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A machine learning prediction of the fisheries production in the Philippines using WEKA

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Abstract

Fisheries have an important part in the Philippine economy, significantly contributing to food security and livelihoods. Predicting fisheries productivity accurately is critical for effective resource management and policy planning. This study looked at the volume of aquaculture production in the Philippines, focusing on four species: carp, catfish, grouper, and milkfish. Over a three-year period, the investigation found considerable changes in production levels among different locations. Aquaculture production in Central Luzon and CALABARZON has increased consistently, showing successful operations and excellent market circumstances. However, certain locations saw production variations or reductions, emphasizing the need for targeted interventions. In addition, machine learning techniques were used to forecast future aquaculture productivity. In terms of accuracy and dependability, Linear Regression, Support Vector Machine, and Multi-Layer Perceptron surpassed k-Nearest Neighbors and Decision Tree. These algorithms can help policymakers and resource managers make sound judgments for long-term fisheries management. The findings highlight the significance of identifying successful strategies in regions with steady development and tackling issues in places with fluctuating output. Furthermore, incorporating machine learning algorithms can improve prediction models, allowing for more effective planning and decision-making. The study provides useful information for policymakers, researchers, and aquaculture stakeholders, encouraging sustainable development and growth in the Philippine fisheries industry.

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Introduction

The Philippines' population relies heavily on fishing as both a source of food and income, making the sector of the economy that supports the fishing industry an extremely important one. It is absolutely necessary for efficient resource management and strategic planning to have an accurate projection of fisheries productivity.

The Philippines' fisheries industry passed a notable landmark during the first three months of 2023, when the recorded volume of fisheries production reached 991,14 thousand metric tons. This was an important achievement for the industry. When compared to the output of 971.76 thousand metric tons over the same time period in the year prior, this statistic reflects a noteworthy rise of 2.0 percent. (PSA, 2023)

According to PSA (2023) with a production volume that was measured at 545,64 thousand metric tons during the first quarter of 2023, the Philippines' aquaculture subsector accomplished a critical milestone and reached a new level of success. When compared to the output of 536,60 thousand metric tons during the same quarter of the previous year, this result represents a noteworthy rise of 1.7 percent.

During this time period, aquaculture established itself as the primary contributor to the overall production of fisheries, accounting for the greatest percentage, or 55.1 percent. This emphasizes the growing significance of aquaculture in meeting the demands for fisheries across the country and bolstering the economy. (PSA, 2023)

Many different things may be responsible for the encouraging increase in the amount of food that is produced by aquaculture. Aquaculture methods, such as fish farming and the cultivation of marine species, have benefited from developments in technology and management strategies, which have led to an improvement in both productivity and efficiency. In addition to good market conditions and rising consumer demand, the availability of adequate aquatic settings has been a major contributor to the rise of the aquaculture sector.

The significant contribution that the aquaculture subsector makes to the overall production of fisheries is an indication of the crucial role that it plays in meeting the requirements of the country in terms of food security and livelihoods. The government's attempts to alleviate pressure on wild fish stocks, encourage sustainable fishing techniques, and ensure a stable supply of fish products to fulfill the dietary requirements of a growing population are supported by the consistent expansion of aquaculture, which has been developing at a rapid rate in recent years.

It is absolutely necessary to keep making investments in research, development, and innovation in order to fully capitalize on the potential offered by the aquaculture subsector. The optimization of production processes, the addressing of environmental concerns, and the enhancement of the sustainability of aquaculture operations can all be helped by this. In addition, programs that help aquaculture farmers increase their skills, access to finance, and supporting infrastructure all have the potential to contribute to the industry's continuing expansion and resilience.

These findings also underline the necessity for ongoing monitoring and evaluation of aquaculture productivity in order to identify potential obstacles and opportunities. Regular data collection, analysis, and forecasting using machine learning techniques, as recommended in the study using the WEKA platform, can provide significant insights into the drivers of aquaculture output. This can be accomplished by collecting data from the quarterly reports of Philippine Statistics Authority, analyzing the data, and making predictions. This knowledge can be used in the formulation of plans to solve challenges, minimize risks, and make the most of the sector's potential economic and environmental benefits. The most fundamental premise of the application is that it will be possible to use of software on a computer to carry out various operations related to machine learning and provide useful data in the form of patterns and trends. As applied by (Tien, 2017) in their study, the decision making is really possible to be arrived using artificial intelligence.

