Scotland, and USD 6.605 billion in Chile in 2022 (FAO 2023). However, poor gill health in fish poses significant challenges for the industry. One of the major causes of poor gill health is amoebic gill disease (AGD), which was first identified in Tasmania, Australia (Munday 1986). AGD is caused by *Neoparamoeba perurans* and, if unmanaged, it has the potential to cause severe economic and welfare impacts. In Tasmania, AGD has previously accounted for 10%–20% of the production costs (Munday et al. 2001; Leef and Nowak 2013), with more recent estimates placing the cost to the Tasmanian salmon industry at approximately AUD 40 million annually in treatment and lost productivity (CSIRO 2021). Similar challenges are observed globally; over 25% of the marine salmon sites in Ireland and Scotland were affected by AGD in 2011 and 2012 (Rodger 2014), with the Scottish industry reporting 10%–20% mortalities (Shinn et al. 2015). In Norway, AGD-related mortalities have ranged from 12% to 82% (Steinum et al. 2008).

Poor gill health can compromise the metabolic performance of fish. For example, AGD impairs gill function through the development of white mucoid patches, which consist of proliferative tissue primarily composed of undifferentiated epithelial cells and mucous cells (Adams et al. 2004). These changes can reduce the functional surface area for gas exchange and increase the thickness of the diffusion barrier, thereby limiting oxygen uptake and decreasing capacity for aerobic activity (Powell et al. 2005, 2008; Adams 2003; Adams and Nowak 2003; Hvas et al. 2017). The structural impairments trigger compensatory responses such as hyperventilation and redistribution of blood flow to under-perfused gill lamellae (Powell et al. 2005; Booth 1978). However, such mechanisms are energetically demanding and, if prolonged, can further compromise respiratory function. The combination of impaired gas exchange, increased metabolic cost, and susceptibility to secondary infections ultimately undermines fish health and welfare, highlighting AGD as a major challenge in aquaculture (Østevik et al. 2022; Marcos-López and Rodger 2020; Munday et al. 1990).

Commercial Atlantic salmon producers usually utilise a categorical field evaluation to monitor gill health at fish pens, which typically involves manually scoring white mucoid patches using a visual system that examines all 16 gill surfaces (Taylor et al. 2009; Taylor et al. 2016). Whilst the gross gill scoring system was developed to monitor AGD, diagnostic tests such as quantitative real-time PCR (qPCR) targeting *N. perurans* or histopathological examination of gill tissues are needed to confirm the presence of AGD. These methods have been widely applied in countries like Australia, Norway, and Scotland (Taylor et al. 2016; Downes et al. 2017; Boerlage et al. 2022; VKM 2014). Additionally, environmental DNA (eDNA) metabarcoding has also been used to detect *Paramoeba* species related to the AGD-causing *P. perurans* (Mertz 2020).

While the gross gill score system provides a reliable measure of gill health when performed by experienced fish health staff (Clark and Nowak 1999; Adams et al. 2004; Bridle et al. 2010), it has limitations. Traditional gill scoring typically samples only 40 fish per pen (Taylor et al. 2016), which may bias results, as healthier fish are often more likely to evade capture. Capturing and handling fish is also inherently stressful for fish. Furthermore, logistical challenges, including commuting to farms, limit the number of pens that can be assessed daily. Moreover, gill lesions may result from multiple pathogens, not solely from *N. perurans* (Gjessing et al. 2019; Herrero et al. 2018), complicating diagnosis and interpretation. Addressing these challenges requires innovative approaches to farm monitoring and management.

Gill health in farmed salmon can also be affected by a range of environmental stressors, including harmful algal blooms, jellyfish swarms, and fluctuations in temperature, all of which can impact ventilation and oxygen uptake. Harmful algal blooms, including diatoms and silicoflagellates, can cause gill disorders, leading to necrosis, lamellar sloughing, respiratory failure (Bruno et al. 1989; Rodger et al. 2011), and mortality (Speare et al. 1989). Diatom spines damage the respiratory epithelium, triggering excessive mucus production that accumulates on the gills and reduces oxygen uptake (Yang and Albright 1992). Additionally, rising water temperatures can also cause an increase in ventilation rates and oxygen consumption (Patra et al. 2009; Paul 1986).

Fish ventilate by rhythmically coordinating the opening and closing of their mouths with operculum movements. This synchronised action allows water to be drawn into the mouth when it is open and expelled across the gills when it is closed. As water passes over the gill surfaces, oxygen is absorbed into the bloodstream, while carbon dioxide is released, facilitating efficient gas exchange. This process is essential for maintaining the oxygen supply necessary to meet the fish's metabolic demands (Shelton 1970; Perry and Gilmour 2010; Jonz 2019; Hughes and Morgan 1973). Damage to gills, such as that associated with AGD, can alter ventilation patterns, prompting fish to increase their ventilation in response to compromised gill function and increased metabolic rates (Leef et al. 2005, 2007; Powell et al. 2005). Water velocity also plays a critical role in ventilation, influencing ventilation rate and amplitude in fish (Randall and Smith 1967). As water velocity increases, fish adjust their mouth and opercular movements to regulate water flow over the gills, balancing active and passive ventilation (Muir and Buckley 1967).

By tracking ventilation rates closely linked to gill function, computer vision can offer an automated, non-invasive method for detecting potential welfare and health issues in farmed Atlantic salmon. This study investigated the association between gross gill score and ventilation rates estimated using a computer vision approach. It was hypothesised that increased ventilation rates were associated with a higher gross gill score. While the computer vision method was not designed as a diagnostic tool, it aims to assist the industry by identifying health and welfare concerns that require further investigation, potentially including conditions such as AGD. This is the first applied test of a computer vision method to monitor ventilation rates in relation to fish health in a commercial aquaculture environment.

2 | Materials and Methods

2.1 | Data Collection

The study was conducted at Atlantic salmon (*Salmo salar*) farms in Southeast Tasmania between 20/11/2023 and 27/11/2024. The fish pens used in the study contained a median of 64,821 fish (range 15,893–129,140). The fish studied had an average weight of 2.47 kg (range 0.19–5.42 kg). Pens of two different sizes were sampled: (1) pens with a circumference of 168 m and a depth of 15–18 m and (2) pens with a circumference of 120 m and a depth of 10–14 m. Fish displayed normal behaviours during filming. Normal behaviours were defined as calm schooling in a single direction, with no signs of erratic or sudden movements, changes in different directions or crowding, which are behaviours typically associated with stress (Jarvis et al. 2021).

Videos were recorded in pens selected by farm managers for manual gill health checks, during which gross gill scores were obtained by trained health inspectors, following the farm's standard protocol (Taylor et al. 2016). These scores were based on visible white mucoid patches on the gill surfaces, a scoring system originally developed to assess lesions commonly associated with AGD; however, laboratory diagnostic methods, such as histological examination or qPCR to confirm the presence of *N. perurans*, were not conducted as part of this study. Scores range from 0 (no visible lesions) to 5 (lesions covering more than 50% of the gill surface), with higher scores indicating more extensive gill damage (Taylor et al. 2016).

