LEVERAGING MACHINE LEARNING ALGORITHMS FOR OPTIMIZING *Gibelion catla* GROWTH ASSESSMENT IN CONTROLLED AQUACULTURE ENVIRONMENTS

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Abstract

This study demonstrates the potential of machine learning to revolutionize carp aquaculture by providing accurate and efficient growth assessments. The study was undertaken at Sirakol in the South 24 Parganas district of West Bengal during 2021 using *Gibelion catla* as the candidate carp species fed with probiotics-based feed. Among the four ponds, Ponds A and B exhibited the highest condition factors (represented by K-values), indicating the best growth conditions for *Gibelion catla*. Conversely, Ponds C and D showed lower K values, suggesting room for improvement. By addressing the factors influencing pond performance and leveraging ML technologies, aquaculture practices can be optimized to achieve higher productivity and sustainability. Future research should focus on enhancing ML model accuracy and exploring new applications to further advance the field of aquaculture.

Keywords: *Artificial Intelligence, Machine Learning, Carp, Condition Index*

1. Introduction

Aquaculture has become an increasingly important sector in global food production, providing a significant portion of the world's fish supply. Within this sector, the cultivation of carp (Cyprinidae) is particularly prominent due to their adaptability, rapid growth rates, and nutritional value. Traditional methods of monitoring and evaluating carp growth have primarily relied on manual measurements and observational techniques. However, these methods can be time-consuming, labour-intensive, and prone to human error. The advent of machine learning (ML) offers promising solutions to enhance the efficiency and accuracy of growth evaluation in aquaculture (Leung et al., 2019).

Machine learning, a subset of artificial intelligence (AI), involves the development of algorithms that enable computers to learn from and make decisions based on data. In recent years, ML has been increasingly applied in various fields of biological research and aquaculture, owing to its ability to handle large datasets and uncover complex patterns. The application of ML in evaluating carp growth is a relatively novel approach that has the potential to revolutionize aquaculture practices.

One of the early studies in this area was conducted by Ahmad et al. (2018), who utilized neural networks (Fig. 1) to predict the growth rates of carp based on various environmental parameters. Their research demonstrated that ML models could effectively predict growth outcomes with higher accuracy compared to traditional statistical methods. This breakthrough highlighted the potential of ML to optimize feeding regimes and environmental conditions, thereby enhancing overall productivity in carp farming.

