

# Development and Validation of a Tilapia Cutaneous Disease Detection System Using Machine Learning

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#### **ABSTRACT**

This study developed and validated a machine learning-based system integrated into a mobile application for detecting cutaneous diseases in tilapia. Focused on Oreochromis niloticus, the system utilized convolutional neural networks (CNN) trained with images from both local sources and online repositories. The application was tested with end users including farmers and IT experts, and evaluated using ISO 25010:2011 Software Quality Standards and the Technology Acceptance Model (TAM). Results showed high acceptability and accuracy, indicating that the system could serve as an effective early warning and disease management tool in aquaculture.

**Keywords:** (machine learning, tilapia, disease detection, aquaculture, convolutional neural network, mobile application, ISO 25010, TAM)

## I. INTRODUCTION

Tilapia farming plays a vital role in global aquaculture and food security, especially in countries like the Philippines. In regions such as Cagayan Valley, it sustains rural livelihoods but remains vulnerable to disease outbreaks that cause significant fish mortality and financial loss. Disease detection methods are mostly manual and reactive, relying on farmers' visual inspections and informal resources like social media, often leading to delayed interventions.

Environmental stressors—such as fluctuating temperature and salinity—exacerbate disease outbreaks, yet local farmers lack tools like water

testing kits or real-time diagnostic systems. This study addresses that gap by developing a machine learning-based mobile application that provides presumptive diagnoses of tilapia cutaneous diseases through real-time image classification using a CNN model. The app, built on .NET MAUI, is designed to be user-friendly, cross-platform, and multilingual for accessibility.

While AI and machine learning have shown potential in agriculture, their application in Philippine aquaculture remains limited. This research pioneers such integration, aiming to empower farmers with a practical and intelligent tool for early disease detection. The study also lays the groundwork for future enhancements, including sensor integration and broader species coverage, promoting a shift toward more data-driven and accessible fish health management.

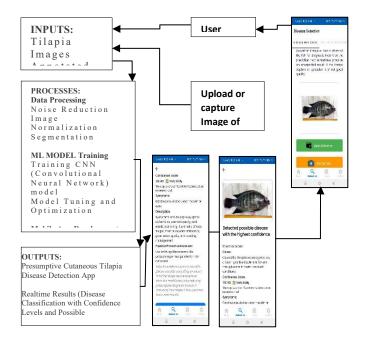
## **Objectives of the Study**

This study aimed to develop and evaluate a mobile application powered by a machine learning model to detect cutaneous diseases in tilapia (Oreochromis niloticus). Specifically, it sought to analyze current disease detection practices, design a CNN-based image classification system, assess software quality using ISO 25010:2011, and evaluate user acceptability via the Technology Acceptance Model (TAM) to ensure effectiveness, usability, and integration into real-world aquaculture practices.

## **Conceptual Framework of the Study**

The conceptual framework of this study was based on the integration of machine learning and image processing techniques for disease detection in tilapia. The process began with the collection of image and video data of tilapia exhibiting various health conditions. The images were preprocessed and analyzed using learning algorithms, machine such convolutional neural networks (CNNs), detect and classify diseases based on visual symptoms. The system's performance was then evaluated based on its accuracy, precision, and recall rates, and integrated into existing farm management practices for real-world testing and validation.

Figure 1. Input Process Output diagram



## SIGNIFICANCE OF THE STUDY

The proposed system offers a transformative tool for small- and large-scale tilapia farmers by enabling early, image-based disease detection through a mobile app that is multilingual, accessible, and easy to use. It reduces mortality rates and economic losses by allowing timely intervention, especially for non-technical users in rural settings. By facilitating real-time diagnoses and simplifying workflows, it aligns with sustainable aquaculture practices and supports food security efforts.

For institutions such as CSU, government agencies, NGOs, and researchers, this system fosters innovation, supports interdisciplinary collaboration, and presents new opportunities in precision aquaculture. It demonstrates how AI can bridge the diagnostic gap in underserved communities and lays a foundation for future research in integrating environmental data and real-time monitoring into mobile-based solutions.