One video per pen was recorded during daytime hours, within 1–2 days before or after the manual gill health assessments. As the effect of manual handling was not a focus of this study, videos were recorded at least 1 day before or after the health assessments to minimise the potential influence of handling-induced stress on fish behaviour. This timing was intended to avoid any transient behavioural changes that could result from recent sampling activities. To avoid feeding confounding behavioural observations, fish were not fed when filmed.

Videos were recorded using Orbit HD underwater feed cameras (https://scaleaq.com/product/orbit-hd/), remotely controlled by ScaleAQ Vision 2 software. The cameras were positioned horizontally at a depth of 5 m to capture lateral views of the fish. Videos, with an average duration of 32 min (range 5–60 min), were recorded in 1280 × 960 pixels resolution at 30 frames per second; however, a lower resolution of 640 × 480 pixels was used in the computer vision analysis to increase the processing speed.

Environmental data, including water temperature (13.9°C–19.3°C) and dissolved oxygen levels (DO, 4.8–8.8 mg/L), were measured using sensors integrated into the underwater cameras. The cameras, temperature sensors, and DO sensors used in this study were the same systems routinely employed by the salmon company for daily monitoring at their commercial farms.

It is acknowledged that other environmental factors, such as water turbidity and phytoplankton concentrations, could also influence observations. For example, elevated phytoplankton levels, including potentially harmful species, may contribute to reduced water clarity and increased respiratory distress in fish. However, these variables were not measured in this study.

A total of 266 videos were collected from 168 fish pens. Among these, 67 pens were filmed multiple times (nine pens were filmed four times, 13 pens were filmed three times, and 45 pens were filmed twice). Consecutive recordings of the same pen were spaced at least 21 days apart.

Ethical approval for animal handling was not required because fish were handled, and gill assessments were conducted by the fish health inspectors of the aquaculture company following their company's procedure. The assessments were for the welfare of the fish, and camera footage was obtained opportunistically.

2.2 | Video Processing by Computer Vision

The collected videos were processed using a computer vision model (Folkman et al. 2025). This model first detected fish heads and classified their mouth states (open or closed) using a convolutional neural network. A tracking-by-detection approach was applied to link detections across frames, forming continuous trajectories for each detected fish head. Each fish head was assigned an ID (Figure 1) and tracked while the fish was swimming across the field of view of the camera. This enabled the duration of open-closed mouth cycles, which was used to estimate fish ventilation rates, to be measured. The duration of the open-closed mouth cycle was calculated as the number of frames for consecutive open-to-closed or closed-to-open mouth ventilation sequences, depending on which state (closed or open mouth) was observed first. Only fish that completed at least one open-closed mouth cycle and were tracked for a minimum of 1 s were included in the calculation of the ventilation rates. Ventilation rates were calculated as:

$$\mathrm{VR}\ [\text{open-¬closed cycles per minute}] = \frac{60 \times \text{frame rate of the video}}{\text{open-¬closed mouth cycle duration [number of frames]}}$$

Because the video quality can be affected by water turbidity, biofouling, blur, and low latency of the network connection to the camera, videos were excluded if the proportion of fish that were tracked for at least 1 s was less than 0.05. Videos with estimated ventilation rates of fewer than 200 fish were excluded from the analysis.

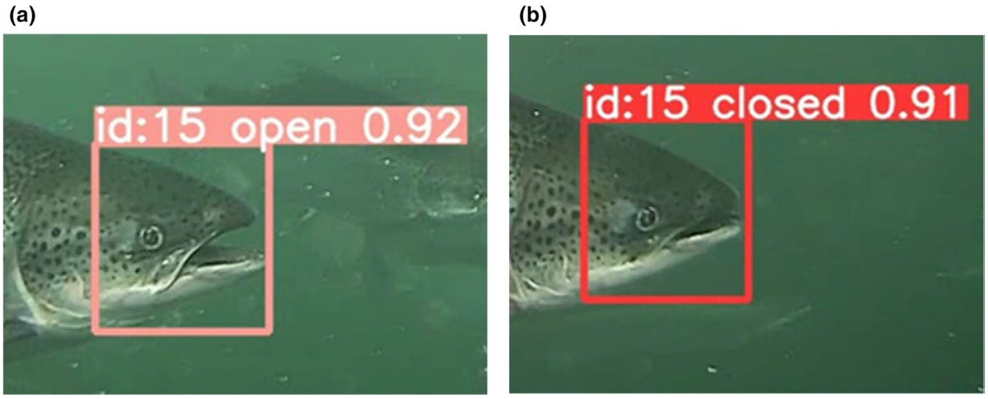

FIGURE 1 | Regions of interest for image processing: (a) a fish head with open mouth; (b) a fish head with closed mouth.

2.3 | Data Analysis

A multiple linear regression model was employed to examine whether ventilation rates were associated with gross gill scores, while accounting for fish weight, water temperature, and DO. To account for non-linear growth patterns, the mean fish weight was log-transformed. Water temperature, DO, and log-transformed mean weight were standardised. The model was specified as follows:

$$\mathrm{VR} = \beta_0 + \beta_{\text{gill score}} \times \text{gill score} + \beta_{\log(W)} \times \log(W) + \beta_T \times T + \beta_{\mathrm{DO}} \times \mathrm{DO} + \beta_{\log(W)\times T} \times (\log(W) \times T) + \beta_{\log(W)\times \mathrm{DO}} \times (\log(W) \times \mathrm{DO}) + \varepsilon$$

where VR is the fish pen's median ventilation rate (measured as the number of open-closed mouth cycles per minute); β_0 is the intercept; $\beta_{\text{gill score}}$, $\beta_{\log(W)}$, β_T and β_{DO} are the regression coefficients for gross gill score, logarithmically transformed mean fish weight in kg ($\log(W)$), temperature in °C (T), and dissolved oxygen levels in mg/L (DO), respectively; and ε is a normally distributed error term (residuals). The terms $\log(W) \times T$ and $\log(W) \times \mathrm{DO}$ represent interaction effects between log-transformed weight and temperature, and between log-transformed weight and dissolved oxygen, respectively. These terms were included because thermal and hypoxia tolerance vary with the size of the salmon (Oldham et al. 2019). All data analyses and visualisations were performed using Python 3.9.13 with the Statsmodels 0.13.2, Pandas 1.4.4, and Seaborn 0.11.2 packages.

3 | Results

3.1 | Fish Detection and Tracking Results Using Computer Vision

The computer vision model analysed 266 fish videos, detecting 7–11,355 fish (median 1576.5) with at least one complete open-closed mouth cycle and a track duration of at least 1 s per video (Figure 2a). The proportion of fish tracked for at least 1 s varied between 0.0025 and 0.254, with a median of 0.11 (Figure 2b). A total of 240 video recordings met the inclusion criteria for statistical analysis after excluding videos with fewer than 200 fish with estimated ventilation rates and videos with a proportion of fish tracked for at least 1 s below 0.05 (Figure 2a,b, respectively).