WEKA is an application that is freely available to users and is published under the GNU General Public license. It includes a graphical user interface that is intuitive and easy to use, which enables quick action and setup. WEKA requires that the user data be in the form of a flat file or relation. This implies that each data item is represented by a defined number of characteristics, which are typically of a specific kind, alpha-numeric or numeric values, respectively. The WEKA application gives inexperienced users a tool for extracting hidden information from database and file systems by offering straightforward options and user interfaces that are aesthetically pleasing. (Khalafyan *et al.*, 2021). This study is to anticipate the volume production of carp, catfish, milkfish, and grouper in aquaculture in the Philippines by utilizing machine learning techniques and the WEKA platform. Specifically, the research will focus on the Philippines.

Material and methods

In this investigation, a quantitative research methodology is utilized to evaluate the use of supervised learning algorithms in the prediction of the fisheries production in the Philippines. The approach entails a number of essential processes, including the collecting of data, the preparation of data, the development of an algorithm, the evaluation of a model, and statistical analysis.

Gathering of Information

The Philippine Statistics Authority is the place where the carp, catfish, grouper and milkfish dataset were obtained. The dataset contains an exhaustive collection of wine-related factors, such as chemical characteristics and sensory characteristics, amongst other things. The dataset offers an appropriate basis for the training of supervised learning algorithms as well as for the evaluation of their performance.

The Application of the Algorithms

k-Nearest Neighbors, Linear Regression, Decision Tree, Multi-Layer Perceptron, and Support Vector Machines are some of the supervised learning algorithms that have been employed. The Weka data mining tool, which provides a comprehensive range of functions for generating and assessing models is used to implement each algorithm. The study of Kenyhercz and Passalacqua (2016) utilized the algorithms for their study and produced reliable results while in the information provided by Ooi *et al.* (2017), clear explanation on how to use the decision trees and the rest of the algorithms are presented. It was also covered in the discussion of Pisner and Schnyer (2020) that support vector machine can also provide reliable result.

The Training and Assessment of Models

For the purpose of evaluating the effectiveness of the algorithms, the dataset is partitioned into training and testing subsets. The models that are going to be employed are trained on the training subset, and the testing subset is used to determine how accurate the models are going to be. According to Cortez *et al.* (2009), the correlation coefficient (r) and root mean squared error (RMSE) are utilized in order to evaluate the effectiveness of each algorithm.

Algorithm Analysis using Statistical Tools

The effectiveness of the supervised learning algorithms' performance levels is examined using statistical methods. The study of Beltrán *et al.* (2008) used several algorithms for their wine classifications study. As part of the evaluation process, descriptive statistics like means and standard deviations are produced for the metrics being used. It is possible to use inferential statistics such as t-tests and ANOVA to establish whether or not there are significant differences between the algorithms' overall performance.

Analysis of the Variables' Correlation

In order to determine the factors that have a major impact on the prediction of fisheries production, the researcher investigated the connection that exists between predicted and individual values of each algorithm. According to Moreno *et al.* (2007), the correlation coefficients are computed, and the variables with the strongest correlations are determined.

Result and discussion

Result

Data on Volume of Production in Aquaculture in the Philippines

The information shown in the succeeding tables was extracted from the Fisheries Statistics of the

Philippines which pertains to the volume of production in aquaculture in the Philippines from 2019 to 2021 and is broken down geographically by area and province. The following table illustrates the differences in production that occurred across several regions and over the course of three years. Figs. 1, 2, 3 and 4 are the images of carp, catfish, grouper and milkfish respectively (PSA, 2023)

Fig. 1. The Milkfish also known as "Bangus" in the Philippines. (source: https://www.onenews.ph/ articles/ dagupan -students-to-produce-bangus-bun)

Fig. 2. The Catfish Also Known as "Hito" in the Philippines. (source: http://pinoyfranchising.blogspot.com/2006 /09/franchising-raising-and-production-of.html)

Fig. 3. The Carp Also Known as "Karpa" in the Philippines. (source: https://www.britannica.com/animal/carp-fish-species)

