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Weight Prediction Model of Red Tilapia (*Oreochromis Niloticus*) Using Linear Regression Algorithm

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Abstract Red tilapia (*Oreochromis sp*) is one of the important fish in the aquaculture production world, and it's widely cultivated in Indonesia. This fish is in great demand because of its delicious and thick flesh. The production of red tilapia needs to be increased. One way to increase the production of red tilapia is by increasing the feeding. This study aimed to construct a linear regression model between the weight of the feed given and the weight of the red tilapia produced. The method used in this research is Machine Learning Lifecycle (MLL). This method consists of four stages: data acquisition, data preprocessing, model training, and model development. The research data was obtained from cultivating red tilapia for nine weeks in 12 aquariums. Model making is done using the programming language Python and Jupiter Notebook. The linear regression equation obtained is $y = 15.51x+22.17$. The model accuracy value is 0.798 using R-square. Based on the R-square, the model obtained is good. This model can later be applied to red tilapia aquaculture activities. Model scalability must be maintained so that model performance remains good. Red tilapia cultivators can utilize this study's results to produce maximum red tilapia production. At a broader level, this research aligns with higher policy objectives related to public engagement and co-creation with stakeholders as specified in Sustainable Development Goals (SDG) like SDG14 (life below water).

Keywords Aquaculture, Fish Weight Forecasting, Growth Estimation, Statistical Modelling, Tilapia Fish

1. Introduction

Red tilapia (*Oreochromis sp*) is one of the important fish in world aquaculture production (Harmilia *et al.* 2019). Hybrid red tilapia is well-developed in Pakistan (Daudpota *et al.* 2016). Red Tilapia (*Oreochromis sp*) is a fish that has been widely cultivated in Indonesia (Zulkhasyni *et al.* 2017). The public demands this fish because the meat is delicious and thick, like red snapper (Zulkhasyni *et al.* 2017; Pamungkas *et al.* 2022). Red tilapia (*Oreochromis sp*) is a freshwater fish commodity with good development prospects (Putra *et al.* 2022; Wibowo *et al.* 2023). Apart from the meat, red fish bone waste can also be used as a raw material for making halal gelatin (Putri *et al.* 2022).

Red tilapia can adapt to a wide range of salinity and thrive in brackish water (Shafry *et al.* 2022). Production of red tilapia continues to grow in various regions (Hendriana *et al.* 2022). The red tilapia business developed using floating net cages is also doing well (Ajeng *et al.* 2022). Besides that, it can also be developed in ponds (Porang *et al.* 2022).

Many studies have been conducted to increase the weight of red tilapia, including by improving genetic quality (Gunadi *et al.* 2021) or providing feed. Feed is a means of production that is most needed in the red tilapia enlargement business (Ajeng *et al.* 2022). Feed plays an essential role in fish farming activities because the need for feed during cultivation can reach 60-70% of the total production cost, and feed is also a factor that significantly influences the productivity of red tilapia (Zulkhasyni *et al.* 2017).

The amount of feed consumption is one of the crucial factors affecting fish growth (Permatasari *et al.* 2022). In the bio floc technique, tilapia are given natural and artificial feed (Putra *et al.* 2022). Artificial feed supplemented with garlic had a significant effect on the increase in the length of tilapia (Rijal *et al.* 2021). Meanwhile, curcumin analog supplementation can improve liver performance to support the reproduction of red tilapia (Mainassy *et al.* 2022). 20% dietary inclusion level of fermented, cooked, and dried flamboyant seed is the best for red tilapia (Umanah dan David 2021). It is also found that increasing protein or energy levels in red tilapia fry diets significantly increases feed intake (Zead 2018). Apart from feed, density also influences the growth of red tilapia (Djaelani dan Sunarno 2022). According to another study, the combination of chromium-L-methionine and a zinc amino acid complex enhanced the growth performance, consumption of feed, and intestinal morphology of red tilapia (Limwachirakhom *et al.* 2022). The combination of chromium-L-methionine and selenomethionine stimulated a natural immune response in red tilapia by increasing the levels of antioxidative enzymes, particularly glutathione. (Limwachirakhom *et al.* 2022).

