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A Systematic Literature Review on Explainable AI-Based Fish Quality Assessment Using Deep Learning

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Abstract

Fish quality assessment is essential for ensuring food safety, maintaining consumer confidence, and supporting the global seafood industry. Recent advances in Artificial Intelligence (AI), particularly deep learning and Explainable Artificial Intelligence (XAI), have enabled accurate, rapid, and non-destructive evaluation of fish freshness and quality. This systematic literature review aims to provide a comprehensive analysis of AI-based fish quality assessment techniques, with a particular focus on explainable deep learning models and their applications in seafood inspection. The review was conducted following the PRISMA 2020 guidelines and included publications from 2019 to 2026 retrieved from Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, and the ACM Digital Library. Following the screening and eligibility process, 220 representative studies were included for qualitative synthesis. The reviewed literature covers Convolutional Neural Networks (CNNs), transfer learning, Vision Transformers (ViTs), hyperspectral imaging, thermal imaging, multimodal sensing, and Explainable AI techniques, including Grad-CAM, LIME, SHAP, saliency maps, and attention visualization. Comparative analysis indicates that deep learning models consistently achieve classification accuracies exceeding 90–95%, while XAI methods significantly improve model transparency, interpretability, and user trust in industrial decision-making. However, challenges such as limited benchmark datasets, poor cross-species generalization, computational complexity, and the absence of standardized explainability evaluation frameworks continue to hinder widespread industrial adoption. This review identifies current research trends, summarizes existing datasets and evaluation metrics, highlights critical research gaps, and proposes future directions, including Edge AI, federated learning, digital twins, multisensor fusion, and trustworthy XAI, to support the development of intelligent, transparent, and reliable fish quality assessment systems.

Keywords: Fish Quality Assessment; Explainable Artificial Intelligence; Deep Learning; Computer Vision; Convolutional Neural Networks; Vision Transformer; Hyperspectral Imaging; Grad-CAM; SHAP; LIME; Seafood Quality Inspection.

1. Introduction

Fish and seafood constitute one of the most important sources of high-quality protein, essential fatty acids, vitamins, and minerals for the world's growing population. As global seafood production and consumption continue to increase, maintaining fish quality throughout harvesting, transportation, processing, storage, and retail distribution has become a critical concern for the seafood industry. Freshness and quality directly influence consumer health, market value, export potential, and compliance with international food safety regulations. Consequently, accurate and timely fish quality assessment has become an essential requirement for producers, regulatory authorities, exporters, and consumers. Traditional quality assessment methods primarily rely on sensory evaluation performed by trained experts together with chemical analyses such as Total Volatile Basic Nitrogen (TVB-N), pH measurement, microbiological testing, and texture analysis. Although these methods provide reliable information, they are often destructive, labor-intensive, time-consuming, expensive, and susceptible to human subjectivity, making them unsuitable for large-scale automated industrial inspection.

Recent advances in Artificial Intelligence (AI), computer vision, and deep learning have transformed food quality inspection by enabling automated, rapid, and non-destructive analysis of visual and sensor data. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable capability in automatically extracting discriminative features from fish images without requiring handcrafted feature engineering. Transfer learning approaches based on architectures such as ResNet, DenseNet, EfficientNet, and MobileNet have significantly reduced training time while achieving high classification performance even with limited datasets. More recently, Vision Transformers (ViTs), hybrid CNN-transformer models, hyperspectral imaging, thermal imaging, and multimodal learning have further improved fish freshness prediction by combining spatial, spectral, and contextual information.

