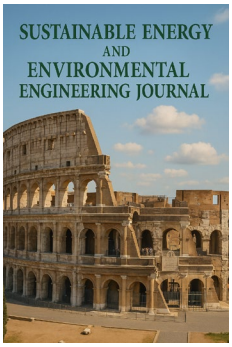
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Causal-Guided HyperMixer Prediction Model for Aquaponic Water-Environment Diagnosis

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Abstract

This paper presents a causal-guided HyperMixer prediction model for aquaponic water-environment diagnosis. To identify abnormal water conditions in the combined fish-plant circulation system early and prevent harm to the health of fish, nitrification stability, plant nutrient absorption, etc., disruption of regular farm operations should be avoided. The method builds multi-source observation windows by collecting dissolved oxygen, pH, ammonia nitrogen, nitrite, nitrate, temperature, electrical conductivity, turbidity, oxidation-reduction potential, feeding intensity, pump status, aeration state, water-return flow and zone metadata from fish tanks, hydroponic beds, biofilters and sump tanks. A causal screening branch reduces misleading weights caused by routine feeding, short sensor gaps, cleaning events, pump cycles, temporary tank disturbance and local root blockage. The HyperMixer branch then conducts a light-weight temporal and channel interaction of the water-quality variables to interpret oxygen decline, ammonia rise, temperature fluctuation, pH drift and circulation instability simultaneously. Conduct experiments on a simulated aquaponics monitoring dataset to perform multi-zone, cross-unit, ablation and disturbance tests. Compared with the previous machine-learning, recurrent, convolutional and mixer baselines, the proposed model has improved diagnosis accuracy, high-risk recall, warning precision and false-review control at a relatively low computational cost for edge deployment. The output is a staff review card that contains a diagnostic label, risk level, affected area, main causal factor, confidence level and suggested inspection action. Therefore, the model is to be used as an aquaponics decision-support tool for warning prioritisation and cause analysis, not as an autonomous water-control command.

Keywords: Aquaponic Water Diagnosis; Causal-Guided Prediction; HyperMixer; Water-Quality Monitoring; Smart Aquaculture; Warning Prioritization

1. Introduction

Aquaponic production links fish culture, microbial nitrification, and plant nutrient uptake inside one circulating water environment [1]. Smart aquaponic monitoring research shows that dissolved oxygen, pH, temperature, and nutrient indicators must be continuously observed because water-quality drift can spread across the fish tank, biofilter, sump tank, and hydroponic bed [2]. Simulation-based water-quality control studies further indicate that aquaponic stability depends on coordinated regulation rather than isolated parameter correction [3]. Bacterial activity in aquaponic systems also changes water quality and system health, which makes biological context necessary for diagnosis [4]. Therefore, aquaponic water diagnosis should not be treated as a simple threshold alarm for one sensor.

In real operation, the same sensor change can have several meanings. A slight ammonia increase after feeding may be tolerable when dissolved oxygen remains stable and the biofilter recovers quickly, but it becomes risky when low oxygen, hot water, unstable pH, or blocked return flow appears at the same time. IoT-driven urban aquaponics research

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[5] shows that monitoring systems must support timely alerts, and machine-learning decision support for aquaponic water prediction [6] shows that multiple indicators should be interpreted together. The revised text therefore frames diagnosis as contextual water-environment interpretation rather than isolated threshold checking.

Cross-zone coupling is the second challenge. A plant-bed obstruction can change the quality of return water, a fish-tank problem may appear later as delayed biofilter recovery, and a pump fault can simultaneously affect temperature, nutrient transfer, and oxygen. Aquaponic monitoring systems [7] and IoT-driven lettuce cultivation research [8] have used both sensor streams and production zones for water control. The revised manuscript therefore emphasizes that the proposed method should preserve transferable fish-plant-water relationships rather than memorizing local routines, repeated feeding schedules, or a fixed sensor position.

The structure of this document is as follows. Aquaponics monitoring, lightweight prediction models, and causative diagnostics for connected fish-plant systems comprise the second section. The third is a causal-guided HyperMixer model that incorporates diagnosis-output building, causal feature interaction, and sensor sequence encoding. The method's evaluation on a simulated aquaponics dataset using baseline comparison, cross-zone testing, ablation analysis, stress testing, and review-oriented warning output is the fourth step. The results, limitations, and future research directions are summarised in the fifth section.

2. Related Work

2.1. Aquaponic System Monitoring and Water-Quality Control

Because aquaponics integrates fish farming with crop production, the regulated water environment must cover both production areas. Comparative aquaponic and hydroponic tests show that nutrient uptake and water-use efficiency differ across culture types [9], while controlled-environment aquaponic research reports that plant growth conditions and circulation structure can influence sensor interpretation [10]. These findings indicate that single-variable prediction is insufficient. The revised related-work section therefore links fish welfare, plant nutrient uptake, microbial nitrification, and circulation design to the proposed diagnostic task.

2.2. HyperMixer and Lightweight Prediction Models

The prediction model should have a low computational cost and maintain feature interaction since aquaponic monitoring solutions frequently operate on edge devices or lightweight servers. Temporal learning can capture delayed changes in dissolved oxygen, pH, temperature, and nutrient content, according to research on smart aquaculture prediction [11] and outdoor recirculation systems [12]. As a result, HyperMixer-style modelling is appropriate; that is, channel variables and temporal tokens may be combined without requiring a strong attention backbone at each layer.

2.3. Causal Diagnosis for Coupled Fish-Plant Environments

Correlated signals are not always causal in aquaponic diagnosis. Feeding, water exchange, aeration correction, pump restart, and plant-bed cleaning can produce short sensor variations without indicating a true abnormal condition. A model that only mixes variables may learn these routine patterns as faults and increase unnecessary staff review. The revised manuscript therefore explains why diagnostic evidence should be screened before warning output. Persistent low oxygen, ammonia accumulation, unstable pH, pump failure, and delayed biofilter recovery should receive stronger causal priority than temporary management routines.

The aquaponic model should distinguish background routines from direct water-environment evidence. If biofilter recovery is normal, a feeding pulse should not be overweighted. In contrast, oxygen decline combined with ammonia rise, pH instability, and pump fluctuation should receive high diagnostic importance. The proposed causal-guided HyperMixer therefore combines lightweight feature interaction with a screening branch and produces a warning score, cause label, confidence label, and review suggestion. The revision makes clear that causal guidance is used to improve review interpretation, not to replace staff judgment.