Median ventilation rates of fish in each pen ($n = 240$) calculated using the computer vision method varied between 85.7 and 156.5 open-closed mouth cycles per minute, with a mean (±SE) ventilation rate of 106.1 ± 12.1 open-closed mouth cycles per minute (Figure 3). The distribution of gross gill scores was spread across the full range of recorded water temperatures (13.9°C–19.3°C) and DO levels (4.8–8.8 mg/L). Gross gill scores, including mild to moderate cases, were observed throughout both temperature and DO gradients, rather than being confined to specific environmental intervals (Figure 4).

3.2 | Identifying the Relationship Between the Ventilation Rate of Fish and Gross Gill Score, Water Temperature, DO, and Fish Weight

The multiple linear regression model [$R^2 = 0.683$, F-statistic (6, 233) = 83.65, $p < 0.001$] revealed significant associations of fish pen median ventilation rate with gross gill score, fish weight, water temperature, DO, and the interaction between weight and temperature. Ventilation rates were positively associated with gross gill scores ($\beta_{\text{gill score}} = 3.52$, SE = 1.20, $p = 0.004$; Figure 5a) and temperature ($\beta_T = 3.46$, SE = 0.51, $p < 0.001$; Figure 5c); while negatively associated with log-transformed mean fish weight ($\beta_{\log(W)} = -6.98$, SE = 0.51, $p < 0.001$; Figure 5b) and DO ($\beta_{\mathrm{DO}} = -1.17$, SE = 0.49, $p = 0.017$; Figure 5d). Additionally, there was an interaction effect between the log-transformed weight and temperature on the ventilation rate ($\beta_{\log(W)\times T} = -1.18$, SE = 0.56, $p = 0.038$), suggesting that the association of temperature with ventilation rates varied depending on the fish weight. An association between ventilation rates and the interaction effect between log-transformed weight and DO was not detected ($p = 0.785$).

4 | Discussion

4.1 | Key Findings

This study found a positive association between ventilation rates and gross gill score, while accounting for the effects of DO, temperature, and fish weight. Although the magnitude of the change was relatively small, the findings align with previous research indicating that gill damage, such as that which may occur during AGD, can increase ventilation activity as fish

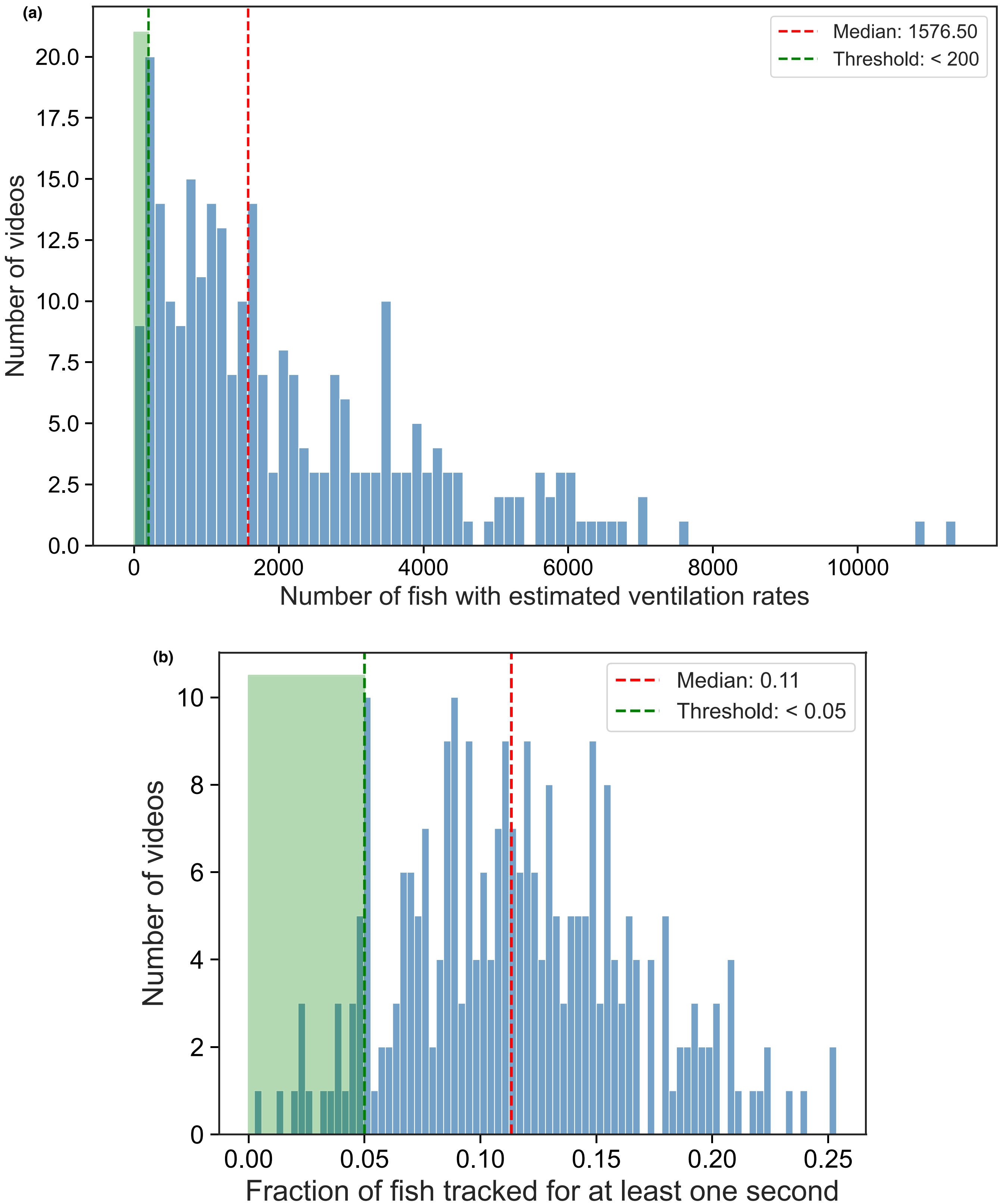

FIGURE 2 | Frequency distribution of (a) the number of fish with estimated ventilation rates in a video; and (b) the fraction of fish tracked for at least 1 s out of the total number of fish detected by the computer vision model in a video. The green panels in the figures represent the videos excluded from the statistical analysis.

attempt to compensate for reduced respiratory efficiency (Powell et al. 2005). In the case of AGD, gill function is compromised through an overgrowth of tissue dominated by undifferentiated epithelial cells and mucous cells, which collectively reduce the surface area available for gas exchange and thicken the diffusion barrier (Adams and Nowak 2003; Adams et al. 2004; Powell et al. 2005). As a compensatory response, fish increase their ventilation effort to maintain adequate oxygen uptake, coordinating faster or more forceful mouth and operculum movements. However, this increased ventilation is energetically demanding and, if sustained, may exacerbate physiological stress and reduce overall welfare. While the computer vision method is not a diagnostic tool, it can identify fish pens with elevated ventilation rates. When combined with relevant environmental observations and the historical performance of the pen's fish population, the estimated ventilation rates can help farmers with selecting pens for manual health inspections. This demonstrates the practical applicability of computer vision models in real-world aquaculture settings, as it provides a proactive and targeted approach for fish health and welfare monitoring.