Despite these impressive advances, most deep learning systems operate as 'black-box' models whose decision-making processes are difficult for human experts to understand. In practical seafood industries, inspectors, quality assurance personnel, and regulatory agencies require transparent and interpretable AI systems before they can be trusted for critical decision-making. Explainable Artificial Intelligence (XAI) addresses this challenge by providing understandable explanations for model predictions. Popular XAI methods, including Gradient-weighted Class Activation Mapping (Grad-CAM), Local Interpretable Model-agnostic Explanations (LIME), SHapley Additive exPlanations (SHAP), attention visualization, and saliency maps, enable users to identify influential image regions and important features responsible for prediction outcomes. Such explanations improve user confidence, facilitate expert validation, support regulatory compliance, and encourage industrial adoption of AI-assisted inspection systems.

Several recent studies have demonstrated the effectiveness of deep learning for automated fish quality assessment. CNN-based models consistently outperform conventional machine learning algorithms because they automatically learn hierarchical image representations. Transfer learning has been widely adopted to overcome limited labeled datasets and has reported classification accuracies exceeding 95% in several fish freshness applications. Vision Transformer architectures have shown superior capability for modeling long-range feature relationships, while hyperspectral imaging integrated with deep learning has enabled accurate prediction of chemical freshness indicators such as TVB-N and moisture content. Furthermore, multimodal frameworks combining RGB images, hyperspectral data, and Internet of Things (IoT) sensors have improved prediction robustness under real-world conditions. Parallel research has highlighted the growing importance of XAI techniques. Grad-CAM has been extensively employed to visualize discriminative image regions responsible for freshness prediction, whereas LIME and SHAP provide local and global feature explanations that improve transparency and facilitate expert interpretation of AI-generated decisions.

Although significant progress has been achieved, several challenges remain unresolved. Existing studies often employ relatively small or proprietary datasets, limiting reproducibility and cross-species generalization. There is a lack of standardized benchmark datasets and consistent evaluation protocols across different fish species, imaging modalities, and environmental conditions. Moreover, only a limited number of studies comprehensively evaluate the quality of explanations generated by XAI methods, and industrial deployment remains constrained by computational cost, real-time processing requirements, and user trust. These research gaps highlight the need for a comprehensive synthesis of current evidence that simultaneously examines deep learning architectures, explainability techniques, available datasets, evaluation metrics, and future research directions.

Accordingly, this systematic literature review provides a comprehensive overview of Explainable AI-based fish quality assessment using deep learning. Following PRISMA-inspired review principles, the paper critically analyzes recent literature on computer vision, deep learning models, transfer learning, Vision Transformers, multimodal sensing, and explainability techniques including Grad-CAM, LIME, SHAP, and saliency maps. In addition, it summarizes publicly available datasets, evaluation metrics, current challenges, and emerging research opportunities such as Edge AI, federated learning, trustworthy AI, digital twins, and human-in-the-loop inspection systems. By integrating findings from recent studies, this review provides researchers and practitioners with a consolidated understanding of the current state of the art while identifying promising directions for future research and industrial implementation..

2. Methodology of the Systematic Literature Review

This systematic literature review (SLR) was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020**)** guidelines to ensure a transparent, rigorous, and reproducible review process. The methodology comprised several stages, including research question formulation, literature search, study selection, quality assessment, data extraction, and qualitative synthesis. A comprehensive search was performed using internationally recognized scientific databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, and the ACM Digital Library, covering publications from 2019 to 2026.