3. Methodology

3.1. Sensor Sequence Encoding for Aquaponic Water State

The model begins by constructing an aquaponic observation window. Each window contains sensor readings, operation events, and zone metadata from the fish tank, hydroponic bed, biofilter, and sump tank. Water-quality variables include dissolved oxygen, pH, ammonia nitrogen, nitrite, nitrate, temperature, electrical conductivity, turbidity, and oxidation-reduction potential. Operation events include feeding, aeration, water replenishment, pump restart, cleaning, and harvest-related disturbance. This design retains both immediate water-quality values and recent management actions so that diagnosis can be linked to the process that generated it.

$$X_t = \text{concat}(W_t, O_t, Z_t) \quad (1)$$

where X_t is the aquaponic water-state input at time t, W_t is the water-quality vector, O_t is the operation-event vector, and Z_t is the culture-zone metadata.

The water-risk target is defined by comparing the current state with a zone-specific safe range. Fish tanks are more sensitive to dissolved oxygen and ammonia, while plant beds are more sensitive to nutrient balance and flow recovery. Therefore, the same numeric value can carry different diagnostic meaning in different zones.

$$R_t = \text{norm}(X_t - B_z) \quad (2)$$

where R_t is the normalized water-risk deviation and Bz is the safe baseline for zone z.

3.2. Causal HyperMixer Feature Interaction

The core module is the causal HyperMixer feature-interaction layer. Figure 1 shows how sensor channels, operation events, and zone states enter the model through separate streams before causal screening and mixer interaction. The figure emphasizes that the model does not simply stack all variables together. It first evaluates which evidence should be treated as diagnostic and which should be treated as contextual. This distinction is important for aquaponics because routine feeding, pump cycling, and cleaning may create short-term changes that should not automatically become urgent warnings.

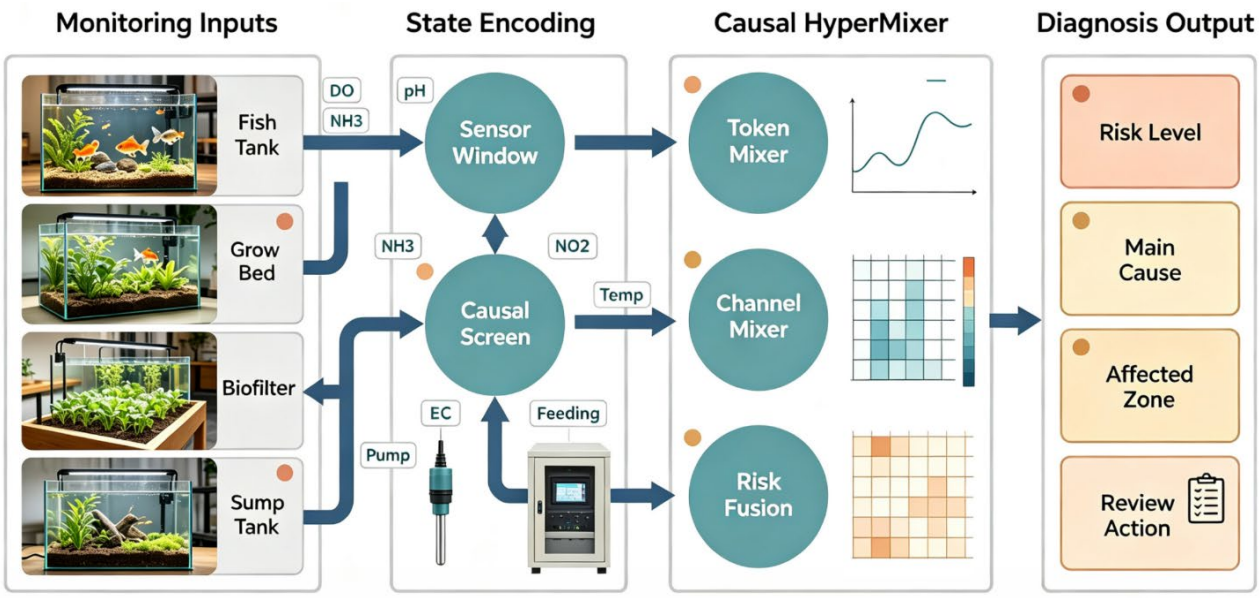


Figure 1. Causal feature interaction and HyperMixer structure.

$$H_t = \text{Encoder}(X_t) \quad (3)$$

where H_t is the encoded aquaponic state generated from the sensor and operation window.

The causal branch estimates the diagnostic importance of each encoded feature. Temporary feeding events, short sensor gaps, and routine pump cycles can receive lower weights when they do not align with sustained water-quality deterioration. Persistent low oxygen, ammonia accumulation, pH shock, and delayed biofilter recovery receive stronger weights.

$$C_t = \text{sigmoid}(W_c H_t) \quad (4)$$

where C_t is the causal screening vector and Wc is the trainable causal projection.

The HyperMixer branch performs token mixing across time and channel mixing across water-quality variables. This structure is lighter than a full attention model, but it still allows dissolved oxygen, ammonia, temperature, pH, flow state, and feeding intensity to interact within the same diagnostic representation.

$$M_t = \text{Mix}_{\text{time}}(H_t) + \text{Mix}_{\text{channel}}(H_t) \quad (5)$$

where $\mathbf{M_t}$ is the mixed representation after temporal and channel interaction.

The screened mixer representation is then formed by combining causal priority with mixed water-environment evidence. This step is important because aquaponic diagnosis should transfer between tanks and production units rather than memorizing a single feeding rhythm or sensor position.

$$U_t = C_t \odot M_t \tag{6}$$

where U_t is the causal-guided mixer representation and $\odot$ denotes element-wise weighting.

A compact residual route is added to preserve stable baseline information. If the causal branch becomes too strict during a noisy interval, the residual state keeps basic water-quality evidence available for the output head.

$$F_t = U_t + W_r H_t \tag{7}$$

where F_t is the final fused feature and Wr is a residual projection.

3.3. Water-Environment Diagnosis and Decision Output

The output layer converts the fused representation into a diagnosis probability and management-oriented warning score. Figure 2 presents the workflow from predicted water state to operator review. The output includes affected zone, risk level, confidence label, main causal factor, and suggested inspection action. This presentation clarifies that the model provides a review-prioritization signal rather than a closed-loop control command. Staff can inspect the evidence before reducing feeding, increasing aeration, cleaning the plant bed, checking the biofilter, or recalibrating sensors.