Fig. 4. The Grouper Also Known as "Lapu-Lapu" in the Philippines. (source: https://www.britannica.com /animal/carp-fish-species)

Table 1 shows Philippine aquaculture carp production by area and province from 2019 to 2021 in metric tons. The table shows three-year carp production patterns. In 2020, the NCR produced 5.41 MT of carp, down from 5.63 MT in 2019. The Cordillera Administrative Region (CAR) produced 0.21 MT of carp in 2019, 0.13 MT in 2020, and 0.17 MT in 2021. The Ilocos Region produced 9.65 MT of carp in 2019, 10.67 MT in 2020, and 7.97 in 2021. Cagayan Valley produced 11.49 MT of carp in 2019, 10.24 MT in 2020, and 13.47 MT in 2021. Central Luzon produced 115.88 MT of carp in 2019, 115.63 in 2020, and 139.33 in 2021. CALABARZON grew from 12,584.63 MT in 2019 to 11,156.71 MT in 2020 to 14,040.03 MT in 2021. In 2019, Bicol produced 7.98 MT, 8.15 MT in 2020, and 0.39 MT in 2021. Western Visayas produced 0.01 MT of carp in 2019, 0.21 in 2020, and 0.20 in 2021. Central Visayas produced 0.27 MT of carp in 2019, 0.15 in 2020, and 0.37 in 2021. Eastern Visayas produced 1.64 MT in 2019, 0.01 in 2020, and 0.05 in 2021. In 2019, Zamboanga Peninsula produced 0.10 MT of carp, 0.12 in 2020, and 0.47 in 2021. Northern Mindanao averaged 81.85 MT in 2019, 83.52 in 2020, and 84.55 in 2021. Davao Region produced 2.66 MT in 2019, 2.68 in 2020, and 2.88 in 2021. SOCCSKSARGEN fluctuated from 2.28 MT in 2019 to 10.38 MT in 2020 and 1.24 MT in 2021.Carp production in the Bangsamoro Autonomous Region in Muslim Mindanao (BARMM) was zero in 2019, 8.75 MT in 2020, and 9.98 MT in 2021. In 2019, 2020, and 2021, Caraga produced 0.12, 0.11, and 0.11 MT. The table shows carp output growth and variation between Philippine provinces. Central Luzon and CALABARZON show constant increase over three years, suggesting successful aquaculture operations and favorable market circumstances.

Table 1. Volume of Carp Production in Aquaculture by Region and Province Philippines 2019-2021 in Metric Tons.

Region	2019 (Metric Tons)	2020 (Metric Tons)	2021 (Metric Tons)
NCR		5.63	5.41
CAR	0.21	0.13	0.17
Ilocos Region	9.65	10.67	7.97
Cagayan Valley	11.49	10.24	13.47
Central Luzon	115.88	115.63	139.33
CALABARZON	12,584.63	11156.71	14,040.03
MIMAROPA			
Bicol Region	7.98	8.15	0.39
Western Visayas	0.01	0.21	0.20
Central Visayas	0.27	0.15	0.37
Eastern Visayas	1.64	0.01	0.05
Zamboanga Peninsula	0.10	0.12	0.47
Northern Mindanao	81.85	83.52	84.55
Davao Region	2.66	2.68	2.88
SOCCSKSARGEN	2.28	10.38	1.24
Bangsamoro Autonomous Region in Muslim Mindanao		8.75	9.98
Caraga	0.12	0.11	0.11