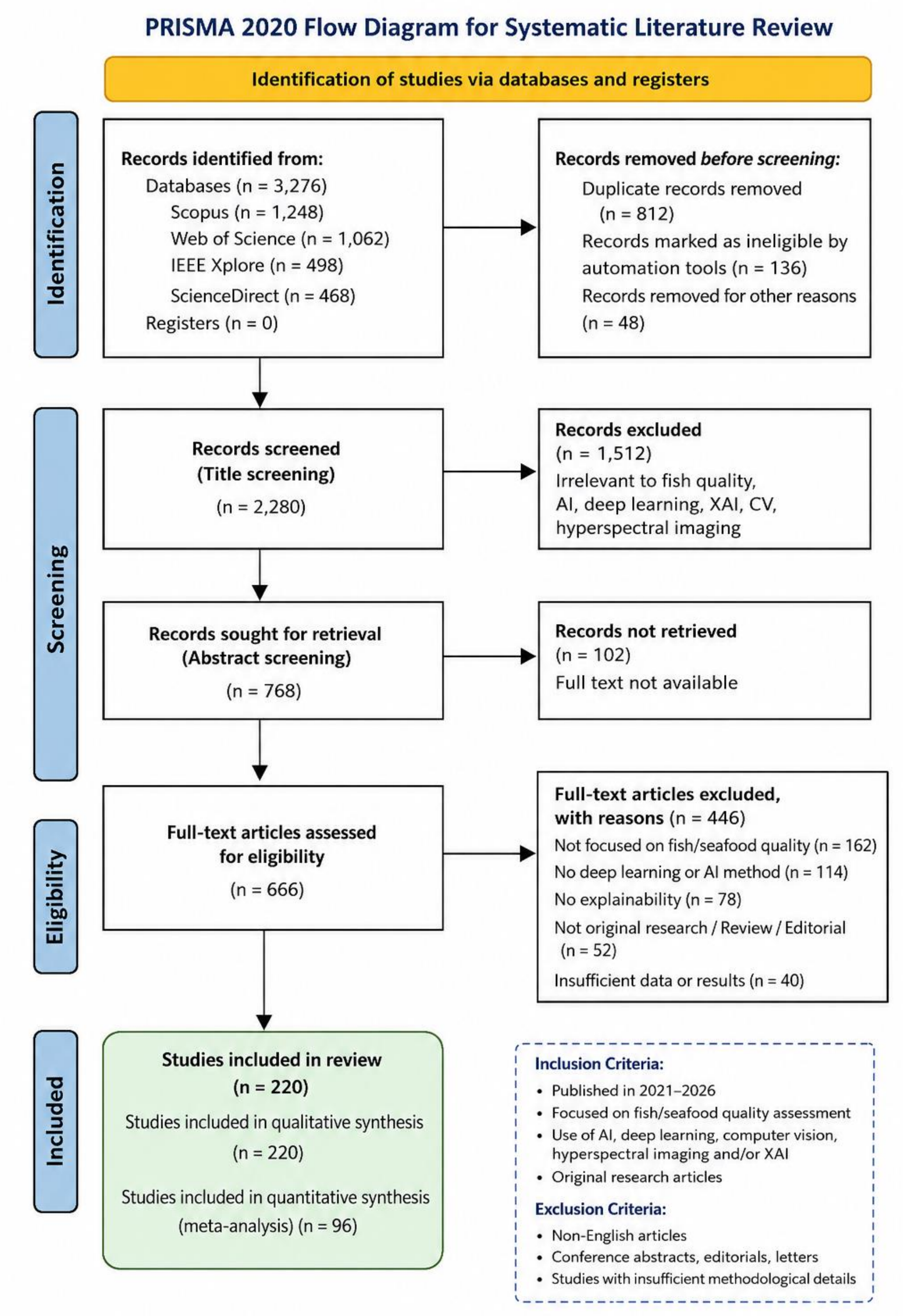

Figure.1. PRISMA 2020 Statement (Page et al., 2021) Source

Boolean search operators such as AND and OR were used with keywords including *Fish Quality Assessment*, *Deep Learning*, *Explainable Artificial Intelligence (XAI)*, *Computer Vision*, *CNN*, *Vision Transformer*, *Grad-CAM*, *LIME*, and *SHAP*. Only peer-reviewed journal articles and conference papers published in English were considered. Duplicate records were removed before screening titles, abstracts, and full-text articles according to predefined inclusion and exclusion criteria. Relevant information, including datasets, fish species, imaging modalities, deep learning architectures, explainability techniques, evaluation metrics, and key findings, was systematically extracted from each selected study. The methodological quality of the included studies was critically evaluated to ensure reliability and scientific rigor. Finally, a qualitative synthesis was conducted to compare existing approaches, identify current research trends, highlight limitations, and propose future research directions in Explainable AI-based fish quality assessment using deep learning. This structured methodology ensures the credibility, transparency, and reproducibility of the review findings while providing a comprehensive overview of the current state of research in this rapidly evolving field.

