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(Review Article)

A comprehensive review of machine learning applications in tilapia aquaculture

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Abstract

Tilapia aquaculture has become a crucial segment of global fish production due to its economic viability and adaptability. However, the industry faces challenges in disease management, water quality control, and feed optimization. This comprehensive review examines the applications of machine learning (ML) in addressing these challenges within tilapia aquaculture. Key areas explored include disease detection and diagnosis, water quality monitoring, feed strategy optimization, and production management. The review highlights various machine learning models and methodologies employed, discusses their effectiveness, and identifies future directions for research and development. The findings suggest that while machine learning offers substantial potential for enhancing tilapia aquaculture, challenges such as data quality, integration, and scalability need to be addressed to fully realize these benefits.

Keywords: Tilapia Aquaculture; Machine Learning; Disease Management; Water Quality Control; Feed Optimization; Predictive Modeling

1. Introduction

Tilapia aquaculture has emerged as one of the most significant contributors to global fish production, owing to its favorable biological and economic characteristics. Tilapia, known for its adaptability to diverse environmental conditions, rapid growth rates, and high nutritional value, is a staple in the diets of many populations worldwide. The expansion of tilapia farming has been driven by the increasing demand for affordable and high-quality protein sources, making it a crucial component of food security and economic development in many regions [1][2]. However, the rapid growth of the industry also brings forth numerous challenges that need to be addressed to maintain its sustainability and profitability.

One of the primary challenges in tilapia aquaculture is disease management [3][4]. Diseases can spread quickly in densely populated farming environments, leading to significant economic losses and jeopardizing fish health and welfare [5]. Traditional methods of disease detection and treatment are often reactive and rely heavily on visual inspection and manual intervention, which can be time-consuming and less effective [6], [7]. The advent of machine learning provides a transformative approach to disease management by enabling early and accurate detection through image analysis and sensor data, facilitating timely interventions that can mitigate the impact of disease outbreaks.

Water quality is another critical factor in tilapia farming, as it directly affects the health and growth of the fish [8], [9]. Maintaining optimal water quality involves monitoring various parameters such as pH, temperature, dissolved oxygen, and ammonia levels. Fluctuations in these parameters can lead to stressful conditions for the fish, increasing their susceptibility to diseases. Machine learning models offer predictive capabilities that can forecast changes in water

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quality based on historical data, allowing for proactive management. These models can also detect anomalies that may indicate pollution or equipment malfunctions, ensuring a stable and healthy aquatic environment.

Feed optimization is a crucial aspect of operational efficiency in tilapia aquaculture, given that feed costs represent a substantial portion of total production expenses [10], [11]. Efficient feed management strategies are essential to maximize growth rates while minimizing waste and costs. Machine learning applications in feed optimization include predicting growth rates based on various factors and analyzing feeding behavior to adjust feed amounts in real-time. By leveraging these advanced data analytics tools, farmers can formulate more efficient diets, reduce feed waste, and enhance overall productivity. This review aims to comprehensively explore these machine learning applications, highlighting their potential to address key challenges in tilapia aquaculture and paving the way for more sustainable and profitable farming practices.

2. Purpose of the literature review

The primary purpose of this literature review is to provide a comprehensive and systematic examination of the current state of machine learning applications in tilapia aquaculture. This review aims to highlight key areas where machine learning has been effectively applied, such as disease management, water quality control, feed optimization, and overall production management. By detailing the specific machine learning models and techniques used in these areas, the review evaluates their effectiveness in addressing the industry's challenges. Finally, the review proposes future research directions to enhance the application of machine learning in tilapia aquaculture, including improving data collection and standardization, developing user-friendly solutions, and ensuring model scalability. This literature review aims to provide valuable insights and guidance for researchers, practitioners, and stakeholders, facilitating the advancement of sustainable and profitable tilapia farming practices through the adoption of machine learning technologies.

3. Materials and methods

A systematic literature search was conducted using databases such as PubMed, IEEE Xplore, Google Scholar, and Web of Science. Keywords included "machine learning", "tilapia aquaculture", "disease management", "water quality", "feed optimization", and "production management". Studies were selected based on relevance, quality, and recency, focusing on peer-reviewed journal articles, conference papers, and reputable industry reports.

The selected studies were categorized into four main areas: disease management, water quality management, feed optimization, and production management. Each category was analyzed to identify common machine learning models, methodologies, and outcomes. The effectiveness of these applications was assessed based on accuracy, efficiency, and practical implementation.

4. Results and discussion

A total of 20 were finally included in this review literature after careful and thorough screening. Table 1 shows the machine learning advancements in Tilapia according to disease management, water quality management, feed optimization, and production management. The type of machine learning used was identified and presented in the table.

4.1. Disease Management

4.1.1. Detection and Diagnosis

Machine learning models, particularly convolutional neural networks (CNNs) and support vector machines (SVMs), have shown high accuracy in detecting diseases from images and sensor data. CNNs have achieved over 90% accuracy in identifying diseases like gill rot and fin rot from fish images. Additionally, sensor data analysis using machine learning has enabled early detection of disease conditions, facilitating timely intervention.

4.1.2. Treatment Optimization

Reinforcement learning (RL) algorithms have been employed to optimize treatment strategies, reducing the reliance on antibiotics and minimizing environmental impact. These models simulate various scenarios to identify the most effective treatments.

4.2. Water Quality Management

4.2.1. Predictive Modeling

Regression models and artificial neural networks (ANNs) have been effective in predicting water quality parameters such as pH, temperature, and ammonia levels. These models allow for proactive management by forecasting adverse conditions.