## **SCOPE AND LIMITATIONS**

This study focused on developing a CNNbased mobile application to detect cutaneous diseases in Nile tilapia using image data sourced primarily from online repositories. The system was designed to perform real-time image classification and deliver presumptive CSU-Aparri's diagnoses, tested within aquaculture facilities under diverse environmental conditions.

Limitations included dependence on non-local image datasets due to the lack of archived local diseased fish images, variability in image quality, and generalizability of disease symptoms. Additionally, resource and budget constraints restricted the use of advanced imaging tools and broader field validation, which may affect the system's scalability and diagnostic depth.

#### II. METHODOLOGY

This study adopted a descriptive and developmental research design. The descriptive phase involved gathering data through surveys, interviews, and observations at aquaculture facilities of Cagayan State University–Aparri to understand current disease detection practices and challenges. These insights helped identify common symptoms, gaps in diagnosis, and informed the design of the system.

The developmental phase utilized the **Sprint Scrum Framework** (Figure 2), an agile methodology that structured the system's creation into iterative sprints, allowing

feedback continuous and incremental improvements. The image dataset—primarily composed of labeled online images—was preprocessed and used to train a convolutional network (CNN) model. neural Data augmentation and transfer learning techniques enhanced the model's generalization to realworld conditions, and classification was focused visible symptoms like lesions discoloration.

Figure 2. Sprint-Scrum Framework



The trained model was integrated into a cross-platform mobile application designed with a user-friendly interface and multilingual support. Field trials were conducted with farmers and fisheries experts who used the app to perform real-time image-based disease detection.

The system was evaluated using ISO 25010:2011 quality metrics and the Technology Acceptance Model (TAM), focusing on accuracy, reliability, and user satisfaction.

## **III.** Summary of Findings

The study aimed to develop and evaluate a mobile-based, machine learning-powered system for the presumptive diagnosis of cutaneous diseases in tilapia. Results showed that traditional disease detection in tilapia farming—particularly in the context of CSU-Aparri and surrounding local farms—relied heavily on manual visual inspection and anecdotal methods. Farmers and hatchery personnel commonly turned to informal sources such as social media or peer-shared practices due to the absence of formal diagnostic tools, often resulting in late interventions, high fish mortality, and limited

documentation of past outbreaks. These challenges underscored the critical need for a more accessible, consistent, and technology-driven solution.

To address this need, the research introduced an intelligent image-based diagnostic system designed to support early detection through visual symptom analysis. The system underwent evaluation using two widely accepted frameworks: the ISO 25010:2011 Software Quality Standard and the Technology Acceptance Model (TAM).

Table 1. Level of Acceptability Among Users

| Dimension             | Mean Score | Interpretation    |
|-----------------------|------------|-------------------|
| Perceived Ease of Use | 4.63       | Excellent         |
| Perceived Usefulness  | 4.20       | Very Satisfactory |
| Self-Efficacy         | 4.59       | Excellent         |
| Response Efficacy     | 4.39       | Very Satisfactory |
| Adoption Intentions   | 4.47       | Very Satisfactory |
| Overall Mean          | 4.45       | Very Satisfactory |

Based on the Technology Acceptance Model (TAM)

The findings indicated that the system achieved high marks across all TAM dimensions, especially in **Perceived Ease of Use (4.63)** and **Self-Efficacy (4.59)**, highlighting the tool's accessibility even for users with limited technical expertise. These results reflect the app's ability to integrate smoothly into existing workflows and foster user confidence in technology use for aquaculture.