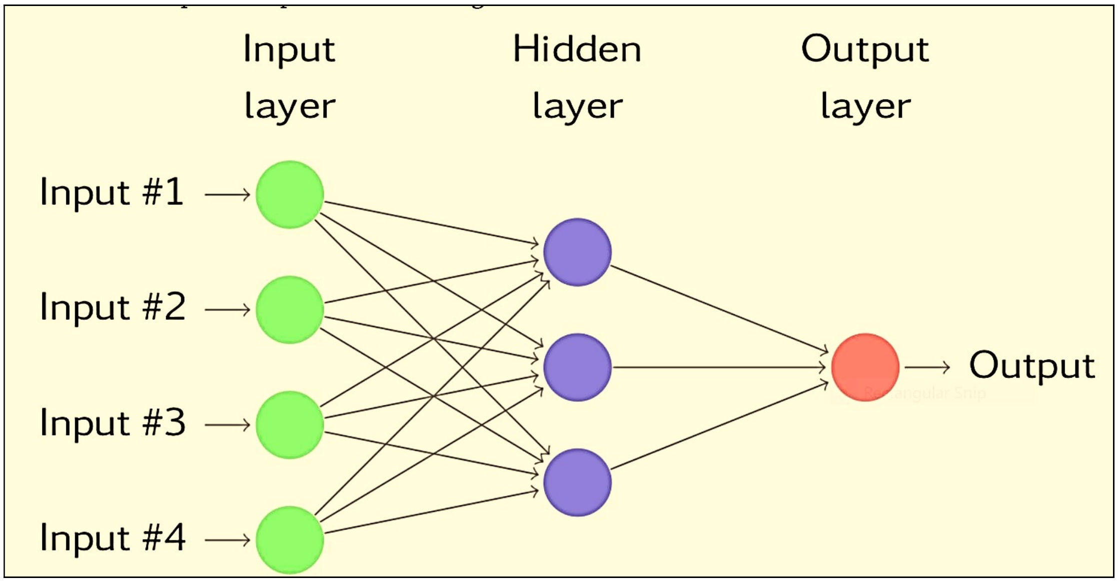

Fig. 1 Schematic representation of an ideal Neural Artificial Regression (NAR) model

The use of ML in aquaculture is not limited to growth evaluation and prediction alone. Tola et al. (2020) explored the application of image recognition technologies, powered by machine learning algorithms, to automatically measure fish sizes and detect health anomalies. Their system leveraged convolutional neural networks (CNNs) to analyse images of carp, providing precise measurements and identifying signs of disease at an early stage. This automated approach reduces the need for manual labour and allows for continuous monitoring, leading to timely interventions and improved fish health.

Moreover, ML has been employed to optimize feeding strategies, which is a crucial factor influencing carp growth. Research by Zhang et al. (2021) integrated ML algorithms with real-time data on water quality, temperature, and fish behaviour to develop adaptive feeding systems. These systems adjust feeding schedules and quantities based on the immediate needs of the carp, minimizing feed waste, and promoting optimal growth conditions. This adaptive approach contrasts sharply with traditional fixed feeding schedules, which often fail to account for dynamic environmental changes.

In addition to practical applications, ML also provides valuable insights into the underlying biological processes affecting carp growth. For instance, Wang et al. (2017) used machine learning to analyse gene expression data, identifying key genetic markers associated with growth traits in carp. By understanding these genetic influences, breeders can make more informed decisions in selective breeding programs, aiming to enhance desirable traits such as growth rate and disease resistance.

While the potential benefits of ML in aquaculture are substantial, several challenges need to be addressed to fully realize its advantages. One major challenge is the requirement for large, high-quality datasets to train ML models effectively. In many cases, such datasets are either unavailable or incomplete, limiting the accuracy and reliability of the predictions. Collaboration between researchers, aquaculture practitioners, and technology developers is essential to generate and share comprehensive datasets (Li et al., 2019).

Another challenge lies in the integration of ML systems with existing aquaculture infrastructure. The successful deployment of ML applications requires not only technical expertise but also a clear understanding of aquaculture operations. According to Huang et al. (2020), there is a need for interdisciplinary research and development efforts to create user-friendly ML tools that can be easily adopted by aquaculturists with varying levels of technical proficiency.

Moreover, ethical considerations must be considered when implementing ML in aquaculture. The use of automated systems to monitor and manage fish populations raises questions about data privacy, the potential for job displacement, and the welfare of the fish themselves. It is crucial to establish ethical guidelines and regulatory frameworks to ensure that the adoption of ML technologies benefits all stakeholders, including the fish (Fernandes et al., 2021).

Despite these challenges, the future of ML in carp aquaculture appears promising. Advances in sensor technologies, data analytics, and computational power are continually improving the capabilities of ML systems. Future research is likely to focus on enhancing the accuracy and robustness of ML models, as well as exploring new applications such as predicting the impact of climate change on carp growth and developing precision aquaculture systems that integrate various ML technologies.

Thus, the application of machine learning in evaluating carp growth represents a significant advancement in aquaculture practices. By leveraging the power of ML, researchers and practitioners can achieve more accurate growth predictions, optimize feeding strategies, and gain deeper insights into the biological factors influencing fish growth. While challenges remain, the ongoing development of ML technologies holds the potential to transform carp farming, making it more efficient, sustainable, and responsive to the needs of both producers and consumers.