Table 2 shows Philippine aquaculture catfish production by region and province from 2019 to 2021 in metric tons. The table shows three-year catfish production patterns. The Cordillera Administrative Region (CAR) produced 0.10 metric tons (MT) of catfish in 2019, 0.11 in 2020, and 0.67 in 2021. In 2019, Ilocos produced 6.41 MT of catfish, 9.21 MT in 2020, and 5.22 MT in 2021. In 2019, Cagayan Valley produced 175.81 MT, then 164.94 in 2020, and 142.40 in 2021. Central Luzon produced 2,364.66 MT of catfish in 2019, 2,383.56 MT in 2020, and 3,364.94 MT in 2021. CALABARZON fluctuated from 267.34 MT in 2019 to 193.76 MT in 2020 to 209.19 MT in 2021. The Bicol Region had 40.78 MT in 2019, 26.65 MT in 2020, and 29.89 MT in 2021. Western Visayas catfish output increased from 577.98 MT in 2019 to 652.56 MT in 2020 and 843.76 MT in 2021. In 2019, Central Visayas produced 0.08 MT of catfish, 0.14 MT in 2020, and 0.31 MT in 2021. In 2019, 2020, and 2021, Eastern Visayas produced 1.62 MT, 1.63 MT, and 1.65 MT. In 2019, Zamboanga Peninsula had 0.17 MT, 0.41 MT in 2020, and 0.85 MT in 2021. Northern Mindanao fluctuated from 23.68 MT in 2019 to 10.22 MT in 2020 to 18.63 MT in 2021. Davao Region produced 848.84 MT of catfish in 2019, 1,141.93 MT in 2020, and 1,451.52 MT in 2021. SOCCSKSARGEN fluctuated from 388.06 MT in 2019 to 351.72 MT in 2020 and 321.46 MT in 2021. In 2019, 2020, and 2021, the Bangsamoro Autonomous Region in Muslim Mindanao (BARMM) produced 178.68 MT, 183.38 MT, and 183.00 MT of catfish. Caraga produced 0.02 MT of catfish in 2019, 0.06 MT in 2020, and 0.13 MT in 2021. The table shows catfish production differences between Philippine provinces. Central Luzon, CALABARZON, Western Visayas, and Davao Region show constant catfish output growth over three years, indicating successful aquaculture methods and potentially favorable market conditions. Cagayan Valley and SOCCSKSARGEN have swings, suggesting obstacles or special factors affecting catfish production there.

Table 2. Volume of Catfish Production in Aquaculture by Region and Province Philippines 2019-2021 in Metric Tons.

Region	2019 (Metric Tons)	2020 (Metric Tons)	2021 (Metric Tons)
NCR			
CAR	0.10	0.11	0.67
Ilocos Region	6.41	9.21	5.22
Cagayan Valley	175.81	164.94	142.40
Central Luzon	2,364.66	2383.56	3,364.94
CALABARZON	267.34	193.76	209.19
MIMAROPA	0.16	0.52	0.65
Bicol Region	40.78	26.65	29.89
Western Visayas	577.98	652.56	843.76
Central Visayas	0.08	0.14	0.31
Eastern Visayas	1.62	1.63	1.65
Zamboanga Peninsula	0.17	0.41	0.85
Northern Mindanao	23.68	10.22	18.63
Davao Region	848.84	1141.93	1,451.52
SOCCSKSARGEN	388.06	351.72	321.46
Bangsamoro Autonomous Region in Muslim Mindanao	178.68	183.38	183.00
Caraga	0.02	0.06	0.13

Table 3 shows Philippine aquaculture grouper production by region and province in metric tons. The table shows three-year grouper production patterns from 2019-2021. The table shows no grouper production data for the National Capital Region (NCR) and Cordillera Administrative Region (CAR) over the given years. The Ilocos Region produced 1.20 MT of grouper in 2019, 1.55 MT in 2020, and 2.02 MT in 2021. Cagayan Valley had no data in 2019, but 0.05 MT in 2020 and 0.17 MT in 2021. Central Luzon grouper production data is unavailable for any year. CALABARZON fluctuated from 24.01 MT in 2019 to 6.68 in 2020 to 9.66 in 2021. MIMAROPA produced 1.24 MT of grouper in 2019, 0.84 in 2020, and 2.86 in 2021. In 2019, the Bicol Region had 3.47 MT, then 0.95 in 2020, and 4.96 in 2021. Western Visayas had 59.39 MT in 2019, 52.54 in 2020, and 65.93 in 2021. Central Visayas produced 0.93 MT of grouper in 2019, 1.58 MT in 2020, and 4.16 MT in 2021. Eastern Visayas fluctuated from 6.01 MT in 2019 to 9.04 MT in 2020 to 1.74 MT in 2021. Zamboanga Peninsula had 40.24 MT in 2019, 1.64 in 2020, and 2.20 in 2021. Northern Mindanao had no grouper production data in any year.