Table 2. ISO 25010 Software Quality Evaluation (IT Experts)

| (        | (11 Experes) |       |                            |  |
|----------|--------------|-------|----------------------------|--|
| ISO      | Quality      | Mean  | Interpretation             |  |
| Attrib   | ute          | Score |                            |  |
| Function | onal         | 3.38  | Satisfactory – core        |  |
| Suitabi  | ility        |       | functions are met; further |  |
|          |              |       | feature refinement         |  |
|          |              |       | needed                     |  |
| Perfor   | mance        | 3.44  | Satisfactory – performs    |  |
| Efficie  | ncy          |       | reliably but may benefit   |  |
|          |              |       | from optimization          |  |

| Compatibility   | 3.43 | Satisfactory – integrates acceptably with other |  |
|-----------------|------|---|--|
|                 |      | systems   |  |
| Usability       | 3.41 | Satisfactory – generally                        |  |
|                 |      | easy to use, minor UI                           |  |
|                 |      | improvements                                    |  |
|                 |      | recommended                                     |  |
| Reliability     | 3.43 | Satisfactory –                                  |  |
|                 |      | consistently operates                           |  |
|                 |      | under normal conditions                         |  |
| Maintainability | 3.56 | Very Satisfactory –                             |  |
|                 |      | system is updatable and                         |  |
|                 |      | testable  |  |
| Portability     | 3.60 | Very Satisfactory –                             |  |
|                 |      | system can be used across                       |  |
|                 |      | different platforms                             |  |
| Overall Mean    | 3.47 | Satisfactory - meets                            |  |
|                 |      | standards but has room                          |  |
|                 |      | for technical                                   |  |
|                 |      | enhancement                                     |  |

The ISO evaluation further affirmed the system's technical adequacy, particularly in **Portability (3.60)** and **Maintainability (3.56)**. While functional correctness and performance were found satisfactory, suggestions for refinement were noted to improve the system's scalability and precision.

Overall, the developed system was well-received from both a user and technical standpoint. It successfully demonstrated the potential of using machine learning to support **presumptive diagnosis** in aquaculture, particularly in resource-limited environments. The high user ratings in perceived ease of use and adoption intentions validate the app's applicability in real-world settings, while its performance across ISO attributes supports its ongoing development and deployment in support of smarter aquaculture practices.

#### IV. Conclusion

This study developed and validated a mobile-based application, *OreoChromDx*, that uses machine learning for presumptive diagnosis of tilapia cutaneous diseases. The findings confirmed limitations in current aquaculture disease detection methods, particularly manual inspection and the lack of

diagnostic tools, especially in CSU-Aparri and nearby areas.

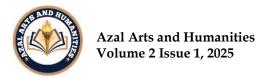
The mobile app, using a CNN-based image classification model, provides an efficient solution that empowers farmers with early detection capabilities. It was rated **Satisfactory** overall by IT experts based on ISO 25010:2011, with **very satisfactory marks** in Maintainability and Portability. End-users evaluated the system as **Very Satisfactory** under the Technology Acceptance Model, with particularly high marks in **Ease of Use (4.63)** and **Self-Efficacy (4.59)**.

Overall, the system demonstrated strong usability, technical reliability, and social acceptability, suggesting that it is both technically viable and operationally valuable for real-world tilapia health management.

#### V. Recommendations

Based on the findings and validation of the system, several recommendations are proposed to further enhance its applicability and impact. First, it is recommended that *OreoChromDx* be piloted within the aquaculture facilities of Cagayan State University-Aparri. deployment This pilot should include structured user training, feedback collection, and continuous monitoring to assess real-world performance and encourage adoption. Training sessions should also be conducted to help users interpret the system's outputs, with an emphasis on understanding that the system provides presumptive diagnoses and is not a substitute for laboratory-based confirmation.

To ensure continued relevance and effectiveness, future enhancements of the system should focus on expanding the disease image database, improving its functionality, and exploring integration with environmental monitoring tools—such as sensors for water temperature, pH, and salinity—to provide context-aware diagnostics. Notably. application already includes offline functionality, which should be emphasized during training and promotion, especially in rural areas with limited internet access. This



feature makes the app highly accessible and practical for small-scale farmers operating in low-connectivity environments.