3. Fundamentals of Fish Quality Assessment

Quality assessment considers freshness, appearance, texture, odor, chemical indicators (TVB-N, pH), microbiological parameters, and traditional sensory evaluation. These indicators provide the basis for AI-driven prediction.

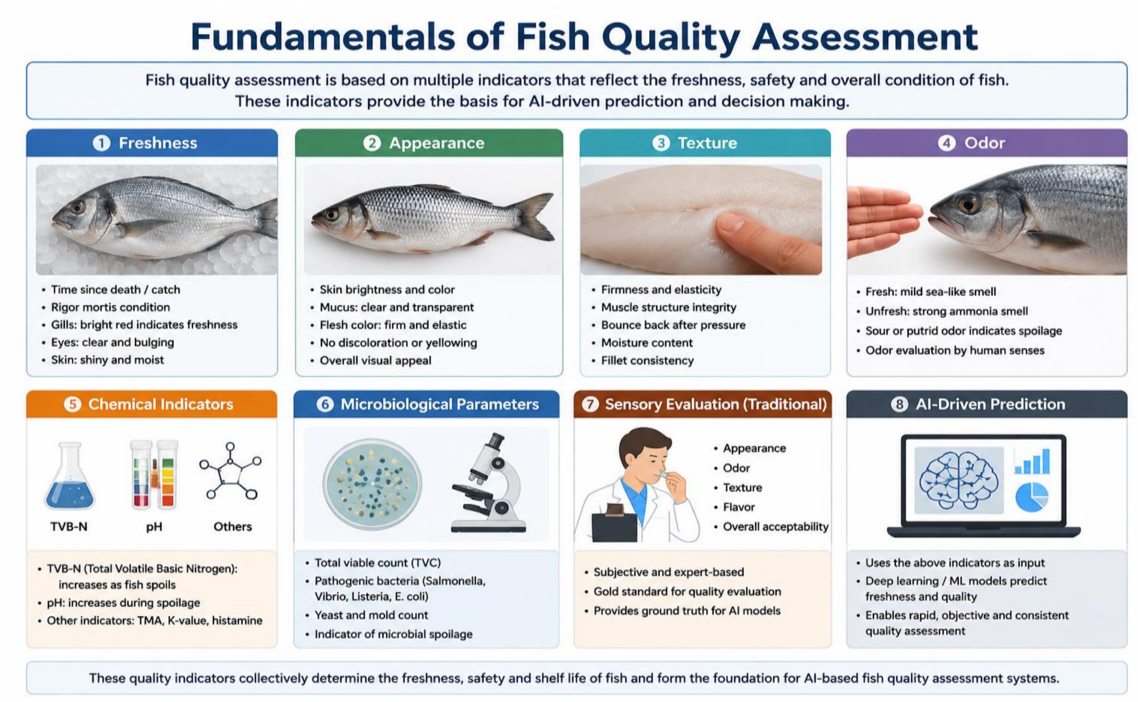

Figure.2. Fundamentals of Fish Quality Assessment

4. Artificial Intelligence in Fish Quality Assessment

Artificial Intelligence (AI) has revolutionized fish quality assessment by enabling rapid, accurate, and non-destructive evaluation of seafood products. AI-based systems integrate machine learning, computer vision, Internet of Things (IoT) sensors, and decision support systems to automate freshness and quality inspection while minimizing human intervention. Traditional machine learning algorithms, such as Support Vector Machines (SVM), Random Forest (RF), Decision Trees (DT), and k-Nearest Neighbors (k-NN), rely on handcrafted features extracted from fish images or sensor measurements. In contrast, deep learning models, particularly Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs), automatically learn discriminative features from raw image data, resulting in improved classification accuracy and robustness. AI techniques have also been successfully combined with hyperspectral imaging, thermal imaging, and multisensor data fusion to predict freshness indicators such as TVB-N, pH, texture, and microbial spoilage. These intelligent systems provide consistent, objective, and real-time quality assessment, making them highly suitable for modern seafood processing industries and smart food quality monitoring applications.