4.2 | Implementation by Industry

Our computer vision model could be integrated into existing aquaculture monitoring systems that use underwater cameras, monitoring software, and centralised control centres. It could function as an additional software module that processes ventilation rate data from video feeds, with integration handled by the company's IT team or in collaboration with monitoring software providers. Some aquaculture companies manage hundreds of fish pens, so to ensure scalability, edge computing solutions—such as local servers or processors—could process video data directly at the pen level. This would reduce bandwidth demands and allow efficient, real-time analysis while leveraging existing infrastructure.

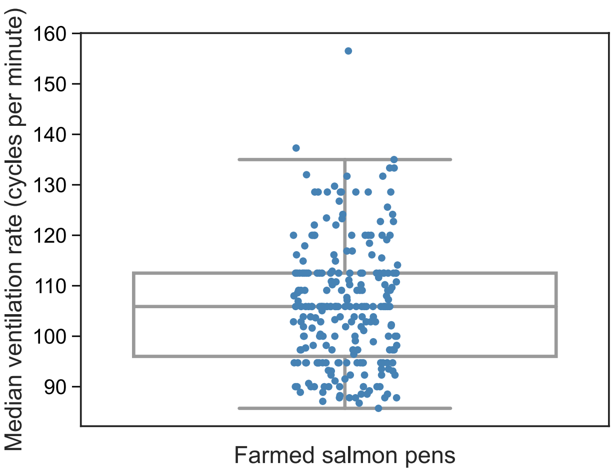

FIGURE 3 | Median ventilation rates of fish in each pen estimated by the computer vision model.

Aquaculture farmers could enhance operational efficiency by using this computer vision method to identify pens containing fish with unusually high ventilation rates and prioritise those pens for manual gill inspections. This targeted approach would enable farmers to concentrate on manual inspections, such as visual gill scoring (Taylor et al. 2016) or laboratory diagnostics like *N. perurans* PCR assays (Young et al. 2008), in pens that may be experiencing gill health issues. This data-driven strategy could reduce reliance on sporadic or rotational health assessments, optimising labour while improving the precision and promptness of interventions.

In contrast to conventional methods that assess the gill health of a limited sample of about 40 fish (Taylor et al. 2016), this computer vision method estimates ventilation rates from hundreds of fish per pen. Assessing a much larger proportion of the population within each pen is likely to improve the robustness and representativeness of gill health monitoring. Given the ease with which video data can be collated, the model could also be used to generate longitudinal data to detect changes in ventilation rates that may indicate emerging gill health or environmental challenges. This technology has the potential to enhance productivity and sustainability in commercial salmon farming by supporting intervention, minimising economic losses, and optimising the allocation of resources.

4.3 | Environmental Parameters and Their Influence on Ventilation Rates

The model incorporated DO, temperature, and fish weight data but lacked data on other factors such as algae (Bruno et al. 1989), swim speed (Palstra et al. 2020), and current velocity (Agbeti et al. 2024) that can also influence respiration rates. The detected associations of ventilation rates with water temperature and DO align with previous studies, which indicate that fish increase ventilation in response to elevated metabolic demands in warmer waters (Shelton 1970; da Silva et al. 2013;

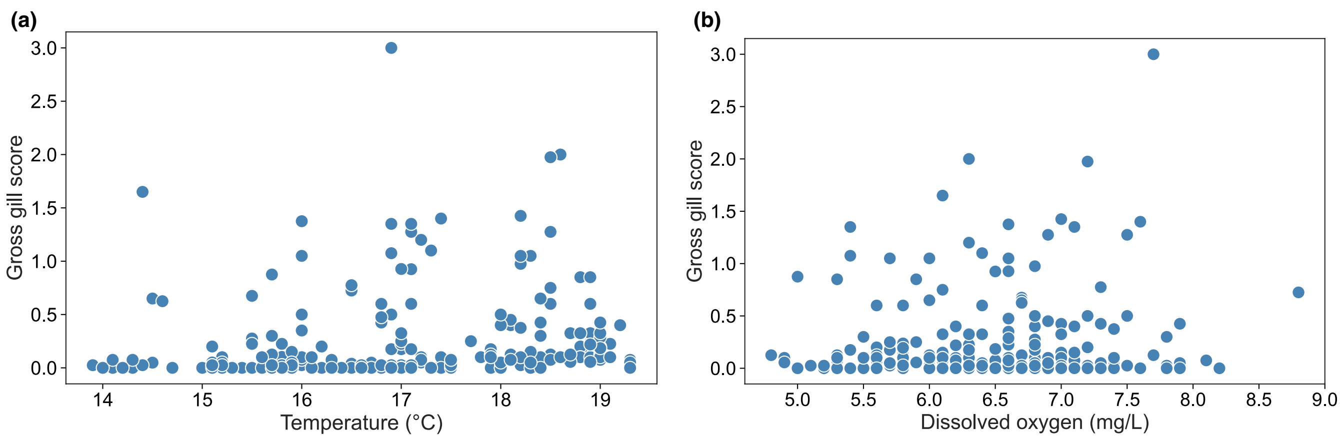

FIGURE 4 | Gross gill scores across (a) temperature and (b) DO range of the collected data.