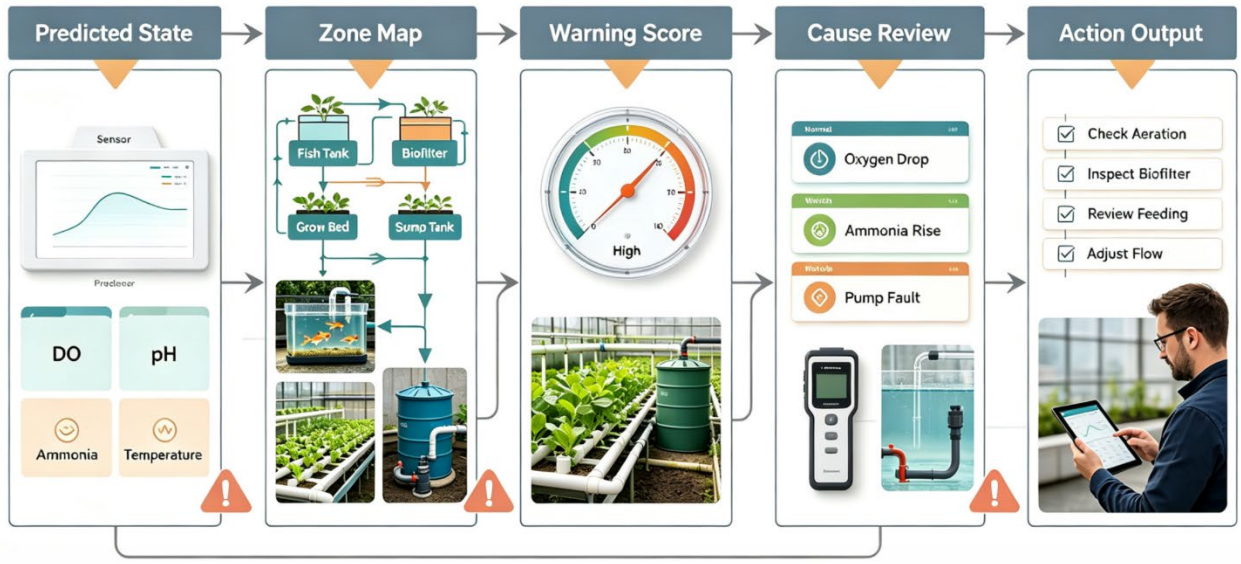


Figure 2. Aquaponic diagnosis warning-output workflow.

$$\hat{y}_t = \text{softmax}(W_o F_t) \tag{8}$$

where $\hat{y}_t$ is the predicted diagnosis distribution and Wo is the output projection.

The warning score combines diagnosis probability with the distance from the safe range. A high-risk output is produced only when the predicted class and the water-risk deviation point to the same abnormal condition.

$$p_t = \text{sigmoid}(\alpha \hat{y}_t + \beta R_t) \tag{9}$$

where p_t is the warning score, α controls diagnosis probability, and β controls deviation strength.

The final diagnosis card is intended for staff review. It can recommend checking aeration, reducing feeding, cleaning the plant-bed return channel, inspecting the biofilter, or recalibrating a sensor. The model is not designed to replace management judgement; it organizes evidence so that the most urgent water-environment risks can be reviewed first.

4. Experiments and Results

4.1. Experimental Data and Water-Risk Categories

A simulated aquaponics monitoring dataset is created to test the model. Smart aquaculture prediction systems [13] show that multiple water indicators should be collected during model evaluation, water-quality monitoring in partial recirculating aquaculture [14] confirms the need for continuous sensing, and IoT-based deep-learning monitoring [15] records both water data and operating condition. The simulated dataset includes 36 aquaponic production units with

fish tanks, hydroponic beds, biofilters, and sump tanks. The revised wording states the simulated nature of the evaluation more directly.

Table 1. Experimental data scale for aquaponic water-environment diagnosis.

Item	Value	Unit	Split	Purpose
Production units	36	unit	All	System source
Monitoring windows	92,400	window	Train/Val/Test	Model input
Sensor channels	18	channel	All	Water evidence
Culture zones	4	zone	All	Spatial context
Diagnosis labels	4	level	All	Warning target
Stress cases	5	type	Test	Robustness
Unseen systems	6	unit	Test	Transfer check

The distribution of the simulated data is shown in Figure 3. Retaining interpretable risk categories in the assessment is supported by explainable deep reinforcement learning for smart aquaculture [16]. Fish-tank conditions are depicted in Figure 3(a); although normal functioning predominates, ammonia buildup and oxygen depletion remain important danger factors. Fish physiology research [17] has also demonstrated the need of monitoring dissolved ammonia and oxygen. Hydroponic-bed conditions, including steady uptake, nutrient deficit, root obstruction, and delayed return flow, are depicted in Figure 3(b). Dissolved oxygen, pH, temperature, ammonia nitrogen, nitrate, and flow indicators are the primary observation channels, according to Figure 3(c), which displays the sensor-source share. The risk-label level is displayed in Figure 3(d), which verifies that high-risk situations are purposefully scarce. Because this is more in line with real aquaponics management, hazardous water conditions are less often but more severe when they do occur.