The present research attempted to use probiotics in the fish feed to reduce the feed cost and upgrade the health of the cultured species. Integrating probiotics with fish meal in polyculture systems can reduce feed costs, which is vital component in deciding the profit from the aquaculture industry. Probiotics have the potential to enhance the digestive efficiency of fish, allowing them to gain more nutrients from less feed. This has been focused in details in the present research conducted during 2021 considering four ponds in the Sirakol region of South 24 Parganas, West Bengal (India).

2. Methodology

2.1. Site selection

The study was conducted from March to October 2021 to evaluate the application of machine learning techniques in assessing the growth of carp (Cyprinidae) in aquaculture. Four ponds, designated as Pond A (22°17'54″N; 88°16'15″E), Pond B (22°17'51″N; 88°16'18″E), Pond C, (22°17'52″N; 88°16'18″E) and Pond D (22°17'49″N; 88°16'18″E), located at Sirakol, were utilized for this study (Fig. 2). Each pond measured approximately 0.1 hectares and was stocked with carp fingerlings of uniform size (both with respect to weight and length of the cultured species, *Gibelion catla*).

Fig. 2 Drone view image of four selected ponds located at Sirakol region of South 24 Parganas, West Bengal (India)

2.2. Pond Preparation, Stocking, and Feeding

Prior to stocking, the ponds were drained, cleaned, and refilled with freshwater. Lime and fertilizer were applied to each pond to enhance the productivity of the aquatic environment. Fingerlings were sourced from a local hatchery and acclimatized to the pond conditions before being released. Each pond was stocked at a density of 10,000 fingerlings per hectare, resulting in 1,000 fingerlings per pond. Probiotics-based feed was provided in all the three ponds as per the value 1%, 2%, and 3% in pond A, D, and C respectively, while in pond B, traditional feed (with dried trash fishes, soyabean etc. as ingredients) was provided to the cultured species.

2.3. Data-Collection

Data collection was conducted monthly. 20-30 fishes were randomly sampled from each pond using a cast net, and used to measure the Average Body Weight (ABW) and Average Body Length (ABL) of the sampled fishes. ABW was determined using a digital weighing scale with an accuracy of 0.01 grams, while ABL was measured using a digital calliper with an accuracy of 0.1 millimetres.

The condition factor (K) of the fish was calculated using the formula:

$$K = \frac{W}{L^3} \times 100$$

This formula helps in assessing the overall health and well-being of the fish, with higher values indicating better condition of the culture pond with respect to environmental parameters.

2.4. Machine Learning Model Development

The value of *K* was generated as the output of a machine learning-based Python program on analysing the Average Body Weight (ABW) and Average Body Length (ABL) of the selected carp species (Scheme 1).

```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

# Sample data generation (Replace this with your actual dataset)
np.random.seed(42)
data_size = 1000
ABW = np.random.uniform(200, 1000, data_size)  # Average Body Weight in grams
ABL = np.random.uniform(20, 50, data_size)  # Average Body Length in cm
CI = (ABW / (ABL ** 3)) * 100  # Condition Index calculation

# Creating a DataFrame
data = pd.DataFrame({
    'ABW': ABW,
    'ABL': ABL,
    'CI': CI
})

# Splitting the data into training and testing sets
X = data[['ABW', 'ABL']]
y = data['CI']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Initializing and training the Random Forest Regressor
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Predicting the Condition Index on the test set
y_pred = model.predict(X_test)

# Evaluating the model
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

print(f'Mean Absolute Error (MAE): {mae}')
print(f'Mean Squared Error (MSE): {mse}')
print(f'Root Mean Squared Error (RMSE): {rmse}')
print(f'R-squared (R2): {r2}')

# Function to predict CI for new data
def predict_CI(abw, abl):
    return model.predict(np.array([[abw, abl]]))

# Example prediction
new_abw = 500  # Example Average Body Weight
new_abl = 30  # Example Average Body Length
predicted_ci = predict_CI(new_abw, new_abl)
print(f'Predicted Condition Index (CI) for ABW={new_abw}g and ABL={new_abl}cm: {predicted_
```