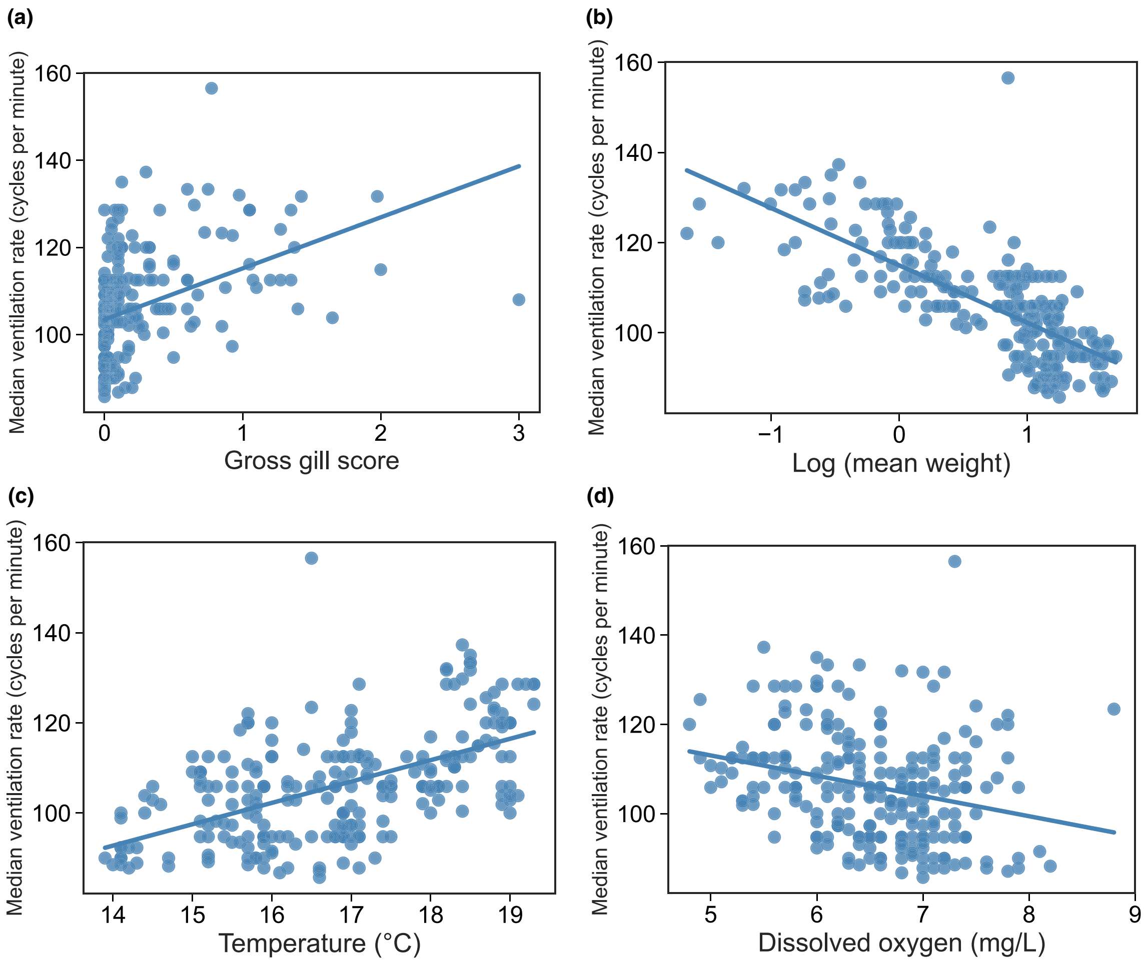

FIGURE 5 | Relationships between (a) gross gill score, (b) log-transformed mean fish weight, (c) temperature, and (d) DO and the median ventilation rate of the farmed Atlantic salmon. The blue lines represent simple linear regression fits, calculated using ordinary least squares for each relationship separately. Median ventilation rate was significantly associated with all four predictor variables ($p < 0.05$).

Steffensen 2005) and at low dissolved oxygen levels (Randall and Shelton 1963). The negative association between ventilation rates and fish weight is consistent with findings that larger fish exhibit greater respiratory efficiency due to the expansion of their gill structures (Hughes and Nyholm 1979; Hughes 1984). Fish weight also influences physiological responses to environmental stressors, which may explain the interaction effect observed between temperature and fish weight on ventilation rates (Jiang et al. 2021; Oldham et al. 2019).

This study employed a computer vision tool to assess the ventilation rates of fish using video recordings with an average duration of 32 min. Videos were taken during daytime hours (between 11 a.m. and 2 p.m.). While these short recordings offer valuable insights, we acknowledge that they represent only a snapshot in time and may not capture the full extent of environmental variability, such as changes in water temperature, dissolved oxygen, tidal currents, and phytoplankton, over a 24-h period. Future studies could benefit from longer or repeated recordings to better account for temporal fluctuations and more accurately identify potential drivers of changes in respiratory behaviour.

Incorporating additional environmental data and estimates of swimming speed could further enhance the model's predictive power and provide deeper insights into gill health and welfare. Variable flow conditions, which fluctuate in speed and direction, increase the energy demands of Atlantic salmon, leading to higher oxygen consumption (Agbeti et al. 2024). As swimming speed increases, so does oxygen demand, which may drive ventilation changes (Palstra et al. 2020). High algal concentrations can also irritate fish gills, causing necrosis, loss of gill lamellae, and, in severe cases, respiratory failure (Bruno et al. 1989). These factors could contribute to ventilation rate variations (Roberts 1975; Svendsen et al. 2018), underscoring the need for future studies to integrate these parameters. This refinement would improve the model's ability to link ventilation rates, fish health, and environmental conditions, enhancing its sensitivity and practical application in commercial aquaculture.

4.4 | Constraints in Validating the Computer Vision Model on Commercial Farms

Limitations of this study were the narrow range of gross gill scores among sampled pens and the lack of laboratory diagnostic methods to confirm gill pathology. Therefore, the gross gill scores should be interpreted as a measure of general gill health rather than a definitive AGD pathology. The narrow range of the gill scores could not have been avoided because commercial farms typically intervene before fish develop severe gill condition (i.e., score > 3). As a result, the dataset was dominated by low scores, with 223 out of 240 (approximately 93%) pens having a score ≤ 1. This imbalance may have reduced the statistical power of the analysis, potentially weakening the observed association between the ventilation rates and gross gill score. While experimental testing in controlled tank conditions could help address this limitation, the computer vision method was not designed for tank-based applications. Retraining the model with data from controlled experimental settings would be necessary to ensure its accuracy.

4.5 | Potential for Broader Applications

Although the computer vision model was developed and validated for the Tasmanian salmon industry, it could be used on salmon farms in other regions of the world. Regional variations in environmental factors such as water temperature and DO can impact ventilation rates. Genetic and physiological differences among salmon strains cause variations in traits such as osmoregulatory capacity, seawater tolerance, and growth rates (Handeland et al. 2003). Hence, the model may require additional training with data collected from farms located in different regions to make it more universally applicable.

5 | Conclusions

This study validated the use of computer vision for monitoring ventilation rates in farmed Atlantic salmon and identified a positive association between ventilation rates and gross gill scores, a measure based on visible gill lesions commonly adopted for monitoring the onset of AGD in commercial fish farms. Although the observed changes in ventilation rate were relatively small, they align with previous findings that gill damage, such as that which may occur during AGD, compromise respiratory efficiency, prompting compensatory increases in ventilation. The study also demonstrated the sensitivity of computer vision in detecting subtle physiological changes, reinforcing its potential as a non-invasive tool for monitoring fish health and welfare. By incorporating environmental variability from commercial fish farms, this research highlights the practical applicability of computer vision models in real-world aquaculture settings. While the model is not intended as a standalone diagnostic tool, it offers a valuable warning system for identifying pens that warrant further investigation, marking an important step toward integrating automated monitoring technologies into aquaculture management.

Author Contributions

Quynh Le Khanh Vo: conceptualization, formal analysis and investigation, data curation, methodology, writing – original draft preparation, writing – review and editing. **Lukas Folkman:** conceptualization, formal analysis and investigation, data curation, methodology, writing – review and editing. **Colin Johnston:** conceptualization, writing – review and editing. **Blair Kennedy:** data curation, writing – review and editing. **Kylie A. Pitt:** conceptualization, methodology, formal analysis and investigation, funding acquisition, writing – review and editing.

Acknowledgements

We gratefully acknowledge the support and collaboration of the Feed Centre and Animal Health Team staff at Tassal Group and their provision of access to and use of facilities for data collection. We also extend our thanks to the Griffith University eResearch Service and Specialised Platforms Team for their support and for providing access to the High-Performance Computing Cluster 'Gowonda', which was instrumental in completing this research. We acknowledge the use of ChatGPT and Grammarly to assist with writing throughout this article, including identifying grammar mistakes, editing and proofreading. Open access publishing facilitated by Griffith University, as part of the Wiley - Griffith University agreement via the Council of Australian University Librarians.