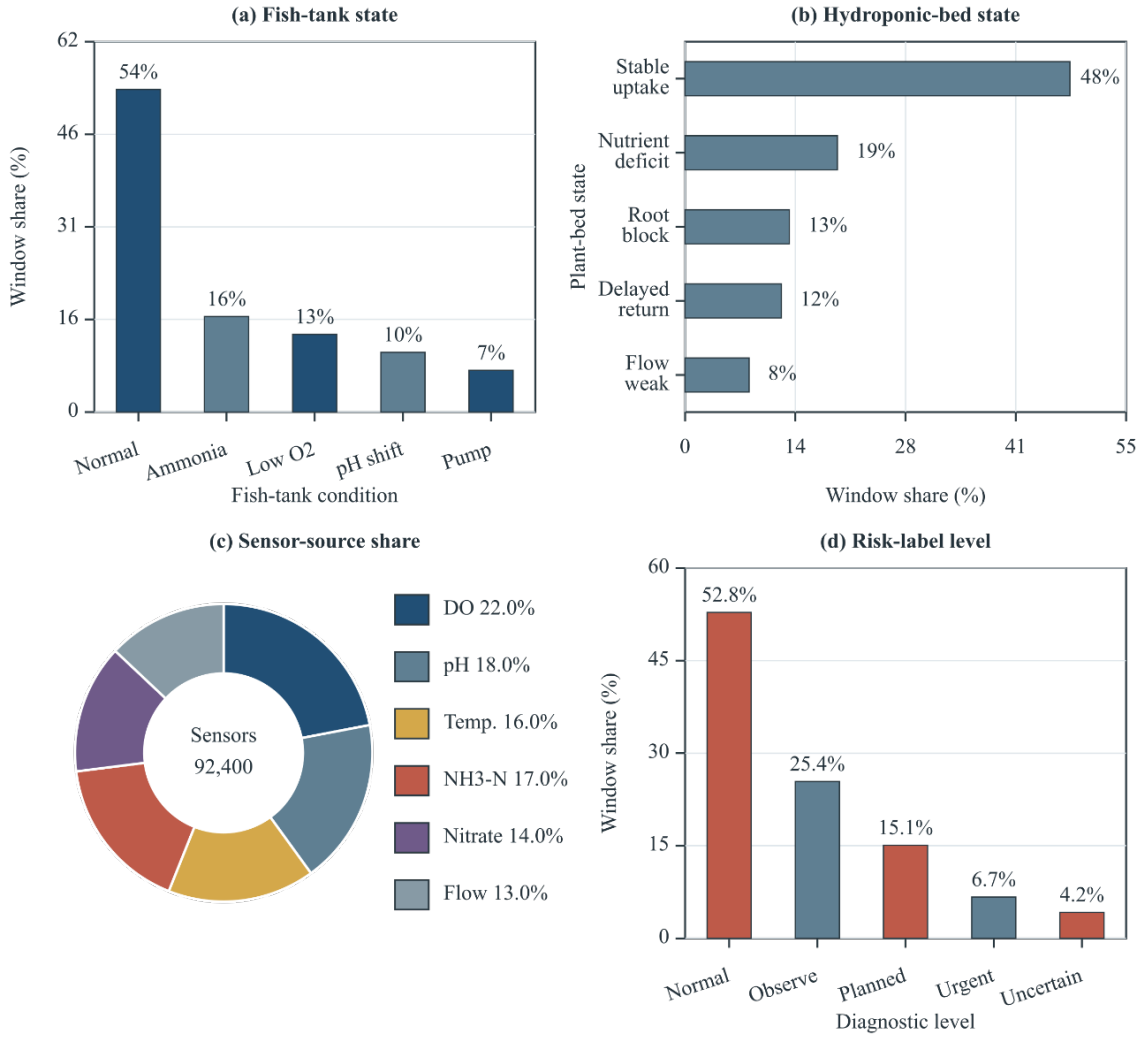


Figure 3. Aquaponic diagnostic dataset distribution. (a) fish-tank state. (b) hydroponic-bed state. (c) sensor-source share. (d) risk-label level.

The Dataset is divided by time and production unit. Twenty-four units are used for training, six for validation and six are left out for testing. Dissolved oxygen prediction research [18] supports chronological evaluation by considering the delayed recovery of oxygen. The revised manuscript specifies that nearby monitoring windows from the same unit should not be randomly distributed in the training and test sets. Random splitting would have made the task easier to deploy, and rhythm feeding, sensor placement and unit-specific recovery patterns could have been leaked into the test set.

The four diagnostic categories are normal, observation, planned review and urgent inspection. Both categorisation and continuous indicator prediction are supported by General Water Quality Monitoring with Machine Learning [19]. Oxygen, pH, temperature, nutrients and flow are all within the normal range. Small deviations that are known as observation windows should still be displayed in the monitoring system, even if they can be automatically adjusted. Slow nitrate accumulation, frequent pH fluctuations and reduced plant-bed flow are examples of chronic but non-urgent problems that have been scheduled for examination. Combined degradation, such as low oxygen and ammonia accumulation, a sharp rise in pH, pump instability, or suspected biofilter failure, can all be identified in the urgent-inspection window. Instead of a statistical risk score, this label design shows the reason for an actual work order.

The ten-minute window is the simulated observation duration; it needs to be long enough to observe changes in feeding and aeration but not so long as to be affected by sensor noise in the dataset. There are six historical observations in each era. This time is long enough for the model to show short-term stabilisation, delayed recovery and initial departure. For example, after feeding, ammonia will rise first, then oxygen, and only then will the pH change due to biofilter stress. This sequence cannot be shown at one time; therefore, a time window must be selected.

The simulated dataset has class imbalance. Ensemble water-quality index prediction [20] supports evaluating models under unequal environmental categories. A well-managed aquaponics system should be relatively stable most of the time, and serious high-risk events are infrequent. The revised manuscript therefore reports high-risk recall and false review load in addition to overall accuracy. A model that predicts too few urgent cases would fail to protect fish welfare, and a model that flags too many routine changes would overburden staff and reduce trust in the warning system.

The general working mode is shown in the simulated data above. Research on AI-based clean-water prediction [21] shows that context enhances the alert effect. Because they may explain the short sensor oscillations, feeding, water replenishment, pump restart, filter cleaning and partial harvest are considered operating events. Without the above data, one cannot know whether changes in turbidity or ammonia are due to the same cause affecting the water. Determine if the adjustment meets the expected recovery requirements based on the event records. As employees are already aware that some temporary disruptions are considered normal operations, this Design aims to reduce the number of unnecessary alarms in the production system.

4.2. Baseline Comparison and Multi-Zone Generalization

Without causal screening, the suggested model is contrasted with Random Forest, LSTM, GRU, Temporal Convolution, conventional MLP-Mixer, and HyperMixer. Comparing ensemble and neural baselines with common metrics is supported by groundwater-quality ensemble modelling [22]. The same sensor channels, operation events, zone information, and train-test split are used across all baselines. Diagnosis accuracy, water-risk MAE, high-risk recall, warning precision, F1-score, and manual review load are the assessment markers.

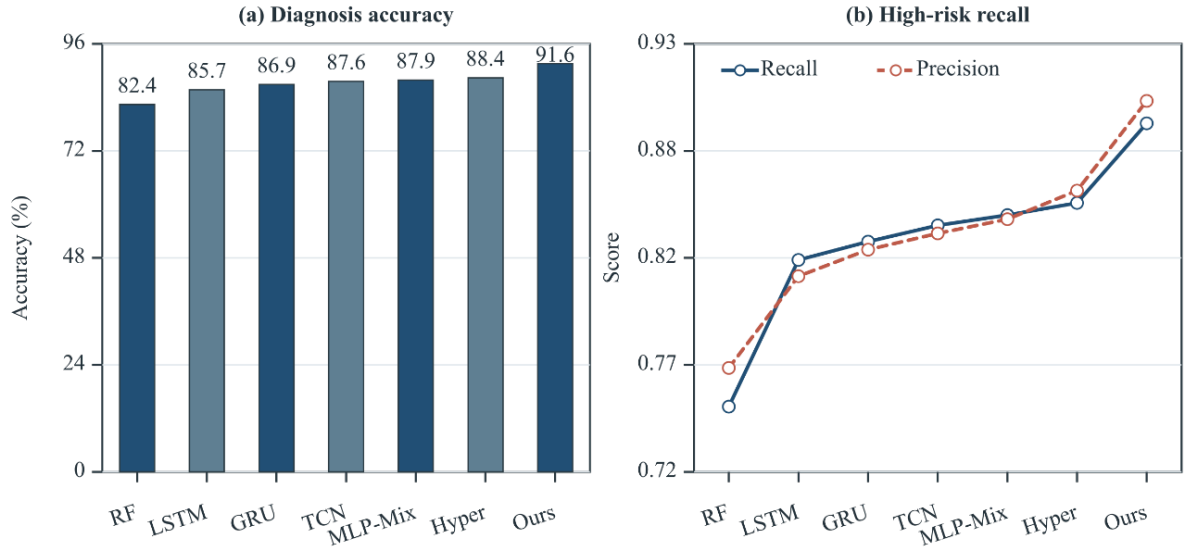


Figure 4. Model comparison results. (a) diagnosis accuracy. (b) high-risk recall.