Table 1 Machine learning advancements in Tilapia according to different categories

Authors	Year	Category	Method Used in Detection and Diagnosis	Accuracy
Poonnoy & Kitcharoen [12]	2022	Production Management	Convolutional Neural Networks	Not Specified
Ahmed et al. [13]	2022	Disease Detection	Image Processing and Segmentation, Support Vector Machine (SVM) algorithm	91.42-94.42 %
Li et al. [14]	2022	Disease Detection	Computer Vision, Image Processing, Support Vector Machine (SVM) algorithm	Not Applicable
Gladju et al. [15]	2022	Production Management	Machine Learning, Artificial Intelligence	Not Applicable
Hu et al. [16]	2022	Feed Optimization, Water Quality Assessment	Computer Vision	93.2%
Cao et al. [17]	2022	Feed Optimization	ResNet34 model	99.72%
Zhang et al. [18]	2023	Feed Optimization	Machine Vision	Not Specified
Hernandez & Hernandez [19]	2019	Production Management	Convolutional Neural Network, Inception Model V3	Not Specified
Suwannasing et al. [20]	2023	Production Management	Computer Vision, Image Segmentation, Image with No Segmentation	82.17% , 59.58%
Ewees et al. [21]	2021	Disease Detection	Support Vector Machine (SVM) algorithm	99.983%
Costa et al. [22]	2023	Production Management	Image Processing, Convolutional Neural Network	95-98%
Li et al. [14]	2022	Water Quality Assessment	Back Propagation Neural Network (BPNN), Radial Basis Function Neural Network (RBFNN), Support Vector Machine (SVM), Least Squares Support Vector Machine (LSSVM)	99%
Tolentino et al. [23]	2020	Production Management	Image Processing and Predictive Analysis	growth of the fishes increased by 47.88%
Jongjaraunsuk & Taparhudee [24]	2024	Water Quality Assessment	Deep Learning and a Hybrid Model	Not Specified
Jongjaraunsuk & Taparhudee [25]	2024	Disease Detection	Data mining, Ensemble learning	90.85%
Mayormente [26]	2024	Feed Optimization	FCR, Multiple Linear Regression	Not Specified

Hendriana [27]	2023	Water Quality Assessment	Lintangsongo, XGBoost, Recursive Feature eElimination (RFE)	Not Specified
Loyola & Lacatan [28]	2020	Water Quality Assessment	IoT	Not Specified
Palconit et al. [29]	2021	Feed Optimization	IoT	Not Specified
Lainez & Gonzales [30]	2019	Production Management	Convolutional Neural Network	99.8%

4.3. Anomaly Detection

Unsupervised learning techniques like clustering and principal component analysis (PCA) have been utilized to detect anomalies in water quality data, indicating potential pollution or equipment failures. Early anomaly detection helps in mitigating risks to fish health.

4.4. Feed Optimization

4.4.1. Growth Prediction

Machine learning models, including random forests and gradient boosting machines, predict tilapia growth rates based on feed composition and environmental factors. These predictions help formulate cost-effective diets that maximize growth.

4.4.2. Feeding Behavior Analysis

Deep learning techniques analyze feeding behavior through image and video data, ensuring optimal feeding by adjusting feed amounts based on real-time behavior monitoring. This reduces waste and enhances growth efficiency.

4.5. Production Management

4.5.1. Inventory Management

Time-series analysis and reinforcement learning models assist in predicting optimal stocking densities and harvest times, promoting sustainable production cycles.

4.5.2. Yield Prediction

Predictive analytics models estimate future yields, aiding in planning and supply chain management. Accurate yield predictions support market strategies and operational decisions.

4.5.3. Economic Analysis

Machine learning models evaluate the economic feasibility of different farming practices, guiding investment and operational decisions to enhance profitability.

4.6. Challenges and Future Directions

Key challenges include data availability and quality, integration into existing systems, and scalability. Future research should focus on developing standardized data collection methods, user-friendly interfaces, and scalable models to facilitate wider adoption of machine learning in tilapia aquaculture.

5. Conclusion

Machine learning holds significant promise in transforming tilapia aquaculture by addressing some of the industry's most pressing challenges. This review highlights the substantial benefits of employing machine learning techniques in disease management, water quality control, feed optimization, and overall production management. The studies reviewed demonstrate that machine learning models, such as convolutional neural networks, support vector machines, and artificial neural networks, can achieve high accuracy in disease detection, predictive water quality modeling, and feed efficiency enhancement. These technologies enable proactive and data-driven decision-making, which can significantly improve the sustainability and profitability of tilapia farming operations. However, the successful implementation of these technologies requires overcoming several challenges, including the need for high-quality and comprehensive data, seamless integration into existing farming systems, and the scalability of these solutions to accommodate diverse and large-scale aquaculture environments.

Despite the promising advancements, the full potential of machine learning in tilapia aquaculture is yet to be realized. Future research should focus on developing standardized data collection practices to ensure the availability of high-quality datasets necessary for training robust machine learning models. Additionally, there is a need for user-friendly interfaces and training programs to facilitate the adoption of these technologies by farmers, many of whom may not have a technical background. Collaborative efforts among researchers, aquaculture experts, and technology developers are essential to create scalable and integrated solutions that can be easily implemented across different farm sizes and conditions. By addressing these challenges, the aquaculture industry can fully leverage the power of machine learning to enhance productivity, ensure fish health, and promote sustainable farming practices, ultimately contributing to global food security and economic development.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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