Fish farmers are likely to cultivate poor-quality fish to accommodate the rising demands for food due to the ever-increasing population (Tolentino *et al.* 2020). Fish growth monitoring greatly helps produce higher-quality fish products, leading to a better impact on the aquatic animal food production industry (Tolentino *et al.* 2020). However, monitoring through manual weighing and measuring stresses them, affecting their health and resulting in poorer quality or even fish kills (Tolentino *et al.* 2020).

It is essential to accurately forecast the weight of fish in aquaculture systems to monitor their growth and determine the optimal feeding strategies (Aljehani *et al.* 2023). This model will assist aquaculture producers in effectively managing tilapia stocks and optimizing feed utilization (Gule dan Geremew 2022). (Jang dan Seo 2023) predicts fish weight for delivery, which is cut into pieces according to the desired weight of group meal providers. Research by (Fernandes *et al.* 2020) uses image segmentation to extract fish body measurements and predict body weight and carcass traits in Nile tilapia. Shrimp Body Weight also has been estimated in aquaculture ponds using morphometric features based on underwater image analysis and a machine learning approach (Setiawan *et al.* 2022). (Tonachella *et al.* 2022) use computer vision to estimate fish biometric parameters, with a mean error of ± 1.15 cm. (Lopez-Tejeida *et al.* 2023) successfully made an improved method to obtain fish weight using machine learning and without a camera with a haar cascade classifier. (Chen *et al.* 2021) use ANN to predict the weight of multi-species fishing. In comparison, Jang and Seo in (Jang dan Seo 2023) used machine vision based on fish cutting point prediction for target weight.

Linear Regression is the simplest method that models the relation between dependent and independent variables (Lokasree 2021). Korjo and Fofanah build machine learning models for price prediction in the coffee market using linear regression, XGB, and LSTM techniques (Korjo Hwase dan Fofanah 2021). Dynamic energy and power usage cost prediction using linear regression-machine learning analysis was built by (Basha *et al.* 2021). Machine learning and regression analysis can also be used to model the length of hospital stay in patients (Ricciardi *et al.* 2022), stock market prediction (Panwar *et al.* 2021), and crime data prediction (Aziz *et al.* 2022).

In the case of red tilapia and other Neotropical farmed finfish, however, there is a paucity of studies that parameterize regression equations for weight prediction based on the amount of food provided (Perazza *et al.* 2019). A weight prediction model for red tilapia can be created using a linear regression algorithm to resolve this knowledge gap. The model will use the fish's diet as the predictive variable and the fish's weight as the response variable. This study aimed to create a predictive model for red tilapia body weight based on the amount of feed given using linear regression.

2. Materials and Methods

The method used in this study is the Machine Learning Lifecycle (MLL) proposed by (Id 2021). MLL consists of four stages (Figure 1): Data Acquisition, Data Preprocessing, Training Model and Evaluation, and Model Deployment. Data processing to analysis is done using Python programming and Jupyter Notebook.

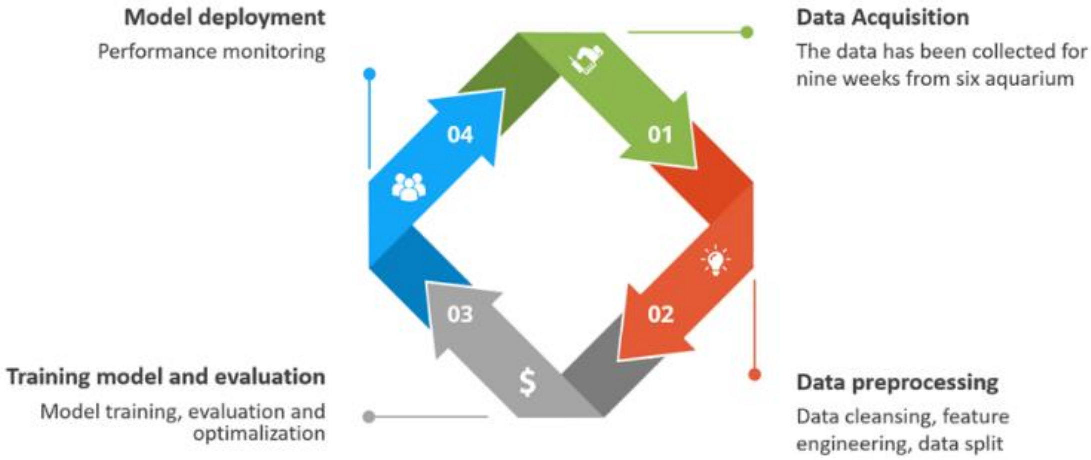

Figure 1. Stages in Machine Learning Lifecycle (MLL)