The model comparison results are displayed in Figure 4. Feature-fusion transformer and MLP-Mixer research [23] supports lightweight mixing for structured feature interaction. Figure 4(a) reports diagnostic accuracy, where GRU reaches 86.9%, conventional HyperMixer reaches 88.4%, and the proposed model reaches 91.6%. Figure 4(b) reports high-risk recall, where the proposed model reaches 0.891 and outperforms LSTM and HyperMixer without causal guidance. The revised discussion connects these metrics to staff workload, missed-risk control, and warning precision.

Figure 5 illustrates cross-zone generalization. Improved MLP-Mixer prediction research [24] suggests that lightweight mixing can support multi-site environmental prediction. Figure 5(a) shows fish-tank results, where the model identifies ammonia accumulation before the rule-based threshold and preserves low-oxygen memory after feeding. Figure 5(b) shows plant-bed results, where conductivity, nitrate, and flow recovery reveal return-channel obstruction. Figure 5(c) shows biofilter recovery, and Figure 5(d) shows sump-tank pump instability. The revised text links each panel to a zone-specific failure mode.

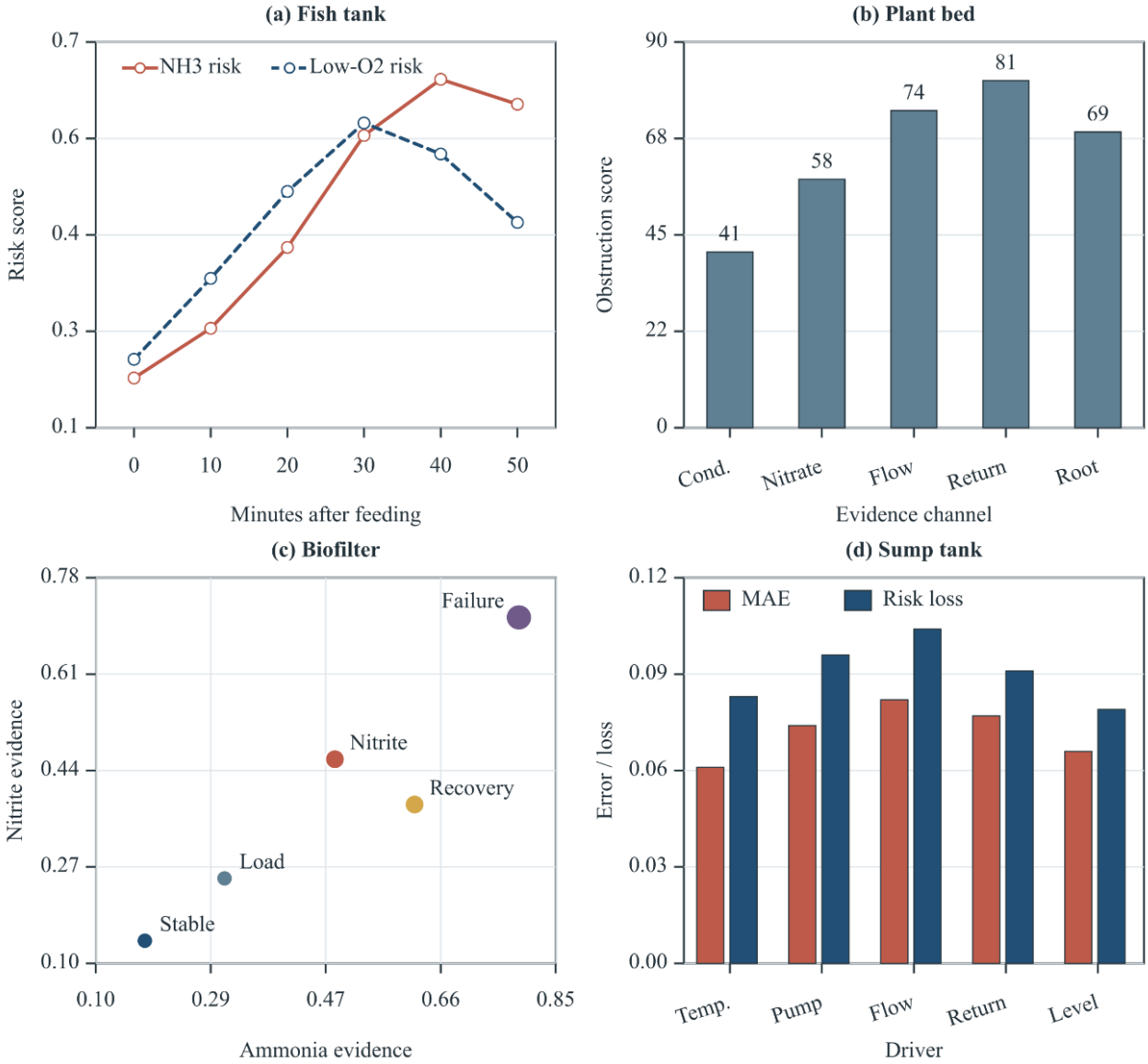


Figure 5. Cross-zone transfer performance. (a) fish tank. (b) plant bed. (c) biofilter. (d) sump tank.

The proposed model has reduced the false alarm rate of the threshold baseline by 20.8% and lowered the water-risk MAE to 0.074. Explainable AI research [25] can help preserve interpretable warning evidence after staff decisions are based on model results. The reasons for the remaining false alarms are mainly sensor drift during cleaning, delayed ammonia recovery after heavy feeding, and unstable flow signals during pump switching. The revised discussion now differentiates between harmless feeding responses and early abnormalities, and explains why review-oriented tools may use a small number of cautious warnings reasonably.

The structure of the aquaponics data is consistent with the basic failure mode. Rare occurrences and delayed responses need to be handled carefully, as shown in the time-series anomaly detection study [26]. Random Forest cannot simulate the delay in biological recovery and is only suitable for stable pH and temperature. LSTM and GRU are used to maintain the temporal order, but zone information is lost. Temporal convolution is very sensitive to short

feeding pulses and may thus fail to detect sudden changes. In the absence of causal screening, the traditional HyperMixer considers local tank practices and recurring feeding regimens as transferable evidence even if it learns feature interactions. It can distinguish between evidence of direct water risk and the general management environment, so the new model is better.