5. Deep Learning Techniques

Deep learning has become the dominant approach for automated fish quality assessment due to its ability to learn complex visual features directly from image data. Convolutional Neural Networks (CNNs) are widely used for fish freshness classification, defect detection, and species identification because of their high accuracy and robust feature extraction capabilities. Transfer learning enables pretrained models such as ResNet, DenseNet, EfficientNet, and MobileNet to achieve excellent performance even with limited datasets while reducing training time and computational cost. More recently, Vision Transformers (ViTs) have improved global feature representation by capturing long-range spatial relationships within images. Furthermore, hybrid CNN–Transformer architectures and multimodal learning approaches integrate RGB images with hyperspectral, thermal, and IoT sensor data to enhance prediction accuracy, robustness, and real-time performance in fish quality assessment systems.

6. Data Acquisition and Dataset Analysis

High-quality datasets play a crucial role in developing reliable deep learning models for fish quality assessment. Data are collected using various imaging modalities, including

RGB cameras, hyperspectral imaging, thermal imaging, multispectral imaging, and IoT-based sensor measurements, to capture both visual and biochemical characteristics of fish. Before model training, preprocessing techniques such as image resizing, normalization, noise removal, segmentation, and background elimination are applied to improve data quality. Additionally, data augmentation methods, including rotation, flipping, scaling, and brightness adjustment, along with dataset balancing techniques, help overcome limited sample sizes and class imbalance. These preprocessing and dataset enhancement strategies improve model robustness, generalization capability, and classification accuracy across different fish species and environmental conditions.

7. Explainable AI Techniques

Explainable Artificial Intelligence (XAI) enhances the transparency and interpretability of deep learning models by providing understandable explanations for their predictions. XAI techniques help identify the most influential image regions and features that contribute to decision-making, thereby increasing user confidence and trust in AI-based fish quality assessment systems. Local explanation methods, such as LIME and Grad-CAM, explain individual predictions by highlighting important features or image regions, whereas global explanation methods, including SHAP and feature importance analysis, provide an overall understanding of model behavior across the entire dataset. These explainability techniques facilitate expert validation, improve regulatory compliance, and support the practical deployment of trustworthy AI systems in the seafood industry.

8. XAI Methods Applied to Fish Quality Assessment

Explainable Artificial Intelligence (XAI) methods play a vital role in improving the transparency and reliability of deep learning models used for fish quality assessment. Grad-CAM generates visual heatmaps that highlight the image regions most influential in predicting fish freshness or quality, enabling intuitive interpretation of model decisions. LIME explains individual predictions by perturbing input samples and identifying the features that contribute most to classification outcomes, while SHAP applies cooperative game theory to quantify the contribution of each feature to the model's prediction. In addition, attention visualization and saliency maps provide graphical explanations that support expert validation, increase user trust, and facilitate regulatory acceptance of AI-based seafood quality inspection systems in real-world industrial environments.

9. Performance Evaluation Metrics

The performance of AI and deep learning models for fish quality assessment is evaluated using several quantitative metrics to ensure accuracy, reliability, and robustness. Classification metrics such as accuracy, precision, recall, F1-score, and Receiver Operating Characteristic–Area Under the Curve (ROC-AUC) are widely used to assess the model's ability to correctly classify fish freshness and quality. For regression-based prediction tasks, metrics including Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) measure the deviation between predicted and actual quality indicators. In addition, inference time, computational complexity, and memory requirements are evaluated to determine the feasibility of real-time industrial deployment. For Explainable AI (XAI) models, the quality of explanations is also considered by assessing their interpretability, consistency, and usefulness, ensuring that model predictions are transparent, trustworthy, and suitable for practical seafood quality inspection applications.