Ethics Statement

All data were collected by the salmon company as a part of their routine operation.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Due to the sensitive nature of the datasets collected for this research, they cannot be shared.

References

Adams, M. 2003. "Pathology of Amoebic Gill Disease in Atlantic Salmon (*Salmo salar* L.)." Doctoral dissertation, University of Tasmania, UTAS Research Repository. https://doi.org/10.25959/23235557.v1.

Adams, M. B., K. Ellard, and B. F. Nowak. 2004. "Gross Pathology and Its Relationship With Histopathology of Amoebic Gill Disease (AGD) in Farmed Atlantic Salmon, *Salmo salar* L." *Journal of Fish Diseases* 27, no. 3: 151–161. https://doi.org/10.1111/j.1365-2761.2004.00526.x.

Adams, M. B., and B. F. Nowak. 2003. "Amoebic Gill Disease: Sequential Pathology in Cultured Atlantic Salmon, *Salmo salar* L." *Journal of Fish Diseases* 26, no. 10: 601–614. https://doi.org/10.1046/j.1365-2761.2003.00496.x.

Agbeti, W. E., A. P. Palstra, S. Black, L. Magnoni, M. Lankheet, and H. Komen. 2024. "Swimming at Increasing Speeds in Steady and Unsteady Flows of Atlantic Salmon *Salmo salar*: Oxygen Consumption, Locomotory Behaviour and Overall Dynamic Body Acceleration." *Biology* 13, no. 6: 393. https://doi.org/10.3390/biology13060393.

Barreto, M. O., S. Rey Planellas, Y. Yang, C. Phillips, and K. Descovich. 2022. "Emerging Indicators of Fish Welfare in Aquaculture." *Reviews in Aquaculture* 14: 343–361. https://doi.org/10.1111/raq.12601.

Boerlage, A. S., A. Ashby, J. I. Eze, G. J. Gunn, and A. Reeves. 2022. "Field Evaluation of Diagnostic Sensitivity (DSe) and Specificity (DSp) of Common Tests for Amoebic Gill Disease (AGD) and Complex Gill Disease (CGD) in Cultured Atlantic Salmon (*Salmo salar*) in Scotland Using Bayesian Latent Class Models." *Preventive Veterinary Medicine* 204: 105654. https://doi.org/10.1016/j.prevetmed.2022.105654.

Booth, J. H. 1978. "The Distribution of Blood Flow in the Gills of fish: Application of A New Technique to Rainbow Trout (*Salmo Gairdneri*)." *Journal of Experimental Biology* 73, no. 1: 119–129. https://doi.org/10.1242/jeb.73.1.119.

Bridle, A., P. Crosbie, K. Cadoret, and B. Nowak. 2010. "Rapid Detection and Quantification of *Neoparamoeba perurans* in the Marine Environment." *Aquaculture* 309: 56–61. https://doi.org/10.1016/j.aquaculture.2010.09.018.

Bruno, D. W., G. Dear, and D. D. Seaton. 1989. "Mortality Associated With Phytoplankton Blooms Among Farmed Atlantic Salmon, *Salmo* *salar*, in Scotland." *Aquaculture* 78: 217–222. https://doi.org/10.1016/0044-8486(89)90099-9.

Clark, A., and B. F. Nowak. 1999. "Field Investigations of Amoebic Gill Disease in Atlantic Salmon, *Salmo salar* L., in Tasmania." *Journal of Fish Diseases* 22, no. 6: 433–443. https://doi.org/10.1046/j.1365-2761.1999.00175.x.

CSIRO. 2021. "Reducing Impact of Atlantic Salmon Gill Disease." https://www.csiro.au/en/research/animals/breeding/salmon-gill-disease-agd.

da Silva, G. S., M. L. Glass, and L. G. Branco. 2013. "Temperature and Respiratory Function in Ectothermic Vertebrates." *Journal of Thermal Biology* 38, no. 2: 55–63. https://doi.org/10.1016/j.jtherbio.2012.11.001.

Downes, J. K., M. L. Rigby, R. S. Taylor, et al. 2017. "Evaluation of Non-Destructive Molecular Diagnostics for the Detection of *Neoparamoeba perurans*." *Frontiers in Marine Science* 4: 61. https://doi.org/10.3389/fmars.2017.00061.

Du, L., Z. Lu, and D. Li. 2022. "Broodstock Breeding Behaviour Recognition Based on Resnet50-LSTM With CBAM Attention Mechanism." *Computers and Electronics in Agriculture* 202: 107404. https://doi.org/10.1016/j.compag.2022.107404.

FAO. 2023. "Salmon – Main Producers See Record-Breaking Exports." https://www.fao.org/in-action/globefish/news-events/news/news-detail/Salmon---Main-producers-see-record-breaking-exports/en.

Folkman, L., Q. L. K. Vo, K. A. Pitt, C. Johnston, and B. Stantic. 2025. "A Computer Vision Method to Estimate Ventilation Rate of Atlantic Salmon in Sea Fish Farms." arXiv:2504.19719. https://doi.org/10.48550/arXiv.2504.19719.

Gjessing, M. C., T. Steinum, A. B. Olsen, et al. 2019. "Histopathological Investigation of Complex Gill Disease in Sea Farmed Atlantic Salmon." *PLoS One* 14, no. 10: e0222926. https://doi.org/10.1371/journal.pone.0222926.

Gupta, A., E. Bringsdal, K. M. Knausgård, and M. Goodwin. 2022. "Accurate Wound and Lice Detection in Atlantic Salmon Fish Using a Convolutional Neural Network." *Fishes* 7, no. 6: 345. https://doi.org/10.3390/fishes7060345.

Handeland, S. O., A. M. Arnesen, and S. O. Stefansson. 2003. "Seawater Adaptation and Growth of Post-Smolt Atlantic Salmon (*Salmo salar*) of Wild and Farmed Strains." *Aquaculture* 220, no. 1–4: 367–384. https://doi.org/10.1016/S0044-8486(02)00508-2.

Herrero, A., K. D. Thompson, A. Ashby, H. D. Rodger, and M. P. Dagleish. 2018. "Complex Gill Disease: An Emerging Syndrome in Farmed Atlantic Salmon (*Salmo salar* L.)." *Journal of Comparative Pathology* 163: 23–28. https://doi.org/10.1016/j.jcpa.2018.07.004.

Huang, J., X. Yu, X. Chen, D. An, Y. Zhou, and Y. Wei. 2022. "Recognising Fish Behaviour in Aquaculture With Graph Convolutional Network." *Aquacultural Engineering* 98: 102246. https://doi.org/10.1016/j.aquaeng.2022.102246.

Hughes, G. M. 1984. "Scaling of Respiratory Areas in Relation to Oxygen Consumption of Vertebrates." *Experientia* 40, no. 6: 519–524. https://doi.org/10.1007/BF01982313.