The other is a function of confidence calibration. Current IoT-based aquaculture monitoring practices [27] support combining sensor status and operation data for warning assessment. The proposed model outputs a high-confidence normal label only when the evidence of oxygen, ammonia, pH, temperature and flow are consistent over the monitoring period. When evidence is ambiguous, the output is changed from urgent inspection to observation and the confidence label is reduced. Therefore, the revised text considers missingness, delayed sampling and unstable communication as confidence evidence rather than hidden preprocessing problems.

Based on the multi-zone data, the fish-tank and biofilter areas have been most frequently screened for causes. Missing data, delayed sampling and unstable communication can all be solved by continuous water-quality monitoring systems [28]. A purely statistical model may be affected by many transient correlations produced during pulse feeding in fish tanks. Remove the delayed recovery of ammonia and nitrite in biofilters from the area of typical sensor variation. A mixer branch is used to adjust the nutrient, conductivity and return-flow of the plant-bed results. Because the temperature and condition of the pump are immediate indications, sumps and tanks are comparatively straightforward. The above changes show that both zone information and feature interaction are required by the model.

New production bases will use this model. Water-quality monitoring using LoRa and IoT [29] has indicated that the limits for communication and sampling must be considered in the evaluation of monitoring systems. Fish numbers, plant-bed sizes, sensor locations and feeding times are all different in these areas. As it transfers local routines from the training unit, the regular HyperMixer has reduced recall in this split. Because it focuses on links that are still necessary for the system, such as extended oxygen deprivation with ammonia accumulation or reduced flow combined with nutritional deficiency, the causal-guided version has a higher recall. Therefore, the proposed way will be used for causal screening.

The volume of work for manual review is determined by how many windows need to be submitted to employees for manual inspection. Explainable water-quality modelling [30] helps to determine whether the management can understand both the numerical projections and the predictions. After feeding and cleaning, the rule-based threshold issues many single-sensor deviations for manual inspection. If recovery evidence is available, then use the transient deviation as the observation for the model and reduce the load. It also continuously transmits the combined degradation for urgent assessment at the same time. This trade-off will enable a feasible process that does not respond to all sensor variations and only handles serious problems.

In addition, the distribution of errors shows that the water-risk MAE alone is not adequate. As the projected class is still at the same review level, some medium-error scenarios will have little management effect. If the forecast exceeds the range of the planned review and urgent inspection, even a small numerical error will have a serious impact. As a result, the experiment provides both classification and regression results in the report. The new model is relatively balanced; it still meets the warning order requirements for daily staff work but has reduced the numerical variance.

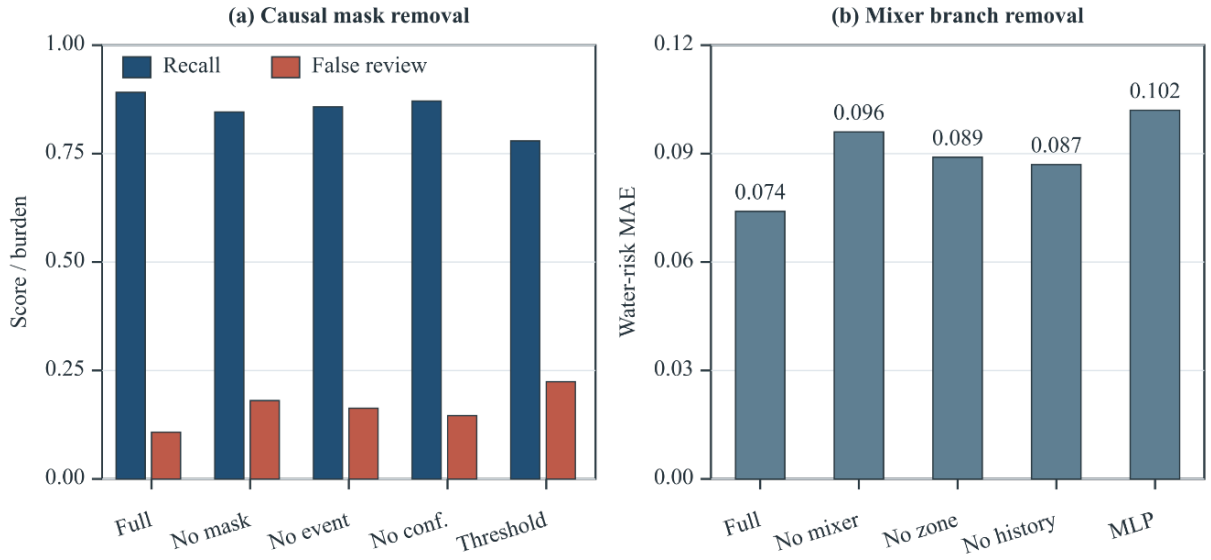


Figure 6. Ablation contribution. (a) causal mask removal. (b) mixer branch removal.

4.3. Ablation, Stress Testing, and Review Output

Ablation analysis is used to identify the contribution of the causal branch and mixer branch. The two main module results are displayed in Figure 6. Figure 6(a) shows that removing the causal mask increases false review burden and decreases high-risk recall from 0.891 to 0.846. Figure 6(b) shows that diagnostic accuracy decreases when the mixer branch is removed because the model cannot capture cross-channel relationships among oxygen, ammonia, pH, and flow. The revised text explains the different functions of these components.

The stress-test results are shown in Figure 7. Figure 7(a) shows sensor drift, where missingness and confidence information help preserve warning precision. Figure 7(b) shows feeding-pulse disturbance, where the causal branch avoids treating every post-feeding ammonia increase as an urgent fault. Figure 7(c) shows pH shock, where unstable oxygen and nitrite make the warning score rise quickly. Figure 7(d) shows aeration interruption through dissolved-oxygen decline. The revised text distinguishes these disturbances as different mechanisms rather than one generic noise category.