Moreover, it is advisable to initiate broader collaborative field testing partnership with the Bureau of Fisheries and Aquatic Resources (BFAR) aquaculture stakeholders. Their involvement in testing and feedback will provide valuable insights for refining the system's usability and applicability across different farming contexts. Finally, academic institutions are encouraged to integrate the system into ongoing research initiatives. Potential areas of exploration include explainable AI (XAI) to enhance model transparency, and hybrid systems that combine image classification with environmental and behavioral data. further enriching diagnostic capability of the tool.

Finally, institutional support and policy backing should be explored to legitimize the role of digital, AI-assisted tools in aquaculture disease management. Establishing formal guidelines for using presumptive diagnosis systems can help bridge the gap between field realities and best practices, ultimately promoting sustainable aquaculture and better fish health outcomes.

#### VI. References

- Adegboye, S. e. (2020). Intelligent feeding systems in aquaculture.
- Ahad, T., Mamun, S. B., Chowdhury, S., Song, B., & Li, Y. (2024). End User Interface
  Design of Mobile-Based Fish Disease
  Detection to Assist Fish Farmers. 4IR
  Research Cell, Daffodil International
  University. Retrieved from
  https://papers.ssrn.com/sol3/papers.cf
  m?abstract\_id=4980536
- Ahmed, M. S., Aurpa, T. T., & Azad, M. A. (2022). Fish disease detection using image-based machine learning technique in

aquaculture. Journal of King Saud University-Computer and Information Sciences, 34(8), 5170-5182. Retrieved from https://www.researchgate.net/publicat ion/376584286\_Image-

Based\_Fish\_Disease\_Detection\_Methods

\_An\_Innovative\_Technique\_for\_The\_Diag nosis Ahmed, M. S., Aurpa, T. T., & Azad, M. A. (2022). Fish Disease Detection Using Image-

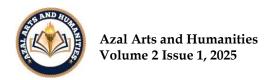
- Fish Disease Detection Using Image-Based Machine Learning Technique in Aquaculture. *Journal of King Saud University-Computer and Information Sciences*, 34(8), 5170–5182.
- Barzegar, R., Moghaddam, N. H., & Deo, R. C. (2020). Short-term water quality prediction using a hybrid CNN-LSTM deep learning model. *Water Research*, 190, 116729. doi:https://doi.org/10.1016/j.watres.2 020.116729
- Delfino, J. C., Manaloto, D. J., & Arboleda, E. R. (2024). A comprehensive review of machine learning applications in tilapia aquaculture. *International Journal of Science and Research Archive*.
- Hernandez, R. M., & Hernandez, A. A. (2019).
  Classification of Nile Tilapia using
  Convolutional Neural Network.

  Proceedings of the International
  Conference on Science, Engineering, and
  Technology (ICSET) (pp. 126 131).
  Manila: IEEE. doi:DOI:
  10.1109/CSPA48992.2020.9068727
- Hernandez, R. M., & Hernandez, A. A. (2020).

  Acceptance Analysis of Mobile

  Application for Nile Tilapia

  Classification using Unified Theory of
  Acceptance and use of Technology.

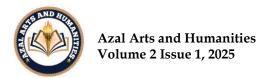


Proceedings of the International Conference on Science, Engineering, and Technology (ICSET) (pp. 266-271). Manila: IEEE. doi:http://dx.doi.org/10.1109/CSPA48 992.2020.9068727