Hughes, G. M., and M. Morgan. 1973. "The Structure of Fish Gills in Relation to Their Respiratory Function." *Biological Reviews* 48: 419–475. https://doi.org/10.1111/j.1469-185x.1973.tb01009.x.

Hughes, G. M., and K. Nyholm. 1979. "Ventilation in Rainbow Trout (*Salmo gairdneri*, Richardson) With Damaged Gills." *Journal of Fish Biology* 14, no. 3: 285–288. https://doi.org/10.1111/j.1095-8649.1979.tb03520.x.

Hvas, M., E. Karlsbakk, S. Mæhle, D. W. Wright, and F. Oppedal. 2017. "The Gill Parasite *Paramoeba perurans* Compromises Aerobic Scope, Swimming Capacity and Ion Balance in Atlantic Salmon." *Conservation Physiology* 5, no. 1: cox066. https://doi.org/10.1093/conphys/cox066.

Jarvis, S., M. A. Ellis, J. F. Turnbull, S. Rey Planellas, and F. Wemelsfelder. 2021. "Qualitative Behavioral Assessment in Juvenile Farmed Atlantic Salmon (*Salmo salar*): Potential for On-Farm Welfare Assessment." *Frontiers in Veterinary Science* 8: 702783. https://doi.org/10.3389/fvets.2021.702783.

Jiang, X., S. Dong, R. Liu, et al. 2021. "Effects of Temperature, Dissolved Oxygen, and Their Interaction on the Growth Performance and Condition of Rainbow Trout (*Oncorhynchus mykiss*)." *Journal of Thermal Biology* 98: 102928. https://doi.org/10.1016/j.jtherbio.2021.102928.

Jonz, M. G. 2019. "Respiratory System." In *The Zebrafish in Biomedical Research: Biology, Husbandry, Diseases, and Research Applications*, edited by S. C. Cartner, J. S. Eisen, and G. E. Sanders, 103–107. Elsevier. https://doi.org/10.1016/B978-0-12-812431-4.00010-5.

Leef, M., J. Harris, and M. Powell. 2005. "Respiratory Pathogenesis of Amoebic Gill Disease (AGD) in Experimentally Infected Atlantic Salmon *Salmo salar*." *Diseases of Aquatic Organisms* 66: 205–213. https://doi.org/10.3354/dao066205.

Leef, M. J., J. O. Harris, and M. D. Powell. 2007. "Metabolic Effects of Amoebic Gill Disease (AGD) and Chloramine-T Exposure in Seawater-Acclimated Atlantic Salmon *Salmo salar*." *Diseases of Aquatic Organisms* 78, no. 1: 37–44. https://doi.org/10.3354/dao01853.

Leef, M. J., and B. F. Nowak. 2013. "Atlantic Salmon Aquaculture Subprogram: The Effects of AGD on Gill Function – Use of a Perfused Gill Model (FRDC Project No. 2011/069)." University of Tasmania. https://www.utas.edu.au/__data/assets/pdf_file/0009/905760/2011-069-DLD-AGD.pdf.

Li, D., G. Wang, L. Du, Y. Zheng, and Z. Wang. 2022. "Recent Advances in Intelligent Recognition Methods for Fish Stress Behavior." *Aquacultural Engineering* 96: 102222. https://doi.org/10.1016/j.aquaeng.2021.102222.

Lindberg, S. K., E. Durland, K. Heia, C. Noble, R. Alvestad, and G. F. Difford. 2023. "Digital Scoring of Welfare Traits in Atlantic Salmon (*Salmo salar* L.) – A Proof of Concept Study Quantifying Dorsal Fin Haemorrhaging via Hyperspectral Imaging." *Frontiers in Animal Science* 4: 1162384. https://doi.org/10.3389/fanim.2023.1162384.

Mandal, A., and A. R. Ghosh. 2024. "Role of Artificial Intelligence (AI) in Fish Growth and Health Status Monitoring: A Review on Sustainable Aquaculture." *Aquaculture International* 32: 2791–2820. https://doi.org/10.1007/s10499-023-01297-z.

Marcos-López, M., and H. D. Rodger. 2020. "Amoebic Gill Disease and Host Response in Atlantic Salmon (*Salmo salar* L.): A Review." *Parasite Immunology* 42, no. 8: e12766. https://doi.org/10.1111/pim.12766.

Mertz, N. 2020. "eDNA Metabarcoding of Amoebic Gill Disease (AGD) Pathogens Exposes Potential Vectors and Reservoirs." Master's dissertation, UiT Norges arktiske universitet. UiT Munin Open Research Archive. https://hdl.handle.net/10037/19100.

Muir, B. S., and R. M. Buckley. 1967. "Gill Ventilation in *Remora remora*." *Copeia* 1967, no. 3: 581–586. https://doi.org/10.2307/1442235.

Munday, B. L. 1986. "Diseases of Salmonids." In *Proceedings of the Workshop on Diseases of Australian Fish and Shellfish*, edited by J. D. Humphrey and J. S. Langdon, Benalla, Victoria, Australia.

Munday, B. L., C. K. Foster, F. R. Roubal, and R. J. G. Lester. 1990. "Paramoebic Gill Infection and Associated Pathology of Atlantic Salmon (*Salmo salar*) and Rainbow Trout (*Salmo gairdneri*) in Tasmania." In *Pathology in Marine Science: Proceedings of the Third International Colloquium on Pathology in Marine Aquaculture*. Gloucester Point, Virginia, USA, October 2–6, 1988, edited by F. O. Perkins and T. C. Cheng, 215–222. Academic Press. https://doi.org/10.1016/B978-0-12-550755-4.50026-4.

Munday, B. L., D. Zilberg, and V. Findlay. 2001. "Gill Disease of Marine Fish Caused by Infection With *Neoparamoeba pemaquidensis*." *Journal* of Fish Diseases 24, no. 9: 497–507. https://doi.org/10.1046/j.1365-2761.2001.00329.x.

Oldham, T., B. Nowak, M. Hvas, and F. Oppedal. 2019. "Metabolic and Functional Impacts of Hypoxia Vary With Size in Atlantic Salmon." *Comparative Biochemistry and Physiology Part A: Molecular & Integrative Physiology* 231: 30–38.

Østevik, L., M. Stormoen, H. Hellberg, et al. 2022. "A Cohort Study of Gill Infections, Gill Pathology and Gill-Related Mortality in Sea-Farmed Atlantic Salmon (*Salmo salar* L.): A Descriptive Analysis." *Journal of Fish Diseases* 45, no. 9: 1301–1321. https://doi.org/10.1111/jfd.13662.

Palstra, A. P., J. Kals, T. Böhm, J. W. M. Bastiaansen, and H. Komen. 2020. "Swimming Performance and Oxygen Consumption as Non-Lethal Indicators of Production Traits in Atlantic Salmon and Gilthead Seabream." *Frontiers in Physiology* 11: 759. https://doi.org/10.3389/fphys.2020.00759.