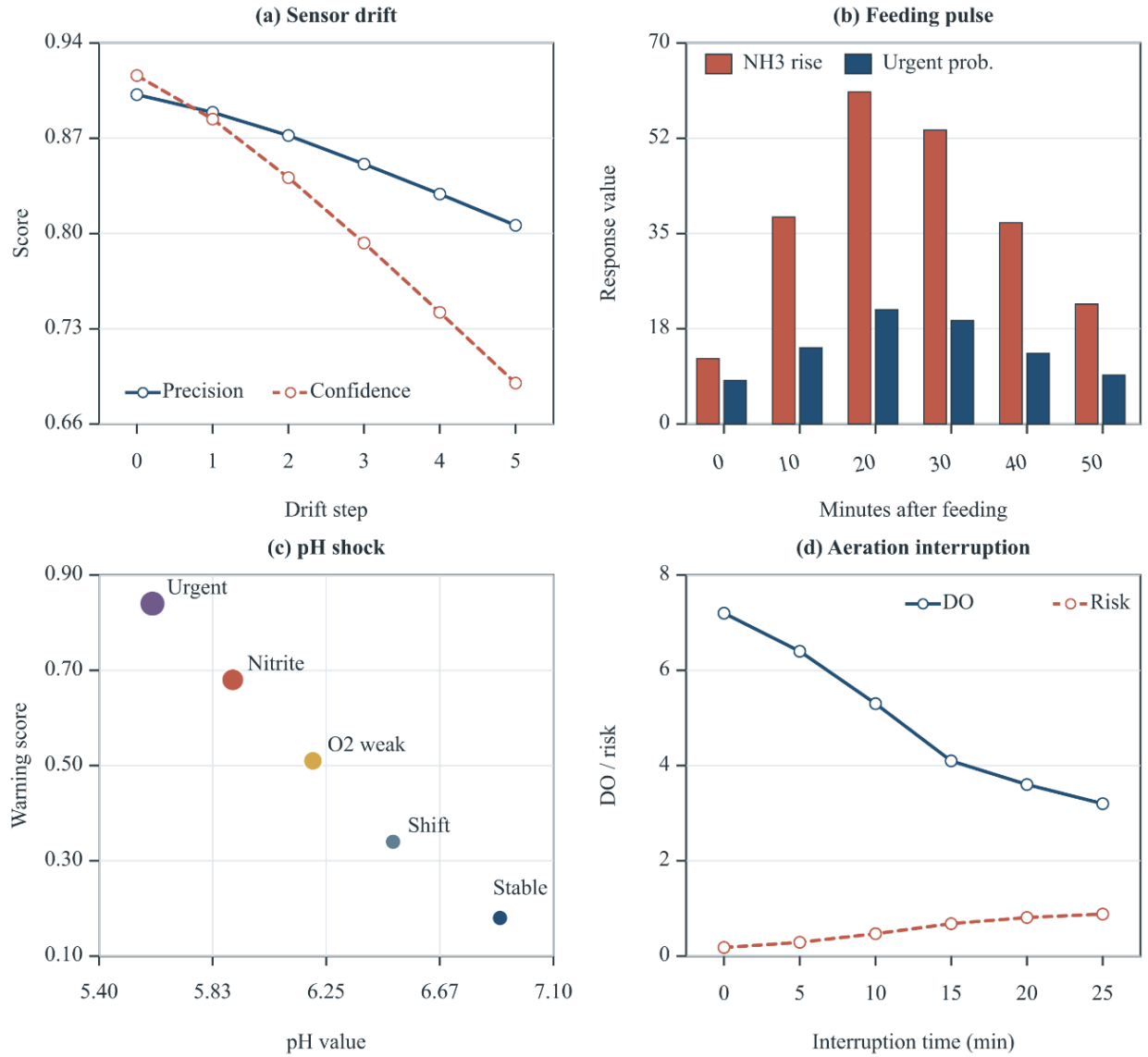


Figure 7. Stress-test results. (a) sensor drift. (b) feeding pulse. (c) pH shock. (d) aeration interruption.

The field-oriented water-environment warning output is displayed in Figure 8. Figure 8(a) shows the zone-level risk map for the fish tank, plant bed, biofilter, and sump tank. Figure 8(b) shows cause labels such as low oxygen, ammonia accumulation, plant-bed obstruction, sensor drift, or pump instability. Figure 8(c) presents an operator review card with risk score, confidence label, affected zone, and recent evidence. Figure 8(d) ranks intervention priority. The revised text presents as a staff workflow rather than an automatic controller.