- Himananto, O., Yoohat, K., Danwisetkanjana, K., Kumpoosiri, M., Rukpratanporn, S., Theppawong, Y., . . . Gajanandana, O. (2024). Strep Easy Kit: A bioenrichment dual ICG-strip test for simultaneous detection of Streptococcus agalactiae serotypes Ia and III in fish samples. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1111/jfd.14000
- Jansen, M. D., Dong, H. T., & Mohan, C. V. (2018.). Tilapia lake virus: a threat to the global tilapia industry? *11*(3), 725-739. doi:doi: 10.1111/raq.12254
- Jongjaraunsuk, R., Taparhudee, W., &
  Matondang, P. (2024). An Ensemble
  Learning Technique for Predicting
  Mortality Rate in Red Tilapia
  (Oreochromis niloticus Linn.). 48, 37 50. Retrieved from
  https://www.researchgate.net/publicat
  ion/379756057\_An\_Ensemble\_Learning
  \_Technique\_for\_Predicting\_Mortality\_Ra
  te\_in\_Red\_Tilapia\_Oreochromis\_niloticu
  s\_Linn\_Fingerlings
- Kaur, G., Adhikari, N., Krishnapriya, S., Wawale, S. G., Malik, R. Q., Zamani, A. S., . . . Osei-Owusu, J. (2023). Recent Advancements in Deep Learning Frameworks for Precision. *Journal of Food Quality*. doi: https://doi.org/10.1155/2023/4399512
- Kisi, O., & Shiri, J. (2020). Prediction of dissolved oxygen in rivers using

- Bayesian model averaging and data-driven models. *Journal of Hydrology*, *583*, 124601. doi:https://doi.org/10.1016/j.jhydrol.2 020.124601
- Kushwaha, B., Maurya, S., & Kumar, M. S.

  (2024). Role of Machine Learning and
  Artificial Intelligence in Transforming
  Aquaculture. *Indian Farming*. Retrieved
  from
  https://epubs.icar.org.in/index.php/Ind
  Farm/article/download/147942/55772
  /429577
- Li, C., Zhang, H., & Wang, Y. (2020). Transfer learning-based biomass estimation of aquatic species using CNNs. *Aquaculture International*, 983-996. doi: https://doi.org/10.1007/s10499-019-00484-6
- Liu, H., Ma, X., yu, Y., Wang, L., & Hao, L. (2023).
  Application of Deep Learning-Based
  Object Detection Techniques in Fish
  Aquaculture: A Review. *Journal of Marine Science and Engineering, 11*(4),
  867.
  doi:https://doi.org/10.3390/jmse1104
  0867
- Luo, L., He, Z.-X., Jia, B.-Z., Kang, R.-Y., Zhang, W.-F., Huang, R.-M., & Xu, Z.-L. (2024). Gold nanocluster-based ratiometric fluorescence immunoassay for broadspectrum screening of five eugenols. *Analytica Chimica Acta, 1310*. doi:https://doi.org/10.1016/j.aca.2024. 342723
- Medina, J. K., Tribiana, P. J., & Villaverde, J. F. (2023). Disease Classification of Oranda Goldfish Using YOLO Object Detection Algorithm. *In 2023 15th International*



Conference on Computer and Automation Engineering (pp. 249-254). IEEE.

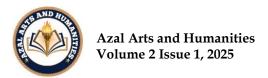
- Modales, A. V., Tsai, Y.-S., & Hung, C.-H. (2024).

  Optimizing Aquaculture: A Deep
  Learning Approach to Predict Bait and
  Body Weight in Fish. Keelung City,
  Zhongzheng District, Taiwan. Retrieved
  from
  https://papers.ssrn.com/sol3/papers.cf
  m?abstract\_id=4992473
- Monkman, G., Kaiser, M. J., Hyder, K., & Hinz, H. (2019). Estimation of fish biomass using deep learning models and image processing techniques. *Marine Ecology Progress Series*, 617, 123-136. doi:https://doi.org/10.3354/meps1298 8
- Morimoto, Y., Watanabe, H., & Nakano, Y. (2018). Behavioral changes of tilapia as indicators of water quality: A machine vision approach. *Aquaculture Environment Interactions, 10,* 59-68. doi: https://doi.org/10.3354/aei00254
- Nayan, A.-A., Mozumder, A. N., Saha, J.,
  Mahmud, K. R., Azad, A., & Kibria, M.
  (2021). A Machine Learning Approach
  for Early Detection of Fish Diseases by
  Analyzing Water Quality. *Trends in Sciences, 18*, 351.
  doi:10.48048/tis.2021.351
- 401.10.10010/113.2021.331
- Pettersen, R., Braa, H. L., Gawel, B. A., Letnes, P. A., Sæther, K., & Aas, L. M. (2019).