Patra, R. W., J. C. Chapman, R. P. Lim, P. C. Gehrke, and R. M. Sunderam. 2009. "Effects of Temperature on Ventilatory Behaviour of Fish Exposed to Sublethal Concentrations of Endosulfan and Chlorpyrifos." *Environmental Toxicology and Chemistry* 28, no. 10: 2182–2190. https://doi.org/10.1897/08-532.1.

Paul, A. J. 1986. "Respiration of Juvenile Pollock, *Theragra chalcogramma* (Pallas), Relative to Body Size and Temperature." *Journal of Experimental Marine Biology and Ecology* 97, no. 3: 287–293. https://doi.org/10.1016/0022-0981(86)90246-7.

Perry, S. F., and K. M. Gilmour. 2010. "Oxygen Uptake and Transport in Water Breathers." In *Respiratory Physiology of Vertebrates: Life With and Without Oxygen*, edited by G. E. Nilsson, 49–94. Cambridge University Press. https://doi.org/10.1017/CBO9780511845178.004.

Powell, M. D., J. O. Harris, J. Carson, and J. V. Hill. 2005. "Effects of Gill Abrasion and Experimental Infection With *Tenacibaculum maritimum* on the Respiratory Physiology of Atlantic Salmon *Salmo salar* Affected by Amoebic Gill Disease." *Diseases of Aquatic Organisms* 63, no. 2–3: 169–174. https://doi.org/10.3354/dao063169.

Powell, M. D., M. J. Leef, S. D. Roberts, and M. A. Jones. 2008. "Neoparamoebic Gill Infections: Host Response and Physiology in Salmonids." *Journal of Fish Biology* 73: 2161–2183. https://doi.org/10.1111/j.1095-8649.2008.02053.x.

Randall, D. J., and G. Shelton. 1963. "The Effects of Changes in Environmental Gas Concentrations on the Breathing and Heart Rate of a Teleost Fish." *Comparative Biochemistry and Physiology* 9, no. 3: 229–239. https://doi.org/10.1016/0010-406X(63)90046-X.

Randall, D. J., and L. S. Smith. 1967. "The Effect of Environmental Factors on Circulation and Respiration in Teleost Fish." *Hydrobiologia* 29: 113–124. https://doi.org/10.1007/bf00142057.

Roberts, J. L. 1975. "Active Branchial and Ram Gill Ventilation in Fishes." *Biological Bulletin* 148, no. 1: 85–105. https://doi.org/10.2307/1540652.

Rodger, H. D. 2014. "Amoebic Gill Disease (AGD) in Farmed Salmon (*Salmo salar*) in Europe." *Fish Veterinary Journal* 14: 16–27. https://doi.org/10.5555/20143250572.

Rodger, H. D., L. Henry, and S. O. Mitchell. 2011. "Non-Infectious Gill Disorders of Marine Salmonid Fish." *Reviews in Fish Biology and Fisheries* 21, no. 3: 423–440. https://doi.org/10.1007/s11160-010-9182-6.

Rushen, J., N. Chapinal, and A. De Passilé. 2012. "Automated Monitoring of Behavioural-Based Animal Welfare Indicators." *Animal Welfare* 21: 339–350. https://doi.org/10.7120/09627286.21.3.339.

Shelton, G. 1970. "The Regulation of Breathing." In *Fish Physiology*, edited by W. S. Hoar and D. J. Randall, vol. 4, 293–359. Academic Press. https://doi.org/10.1016/S1546-5098(08)60133-8.

Shinn, A., J. Pratoomyot, J. Bron, G. Paladini, E. Brooker, and A. Brooker. 2015. "Economic Impacts of Aquatic Parasites on Global Finfish Production." Global Seafood Alliance. https://www.globalseafood.org/advocate/economic-impacts-of-aquatic-parasites-on-global-finfish-production/.

Speare, D. J., J. Brackett, and H. W. Ferguson. 1989. "Sequential Pathology of the Gills of Coho Salmon With a Combined Diatom and Microsporidian Gill Infection." *Canadian Veterinary Journal* 30, no. 7: 571–575.

Steffensen, J. F. 2005. "Respiratory Systems and Metabolic Rates." *Fish Physiology* 22: 203–238. https://doi.org/10.1016/S1546-5098(04)22005-2.

Steinum, T., A. Kvellestad, L. B. Rønneberg, et al. 2008. "First Cases of Amoebic Gill Disease (AGD) in Norwegian Seawater Farmed Atlantic Salmon, *Salmo salar* L., and Phylogeny of the Causative Amoeba Using 18S cDNA Sequences." *Journal of Fish Diseases* 31, no. 3: 205–214. https://doi.org/10.1111/j.1365-2761.2007.00893.x.

Svendsen, M. B. S., N. R. Andersen, P. J. Hansen, and J. F. Steffensen. 2018. "Effects of Harmful Algal Blooms on Fish: Insights From *Prymnesium parvum*." *Fishes* 3, no. 1: 11. https://doi.org/10.3390/fishes3010011.

Taylor, R., C. Huynh, D. Cameron, B. Evans, M. Cook, and G. Ritchie. 2016. *Gill Score Guide: Amoebic Gill Disease (AGD) Management Training Document*. Tassal Ltd, Marine Harvest, CSIRO. https://research.csiro.au/aquaculture/wp-content/uploads/sites/217/2018/03/Download-pdf-version.pdf.

Taylor, R. S., W. J. Muller, M. T. Cook, P. D. Kube, and N. G. Elliott. 2009. "Gill Observations in Atlantic Salmon (*Salmo salar*, L.) During Repeated Amoebic Gill Disease (AGD) Field Exposure and Survival Challenge." *Aquaculture* 290, no. 1–2: 1–8. https://doi.org/10.1016/j.aquaculture.2009.01.030.

Tuckey, N. P. L., D. T. Ashton, J. Li, et al. 2022. "Automated Image Analysis as a Tool to Measure Individualised Growth and Population Structure in Chinook Salmon (*Oncorhynchus tshawytscha*)." *Aquaculture, Fish and Fisheries* 2, no. 5: 402–413. https://doi.org/10.1002/aff2.66.

VKM. 2014. "VKM Report 2014: Risk Assessment of Amoebic Gill Disease." Panel on Animal Health and Welfare, VKM. https://vkm.no/english/riskassessments/allpublications/riskassessmentofamoebicgilldiseaseinfish.4.27ef9ca915e07938c3b2909f.html.

Yang, C. Z., and L. J. Albright. 1992. "Effects of the Harmful Diatom *Chaetoceros concavicornis* on Respiration of Rainbow Trout *Oncorhynchus mykiss*." *Diseases of Aquatic Organisms* 14, no. 2: 105–114. https://doi.org/10.3354/DAO014105.

Young, N. D., I. Dyková, B. F. Nowak, and R. N. Morrison. 2008. "Development of a Diagnostic PCR to Detect *Neoparamoeba perurans*, Agent of Amoebic Gill Disease." *Journal of Fish Diseases* 31: 285–295. https://doi.org/10.1111/j.1365-2761.2008.00903.x.