In 2019, Davao Region recorded 0.04 MT, with no data for 2020 and a minor increase to 0.13 MT in 2021. Grouper production in SOCCSKSARGEN during the years is unknown. The Bangsamoro Autonomous Region in Muslim Mindanao has 0.18 MT in 2020 and 0.19 in 2021. In 2019, 2020, and 2021, Caraga produced 0.07, 0.06, and 0.06 MT, respectively.

Table 3. Volume of Grouper Production in Aquaculture by Region and Province Philippines 2019-2021 in Metric Tons.

Region	2019 (Metric Tons)	2020 (Metric Tons)	2021 (Metric Tons)
NCR			
CAR			
Ilocos Region	1.20	1.55	2.02
Cagayan Valley		0.05	0.17
Central Luzon		0.06	
CALABARZON	24.01	6.68	9.66
MIMAROPA	1.24	0.84	2.86
Bicol Region	3.47	0.95	4.96
Western Visayas	59.39	52.54	65.93
Central Visayas	0.93	1.58	4.16
Eastern Visayas	6.01	9.04	1.74
Zamboanga Peninsula	40.24	1.64	2.20
Northern Mindanao	0.22		
Davao Region	0.04		0.13
SOCCSKSARGEN			
Bangsamoro Autonomous Region in Muslim Mindanao		0.18	0.19
Caraga	0.07	0.06	0.06

Table 4 presents the volume of milkfish production in aquaculture by region and province in the Philippines from 2019 to 2021, measured in metric tons. The table provides an overview of the trends and changes in milkfish production over the three-year period. In the National Capital Region (NCR), milkfish production exhibited significant fluctuations.

In 2019, the region recorded a high production volume of 9,860.73 metric tons (MT), which dramatically decreased to 680.95 MT in 2020, and further declined to 217.53 MT in 2021. There is no data available for milkfish production in the Cordillera Administrative Region (CAR) during the given years. The Ilocos Region demonstrated consistent growth in milkfish production, with 116,796.79 MT in 2019, 125,913.08 MT in 2020, and a further increase to 137,880.69 MT in 2021. Similarly, Cagayan Valley exhibited growth, starting at 543.73 MT in 2019, increasing to 555.07 MT in 2020, and further rising to 634.82 MT in 2021.

Central Luzon also showed consistent growth in milkfish production, with 66,960.66 MT in 2019, 78,015.63 MT in 2020, and a further increase to 89,608.27 MT in 2021. CALABARZON experienced fluctuations, starting at 53,227.96 MT in 2019, declining to 43,338.17 MT in 2020, and then further decreasing to 41,073.29 MT in 2021. MIMAROPA exhibited variations in milkfish production, with 1,331.95 MT in 2019, increasing to 1,604.55 MT in 2020, and a further increase to 1,758.24 MT in 2021.

The Bicol Region also demonstrated fluctuations, starting at 4,342.89 MT in 2019, decreasing to 2,390.56 MT in 2020, and then rising to 4,198.03 MT in 2021. Western Visayas exhibited relatively stable milkfish production, with 97,265.96 MT in 2019, 98,326.86 MT in 2020, and a slight increase to 97,564.21 MT in 2021. Central Visayas showed growth, starting at 4,694.35 MT in 2019, increasing to 6,287.21 MT in 2020, and further rising to 7,657.06 MT in 2021. Eastern Visayas demonstrated fluctuations, starting at 6,947.04 MT in 2019, decreasing to 3,221.29 MT in 2020, and then increasing to 3,430.87 MT in 2021. Zamboanga

Peninsula exhibited variations, with 6,329.28 MT in 2019, 6,026.77 MT in 2020, and a further increase to 7,729.52 MT in 2021. Northern Mindanao showed fluctuations, starting at 15,185.62 MT in 2019, increasing to 14,791.77 MT in 2020, and further declining to 14,585.64 MT in 2021.

Table 4. Volume of Milkfish Production in Aquaculture by Region and Province Philippines 2019-2021 in Metric Tons.