  Detection and classification of
  Lepeophterius salmonis using
  underwater hyperspectral imaging.

  Engineering in Aquaculture, 87, 102025.
  Retrieved from
  https://www.researchgate.net/publicat
  ion/376584286\_ImageBased\_Fish\_Disease\_Detection\_Methods

- \_An\_Innovative\_Technique\_for\_The\_Diag nosis
- Ramírez-Coronel, F. J., Rodríguez-Elías, O. M., Esquer-Miranda, E., Pérez-Patricio, M., Pérez-Báez, A. J., & Hinojosa-Palafox, E. A. (2024). Non-Invasive Fish Biometrics for Enhancing Precision and Understanding of Aquaculture Farming through Statistical Morphology Analysis and Machine Learning. *Animals*, 14(13), 1850. Retrieved from https://doi.org/10.3390/ani14131850 ​:contentReference[oaicite:0]{in dex=0}​:contentReference[oaicite:1]{index=1}​:contentReference[oaicite:2]{index=2}.
- Seth, T., Ranjan, D., Saha, S., & Sarkar, P. (2023).
  Image-based fish disease detection
  methods: An innovative technique for
  the diagnosis. *Veterinary Today, 1*(12),
  286-288. Retrieved from
  https://www.researchgate.net/publicat
  ion/376584286\_ImageBased\_Fish\_Disease\_Detection\_Methods
  \_An\_Innovative\_Technique\_for\_The\_Diag
  nosis
- Sun, M., Yang, X., & Xie, Y. (2020). Deep Learning in Aquaculture: A Review. *Journal of Computing, 31*(1), 294-319. doi:doi:10.3966/199115992020023101 028
- Syahidah, D., & Hastilestari, B. (2022). Machine Learning Approach for Early Detection of Plant and Fish Diseases.
- Syanya, F. J., Mahadevan, H., Khanna, A. R., Mathia, W. M., Mumina, P., Litabas, J. A., & Sifuna, C. (2025). Biosecurity protocols and fish health management in Kenyan fish hatcheries: A key to sustainable production of quality fish



seed. *Marine and Fishery Science Journal*, 357. doi:https://doi.org/10.47193/mafis.38 12025010102

- Vikash, M. (2019). DETECTION OF FISH
  DISEASES USING IMAGE PROCESSING.
  Retrieved from www.ece.anits.edu:
  https://www.ece.anits.edu.in/4B\_201819\_projects/KP\_NSN\_2018-19\_B.pdf
- Yang, X., Zhang, S., Liu, J., Gao, Q., Dong, S., & Zhou, C. (2021). Deep learning for smart fish farming: Challenges and opportunities. *Aquaculture Reviews*, 13(1), 66-90. Retrieved from https://www.researchgate.net/publicat ion/376584286\_Image-Based\_Fish\_Disease\_Detection\_Methods \_An\_Innovative\_Technique\_for\_The\_Diag nosis
- Zhao, S., Zhang, S., Liu, J., Zhu, J., & Li, D. (2021).

  Application of machine learning in intelligent fish aquaculture: A review.

  Aquaculture, 540, 724-736.

  doi:https://doi.org/10.1016/j.aquaculture.2021.736724.
- Zhou, X., Liu, T., & Zhang, W. (2018). Intelligent feeding control system for aquaculture based on near-infrared imaging and ANFIS. *Computers and Electronics in Agriculture, 153,* 174-182. doi:https://doi.org/10.1016/j.compag.2 018.08.004