10. Comparative Analysis

A comparative analysis of the reviewed studies reveals that most deep learning models achieve high classification accuracies, often exceeding 90–95%, demonstrating the effectiveness of AI-based approaches for fish quality assessment. However, significant differences exist in terms of dataset size, fish species, imaging modalities (RGB, hyperspectral, thermal), preprocessing techniques, deep learning architectures, and explainability methods, making direct comparison challenging. While CNN-based models remain the most widely adopted, recent studies have shown promising results using Vision Transformers and hybrid CNN–Transformer architectures. Furthermore, the application of Explainable AI (XAI) varies considerably, with Grad-CAM being the most frequently used technique, whereas comprehensive evaluation of explanation quality remains limited. The review also highlights the scarcity of publicly available benchmark datasets and standardized evaluation protocols, emphasizing the need for larger, diverse datasets and unified performance assessment frameworks to facilitate fair comparison and accelerate industrial adoption.

11. Challenges and Research Gaps

Despite significant advancements in AI-based fish quality assessment, several challenges continue to limit its widespread adoption in industrial applications. Most existing studies rely on small or proprietary datasets, resulting in limited model generalization and poor performance across different fish species and environmental conditions. Issues such as class imbalance, variations in image quality, inconsistent data acquisition methods, and the lack of standardized benchmark datasets further affect model reliability and fair comparison. Additionally, although Explainable Artificial Intelligence (XAI) techniques have improved model transparency, there are no universally accepted evaluation standards for assessing the quality and reliability of explanations. Future research should focus on developing large-scale public datasets, standardized evaluation frameworks, robust cross-species models, and efficient real-time XAI systems to facilitate trustworthy and scalable deployment in the seafood industry.

12. Future Research Directions

Future research should focus on developing efficient, interpretable, and real-time AI systems for fish quality assessment to support large-scale industrial deployment. Emerging technologies such as Edge AI can enable on-device processing for rapid decision-making, while federated learning offers privacy-preserving collaborative model training across multiple organizations without sharing sensitive data. In addition, multisensor fusion, integrating RGB, hyperspectral, thermal imaging, and IoT sensor data, has the potential to significantly improve prediction accuracy and robustness. Further efforts are also needed to develop trustworthy Explainable AI (XAI) frameworks with standardized evaluation methods, alongside digital twins and intelligent monitoring systems for continuous quality assessment throughout the seafood supply chain. These advancements will contribute to more reliable, scalable, and sustainable fish quality inspection systems in future smart food industries.

13. Discussion

The findings of this systematic literature review demonstrate that deep learning has significantly transformed fish quality assessment by enabling accurate, rapid, and non-destructive inspection of seafood products. Convolutional Neural Networks (CNNs), transfer learning models, and Vision Transformers have consistently achieved superior performance compared to conventional machine learning approaches. Furthermore, the integration of Explainable Artificial Intelligence (XAI) techniques, such as Grad-CAM, LIME, and SHAP, has improved model transparency by providing visual and feature-based explanations for prediction outcomes. These explainability methods enhance user confidence, facilitate expert validation, and support regulatory compliance in industrial applications. However, the literature also highlights several challenges, including limited benchmark datasets, poor cross-species generalization, computational complexity, and the absence of standardized evaluation frameworks for explainability. Future research should focus on developing robust, interpretable, and real-time AI systems using multimodal data, Edge AI, and federated learning to improve industrial adoption and ensure trustworthy decision-making in fish quality assessment.