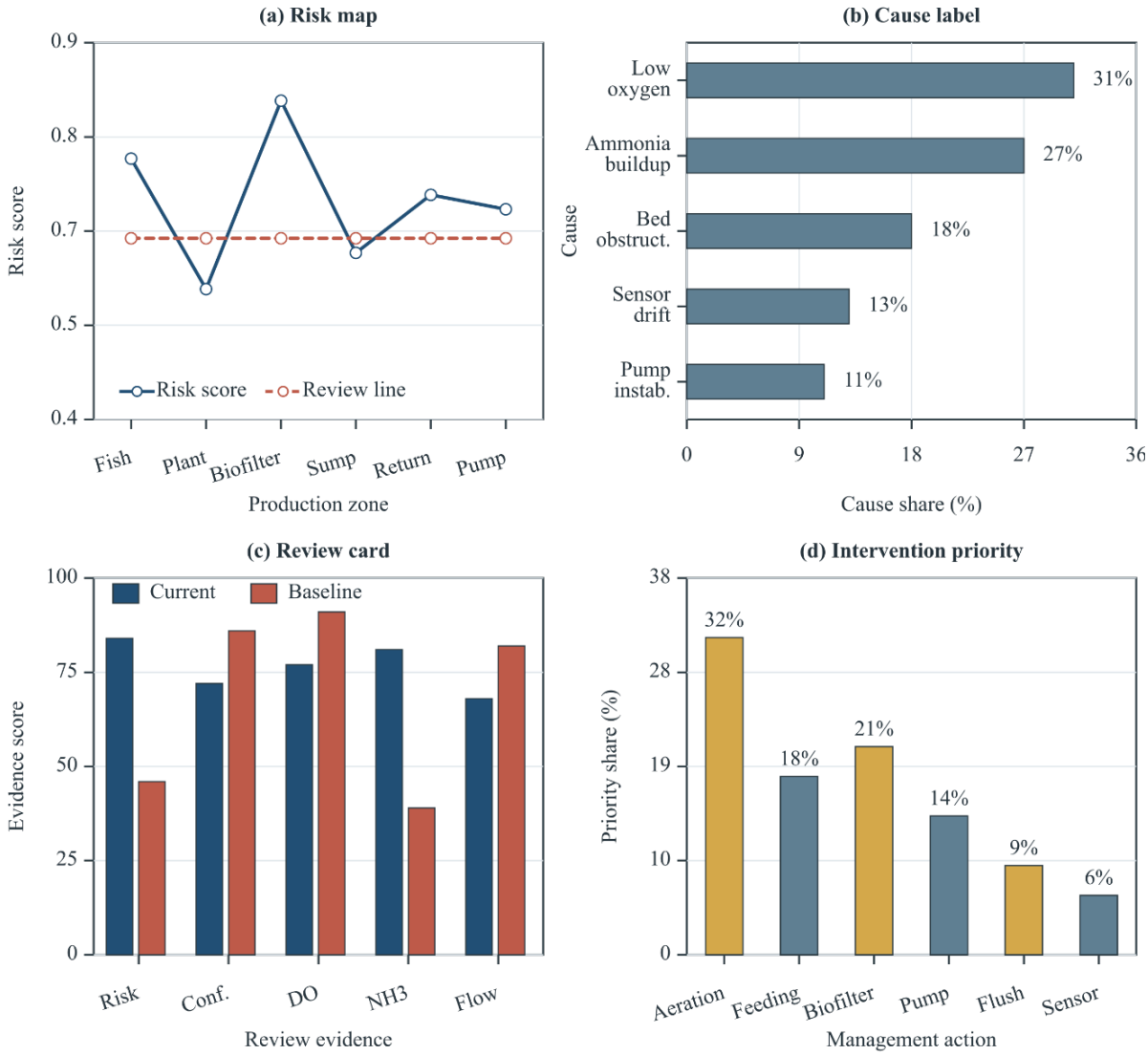


Figure 8. Field-oriented water-environment warning output. (a) risk map. (b) cause label. (c) review card. (d) intervention priority.

Compare the amount of work done by staff before and after model screening to provide a reference for the review-oriented results. In the hypothetical case, 52.8% of the windows are under regular monitoring, 25.4% are being observed, 15.1% are scheduled for review, and 6.7% require urgent inspection. The warning area will be extended by the model. When oxygen, ammonia, pH and flow data all show the same decline trend, it is considered an urgent label for a combined risk event. As a result, none of the short-term changes in the large-scale monitoring platform are displayed for the aquaponics crew. When many weak signals occur at the same time, the model is most useful. A relatively small increase in ammonia may be due to food intake, and a slight drop in oxygen does not require immediate action. The model will issue a warning if the change occurs during an abnormal pH fluctuation and a delay in flow recovery. At the same time, if only one sensor deviates and the nearby evidence is consistent, then the confidence label will be reduced. The management's demand that diagnosis is to supplement human judgment rather than replace it is in line with this behaviour.

Deployment constraints are also the reasons for the other problems. Nitrate and Conductivity will be affected by the quality of sensor calibration. As ageing in biofilters cannot be monitored in real time, it is inferred from a decline in water quality. No flow sensor is used; therefore, a pump failure will not be identified. The future system will combine sensor predictions with maintenance records, microbial indicators, pictures of tanks and roots, etc., under various circumstances. Although the simulated results of this study are sufficient to demonstrate the feasibility of causal-guided HyperMixer diagnosis, actual production verification is still required. According to the stress results, the damage caused by the disruption is not uniform. The main reason for reduced confidence is sensor missingness; otherwise, the model can still use nearby variables and operation events. Feeding pulses have good protective effects against causality because they mainly affect the interpretation of ammonia and oxygen. Aeration interruption is generally recognised earlier and has a more pronounced irregular shape. Because its signal extends over many

windows through conductivity, nitrate and flow recovery, plant-bed obstruction is more difficult. The two are shown separately, and both a danger label and a cause label are available.

Determine whether the suggested actions correspond to the simulated anomaly and qualitatively evaluate the review card. Low-oxygen events: Reduce the number of fish and provide oxygen (aerate). Ammonia accumulation shows that the biofilter is working but there is no food. Return-channel or root-zone problems are the cause of plant-bed obstruction. Water changes will not help; sensor drift is caused by calibration. An excessive response to a model alert due to measurement errors and no actual water loss can be prevented by this action mapping. The proposed method is not a closed-loop controller, and a dashboard can be used to display and analyze the results. The dashboard shows trend graphs, affected regions, confidence labels, recent operation events and recommended review actions. Staff can then choose to clean the biofilter, inspect the plant bed, increase aeration, reduce feeding or recalibrate sensors. As aquaponics are biological systems and management measures affect both crop production and fish welfare, a human-in-the-loop review will still be required.

The old query is supported by the model. The matching sensor window, causal weights and action record can be saved as a case when the staff confirms a high-risk incident. The above cases will help the management compare the production units, identify recurring equipment problems, and adjust farm-specific criteria in the future. This input will improve the calibration of future confidence based on the discovery of a sensor error. A learning loop can be used to expand the aquaponics farm from a single demonstration unit to multiple production units with different crop arrangements and fish densities.

5. Conclusion

This study presented a causal-guided HyperMixer model for aquaponic water-environment diagnosis. Multi-source observation windows were constructed from water-quality sensors, operation events, and culture-zone information. Lightweight mixer interaction was combined with causal filtering to reduce misleading routine correlations and preserve cross-channel water-quality evidence. Experiments on a simulated aquaponic dataset show improved diagnosis accuracy, high-risk recall, water-risk prediction, and review efficiency compared with machine-learning, recurrent, convolutional, and mixer baselines. The system should be interpreted as staff decision support rather than a replacement for farm-specific calibration or validated management procedures.

Several limitations remain. The simulated dataset cannot fully cover microbiological collapse, unexpected fish infection, unrecorded water exchange, sensor fouling, long-term biofilter aging, plant-root obstruction, or changes in farm layout and crop type. Some biological processes can only be inferred indirectly from sensor data, and explanation accuracy declines when key indicators or operation records are missing. The revised manuscript therefore emphasizes stable sensor calibration, maintenance records, staff observation, and model retraining after production layout or crop changes. Real-farm validation is required before deployment.

Future work will integrate the model with real aquaponic-farm data, image monitoring, microbiological indicators, maintenance logs, and adaptive control logs. A practical system should include human feedback, cross-farm transfer learning, uncertainty calibration, sensor-replacement records, and safer intervention recommendations. Staff-confirmed events can be retained as review cases for farm-specific threshold adjustment and confidence calibration. These extensions will help transform aquaponic diagnosis from simulated model testing into a dependable decision-support system that remains accountable to biological observation and farm management practice.

6. Declarations

6.1. Author Contributions

Zisis Apostolou contributes to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision, project administration, and funding acquisition. All authors have read and agreed with the manuscript before its submission and publication.

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6.3. Institutional Review Board Statement

Not applicable.

6.4. Informed Consent Statement

Not applicable.

6.5. Data Availability

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

6.7. Declaration of generative AI and AI-assisted technologies

During the preparation of this manuscript, the authors utilized Grammarly for linguistic polishing, logical organization and draft revision. The generative AI tool was not involved in research design, data collection, data analysis, or the equation of core conclusions. All outputs generated by AI were reviewed, revised and verified manually by the authors. The authors take full responsibility for all content of this manuscript.

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