Scheme 1 ML-based Python program to evaluate K values of the carp species

Results

The results indicated that the machine learning approach provided accurately the value of condition index for four selected ponds (Figs. 3-6). The condition factor (K) values indicate better health and well-being of the fish in the adaptive feeding regime. Higher K values indicate better health and growth conditions for the carp (Mitra, 2013; Trivedi et al., 2015; Biswas et al., 2018; Mitra et al., 2022; Sarker et al., 2022; Mitra et al. 2023). The results are as follows:

- **Pond A**: The K value (1.97) indicated robust growth conditions, reflecting good health and well-being of the carp.
- **Pond B**: Pond B exhibited lowest K value (1.35), suggesting unfavourable growth conditions.
- **Pond C**: The K value (1.60) was lower than those of Ponds A and D, indicating comparatively less optimal conditions.
- **Pond D**: This pond showed the second highest K value (1.70) among the four, suggesting that the growth conditions were favourable during the culture tenure.

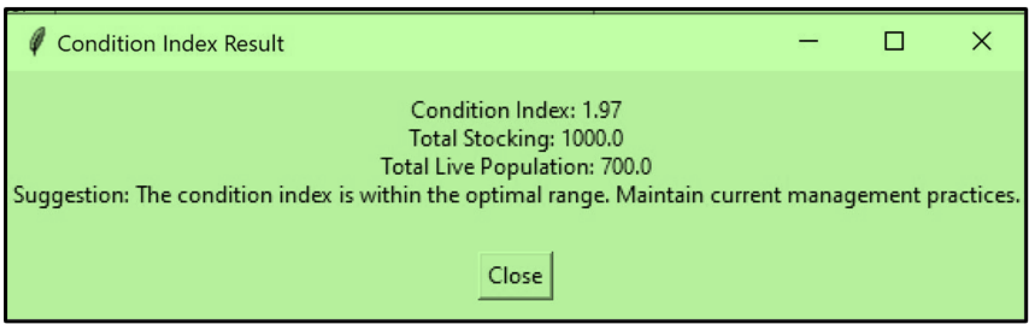

Fig. 3 Condition Index of *Gibelion catla* in Pond A based on ABW and ABL during October 2021

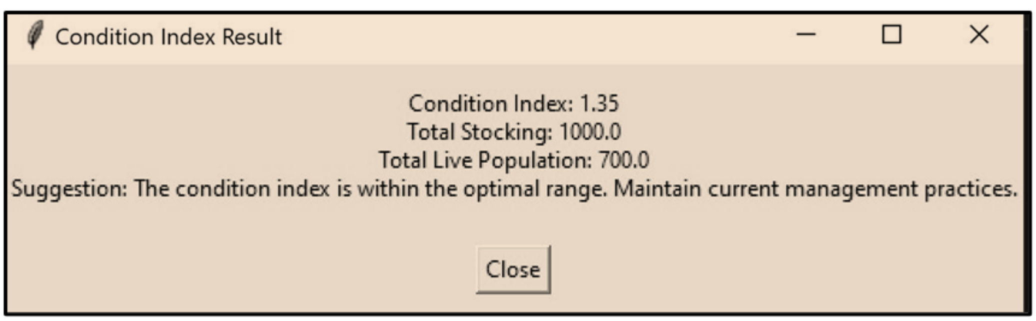

Fig. 4 Condition Index of *Gibelion catla* in Pond B based on ABW and ABL during October 2021