14. Conclusion

This systematic literature review provides a comprehensive overview of recent advances in Explainable Artificial Intelligence (XAI)-based fish quality assessment using deep learning. The findings indicate that deep learning techniques, particularly Convolutional Neural Networks (CNNs), transfer learning models, and Vision Transformers (ViTs), have significantly improved the accuracy, efficiency, and automation of fish freshness and quality evaluation compared with traditional inspection methods. Furthermore, Explainable AI techniques, including Grad-CAM, LIME, SHAP, saliency maps, and attention visualization, have enhanced model transparency by providing interpretable explanations that support expert validation and increase user trust. The review also highlights the growing importance of hyperspectral imaging, multisensor data fusion, and computer vision technologies for non-destructive seafood quality assessment. Despite these advances, several challenges remain, including limited public benchmark datasets, poor cross-species generalization, computational complexity, and the lack of standardized frameworks for evaluating explainability. Addressing these limitations is essential for improving the reliability and industrial adoption of AI-based quality inspection systems. From a practical perspective, integrating trustworthy AI into seafood processing can enhance food safety, reduce inspection costs, improve operational efficiency, and support regulatory compliance. Future research should focus on developing large-scale public datasets, robust multimodal learning frameworks, Edge AI, federated learning, digital twins, and standardized XAI evaluation methods to enable scalable, transparent, and real-time fish quality assessment. Overall, the integration of deep learning and Explainable AI represents a promising direction for building intelligent, reliable, and sustainable seafood quality inspection systems that can meet the evolving demands of modern food industries.

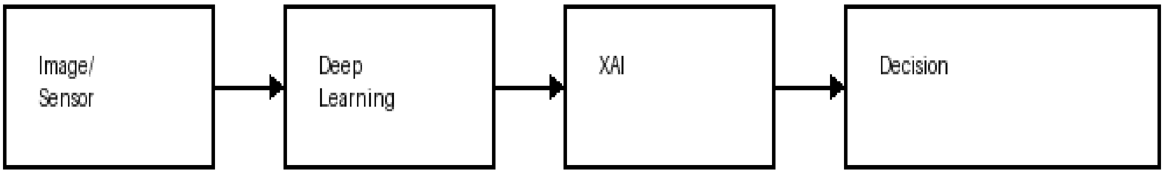

Figure.3. General Explainable Fish Quality Assessment Framework

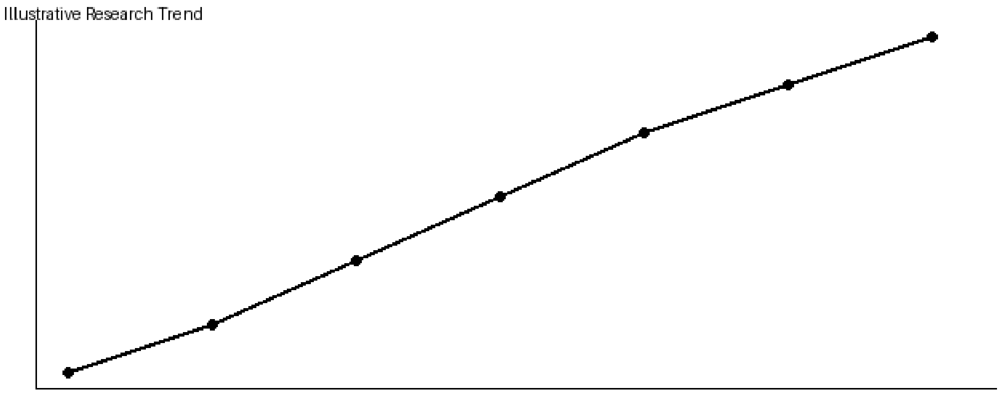

Figure.4. Illustrative Trend of Research Interest

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Conflict of Interest/Competing Interests

No conflict of interest.

Data Availability

The raw data supporting the findings of this research paper will be made available by the authors upon a reasonable request.

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