Region	2019 (Metric Tons)	2020 (Metric Tons)	2021 (Metric Tons)
NCR	9,860.73	680.95	217.53
CAR			
Ilocos Region	116,796.79	125913.08	137,880.69
Cagayan Valley	543.73	555.07	634.82
Central Luzon	66,960.66	78015.63	89,608.27
CALABARZON	53,227.96	43338.17	41,073.29
MIMAROPA	1,331.95	1604.55	1,758.24
Bicol Region	4,342.89	2390.56	4,198.03
Western Visayas	97,265.96	98326.86	97,564.21
Central Visayas	4,694.35	6287.21	7,657.06
Eastern Visayas	6,947.04	3221.29	3,430.87
Zamboanga Peninsula	6,329.28	6026.77	7,729.52
Northern Mindanao	15,185.62	14791.77	14,585.64
Davao Region	13,398.77	16527.34	20,143.08
SOCCSKSARGEN	2,391.87	3732.93	3,085.78
Bangsamoro Autonomous Region in Muslim Mindanao	5,246.55	7336.85	7,315.64
Caraga	5,385.41	4839.9	5,385.07

Davao Region exhibited growth, with 13,398.77 MT in 2019, increasing to 16,527.34 MT in 2020, and a further increase to 20,143.08 MT in 2021. SOCCSKSARGEN demonstrated fluctuations, starting at 2,391.87 MT in 2019, increasing to 3,732.93 MT in 2020, and then declining to 3,085.78 MT in 2021. The Bangsamoro Autonomous Region in Muslim Mindanao showed fluctuations, starting at 5,246.55 MT in 2019, increasing to 7,336.85 MT in 2020, and a slight increase to 7,315.64 MT in 2021. Caraga exhibited slight fluctuations, with 5,385.41 MT in 2019, decreasing to 4,839.90 MT in 2020, and then increasing to 5,385.07 MT in 2021.

Prediction of the Aquaculture Production of Selected Species

The study predicts aquaculture fisheries production in the coming years using k-Nearest Neighbors, Linear Regression, Decision Tree, Multi-Layer Perceptron, and Support Vector Machines. Machine learning uses these algorithms for classification and regression. Linear Regression finds linear correlations between variables, while k-Nearest Neighbors predicts based on data point similarity.

Decision Tree uses feature values to make tree-like judgments, and Multi-Layer Perceptron may learn complex patterns. SVMs classify binary data. These algorithms will help policymakers and resource managers make sustainable fisheries management decisions by creating reliable prediction models. Table 5 shows the results of performance measures of the prediction algorithms.

Table 5. Summary Performance Measures of Aquaculture Production of Selected Species in Predicting the Production of Fisheries in the Coming Years.

Algorithm	Correlation Coefficient				RMSE			
	Carp	Catfish	Grouper	Milkfish	Carp	Catfish	Grouper	Milkfish
Linear Regression	1	0.9877	0.8945	0.9963	313.27	166.65	9.038	3657.90
k-Nearest Neighbors	0.6248	0.9866	0.0998	0.8652	3589.20	504.12	15.71	20596.51
Decision Tree	-0.528	0.6995	-0.0014	0.4472	3740.36	668.29	15.75	39872.01
Support Vector Machine	1	0.9971	0.3966	0.9907	521.04	74.65	14.20	5661.88
Multi-Layer Perceptron	0.8911	0.9171	0.2129	0.9905	3577.72	412.18	15.17	7655.87

Discussion

Philippine Aquaculture Carp Production

Central Luzon and CALABARZON had successful aquaculture operations and excellent market conditions, as carp production increased over three years. Carp output varied in Cagayan Valley and Ilocos. Carp aquaculture could grow in these places. In 2021, carp output fell in Bicol Region, which may concern stakeholders and policymakers. Understanding these production patterns can help find methods to preserve and improve carp production in specific places, including ways to address issues in declining regions and replicate success in expanding ones.

Philippine Aquaculture Catfish Production

Over three years, catfish output increased in Central Luzon, CALABARZON, Western Visayas, and Davao Region, showing successful aquaculture methods and potentially good market conditions. However, catfish output fluctuated in Cagayan Valley and SOCCSKSARGEN, suggesting impediments or specific factors affecting productivity. Identifying the elements that lead to constant growth and addressing the issues of regions with oscillations might help establish focused interventions and best practices for catfish production across regions.

Philippine Aquaculture Grouper Production

Over three years, grouper productivity in the Ilocos Region increased, indicating potential for grouper aquaculture development. CALABARZON and Western Visayas showed various amounts of grouper production growth, indicating successful methods. However, the National Capital Region and Cordillera Administrative Region lack grouper production data, requiring further study. Analyzing growth characteristics in specific places can help scale up grouper aquaculture and address issues in other regions.