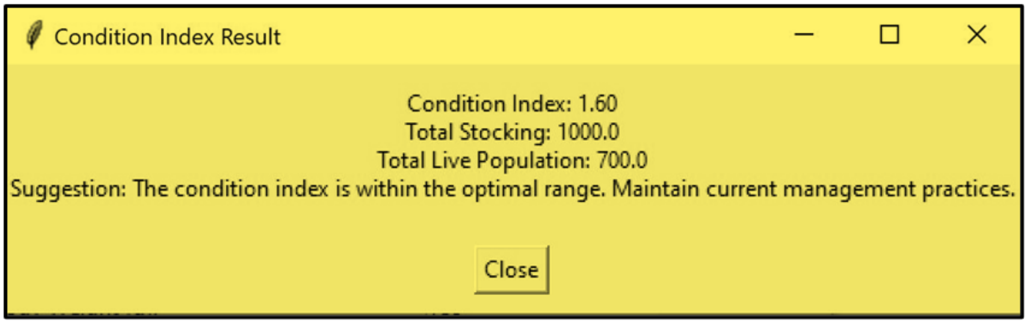

Fig. 5 Condition Index of *Gibelion catla* in Pond C based on ABW and ABL during October 2021

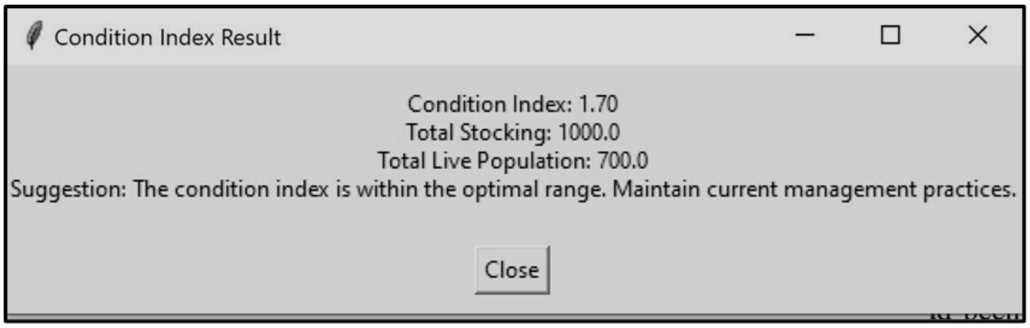

Fig. 6 Condition Index of *Gibelion catla* in Pond D based on ABW and ABL during October 2021

Discussion

This study demonstrated the potential of machine learning to monitor the condition index and management in carp aquaculture, offering a promising approach to improving productivity and sustainability in the industry. Several factors could influence the variation in K values across the ponds as highlighted here:

1. **Water Quality**: The quality of water, including parameters such as pH, dissolved oxygen, and temperature, plays a critical role in fish health. Differences in these parameters could lead to variations in the condition index.
2. **Feeding Regime**: The efficiency of feeding strategies significantly impacts fish growth. Ponds with adaptive feeding systems, informed by real-time data on water quality and fish behaviour, likely provided better growth conditions.
3. **Environmental Conditions**: External environmental factors such as weather, sunlight, and rainfall can affect the aquatic environment, influencing the growth of algae and other microorganisms that constitute the food web for carp.
4. **Management Practices**: The level of human intervention in managing the ponds, including regular monitoring and timely interventions, could also account for differences in the condition factor.

The application of ML in this study offered several advantages:

- **Accuracy**: ML models provided precise calculations of the condition index, reducing the likelihood of human error.
- **Efficiency**: Automated data analysis streamlined the process, allowing for continuous monitoring and timely adjustments.

- **Insight**: ML algorithms can uncover complex patterns and correlations that traditional methods might overlook, offering deeper insights into the factors influencing fish growth.

To optimize the growth conditions across all ponds, the following recommendations can be made:

1. **Enhanced Water Quality Monitoring**: Implementing advanced sensor technologies to continuously monitor water quality parameters and adjust conditions in real-time.
2. **Adaptive Feeding Systems**: Utilizing ML algorithms to develop adaptive feeding regimes that respond to the immediate needs of the carp, minimizing feed waste and promoting optimal growth. Optimization of probiotics-based feed is an integral part of this step.
3. **Regular Health Assessments**: Employing image recognition technologies to automate the measurement of fish sizes and detect health anomalies early.
4. **Data Sharing and Collaboration**: Encouraging collaboration between researchers and practitioners to generate comprehensive datasets that can improve the accuracy of ML models.

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