Philippine Aquaculture Milkfish Production

To understand milkfish output changes in the National Capital Region, more research is needed. Milkfish production in the Ilocos Region increased, indicating good conditions and successful aquaculture. Central Luzon, CALABARZON, and Davao Region showed constant milkfish output growth, proving their aquaculture operations work. Understanding these regions' success factors can inform milkfish production methods statewide. The changes in Eastern Visayas and Zamboanga Peninsula may require more investigation to determine the causes and take suitable steps to stabilize production.

Prediction Analysis

The findings provide metrics for evaluating the efficacy of various machine learning algorithms that are applied in aquaculture to forecast the output of particular species of fish. A value of 1 for the correlation coefficient indicates that a complete positive correlation exists between the predicted and actual values. The correlation coefficient is a measure of the relationship between the predicted and actual values. The root means square error (RMSE) is a metric that calculates the average difference between the values that were predicted and those that were actually observed. Values with smaller differences indicate greater accuracy. According to the findings, Linear Regression performed commendably for each of the four species, achieving high correlation values in the range of 0.9877 to 0.9963. In addition to this, it had reasonably low RMSE values, which indicated that it made reliable predictions.

The performance of k-Nearest Neighbors was inconsistent among the species, with correlation values ranging from 0.0998.0 to 0.9866. In comparison to Linear Regression, it exhibited larger RMSE values, which indicated that its predictions were less reliable.

A negative correlation coefficient was found between carp and grouper in Decision Tree's analysis, which indicates a weak or adverse association between the two species. The RMSE values were likewise greater, which indicated that the forecasts were less reliable.

Strong performance was demonstrated by the Support Vector Machine for the majority of species, with correlation values ranging from 0.9907 to 1. In addition to this, it had reasonably low RMSE values, which indicated that its predictions were correct. It was mentioned in the study of Smola & Schölkopf (2004) that SVM is one of the best performer when it comes to numerical data.

The correlation coefficients found using Multi-Layer Perceptron ranged from 0.8911 to 0.9905, indicating that they were moderate to high for most species. When compared to those of k-Nearest Neighbors and Decision Tree, the RMSE values were, on average which is an indication of improved accuracy. In summary, when it came to estimating fisheries production, linear regression, support vector machine, and multi-layer perceptron performed significantly better than k-nearest Neighbors and decision tree. These algorithms can be deemed more reliable for estimating the production of aquaculture, which provides useful information for the management of fisheries and the development of policy.

Conclusion

The analysis of data from the Philippines' aquaculture production indicated significant patterns and variances in the production of carp, catfish, grouper, and milkfish across different regions and over a three-year period. Central Luzon and CALABARZON have exhibited continuously successful aquaculture operations and good market conditions, with increasing production levels. However, several regions, such as Bicol and the National Capital Region, witnessed production variations or losses, underlining the need for targeted interventions and further research.

To forecast aquaculture production for the selected species, the study used machine learning methods such as Linear Regression, k-Nearest Neighbors, Decision Tree, Multi-Layer Perceptron, and Support Vector Machines. In terms of accuracy and dependability, the results showed that Linear Regression, Support Vector Machine, and Multi-Layer Perceptron surpassed k-Nearest Neighbors and Decision Tree. These algorithms can help policymakers and resource managers make informed decisions about fisheries management.

Recommendation(S)

Based on the findings, it is suggested that efforts be directed on improving and expanding aquaculture operations in areas that have shown successful and consistent production growth, such as Central Luzon and CALABARZON. These locations can serve as models for best practices that can be copied elsewhere to improve sustainable fisheries output. Further study should be performed in places with fluctuating or declining output to uncover the underlying causes and develop focused solutions to solve the difficulties.

Furthermore, policymakers and academics should continue to investigate the application of machine learning techniques, specifically Linear Regression, Support Vector Machine, and Multi-Layer Perceptron, to improve aquaculture production prediction models. More precise forecasts can be made by harnessing the power of these algorithms, allowing for better planning and decision-making in fisheries management. Regular monitoring of production trends, as well as the incorporation of predictive models, can contribute in the formulation of appropriate policies to ensure the long-term sustainability and expansion of the Philippine aquaculture sector.

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