2.1. Data Acquisition

Data acquisition is the earliest stage in this process. Data were collected for nine weeks. The data comes from measuring red tilapia in 12 aquariums. Each aquarium was filled with 15 red tilapias. Red tilapias were fed twice a day for nine weeks.

Data for the study were obtained from the rearing of red tilapia for nine weeks. Red tilapias were placed in 12 aquariums measuring 60 x 40 x 40 cm. Each aquarium contains 15 red tilapias. Red tilapias were fed twice a day, namely every morning and evening. The feed given is fish pellets PF 1000 Prima Feed. The calculated data is the weight of the feed given and the weight of the fish in the aquarium every week. The total data obtained is 108 data. The measured data is named data_nila.csv.

2.2. Data Preparation

The data preparation stage consists of three main activities as follows:

2.2.1. Data Cleansing

This process detects and corrects or removes corrupted data from the dataset to improve data quality.

2.2.2. Feature Engineering

This process is the process of changing the dataset by extracting a column into other columns, or it can also be called the process of reducing columns. A good feature must have the following criteria: informative, data availability, and discriminant.

2.2.3. Data Split

This process divides the data into training, testing, and validation data. The training data size is usually more significant than the test data.

2.3. Model Training

Model training is the process of extracting patterns or knowledge from training data using specific algorithms. Various algorithms can be used depending on the problem to be solved. The output of this stage is a machine-learning model. This study used a linear regression algorithm. Model evaluation is a process for measuring the performance of models that have been produced in the previous process. In this linear regression algorithm, R-square is used to evaluate the model. The prediction model is good if the R-Square value is close to 1.

3. Results and Discussions

Data_nila.csv consists of two columns: the fish_food column and the fish_weight column. The fish_food column is the weight data of the feed given to red tilapia every week, and the fish_weight column is the total weight of red tilapia in each aquarium weekly. The data obtained consisted of three columns: the aquarium column per week, the feed weight data column per week, and the fish weight data column per week. Column names and data types are presented in Figure 2.

```
dataset.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 106 entries, 0 to 105
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   aquarium_week  106 non-null    object
 1   fish_food      106 non-null    float64
 2   fish_weight    106 non-null    float64
dtypes: float64(2), object(1)
memory usage: 2.6+ KB
```

Figure 2. Column names and data types of data_nila

Descriptive statistics are used to summarize data in an organized manner by describing the relationship between variables in a sample or population (Kaur *et al.* 2018).

Descriptive statistics for data_nila are given in Figure 3. From Figure 3, the average fish_food is 4.3 grams, and the standard deviation is 2.7. The average fish_weight is 89.8 grams, and the standard deviation is 48.15. The mode value of each data is searched for each column. The fish_food mode value is 2.47, and the fish_weight mode value is 78.6. Based on the size of the central tendency of the fish_food data, the mode value (2.47) < median value (3.5) < mean (4.3) so that the distribution curve will deviate to the right. From the fish_weight data, the mode value is (78.6) < median (79.9) < mean (89.8). The distribution curve for fish_weight also deviates to the right. This was stated in (Martias 2021).

	fish_food	fish_weight
count	106.000000	106.000000
mean	4.319811	89.796274
std	2.735671	48.147205
min	0.540000	7.550000
25%	2.507500	54.957500
50%	3.505000	79.900000
75%	5.770000	114.325000
max	11.670000	213.600000

Figure 3. Descriptive statistics of data_nila

The second stage is data preprocessing. This stage begins with data cleansing. Data cleansing is the process of detecting and repairing or removing damaged data from a dataset to improve data quality. Of the 108 data obtained, two were damaged (value 0). Handling is done by deleting the two damaged data. In addition, the data is also checked to determine whether it has outliers. Outliers are suspicious observations or measures because they are much smaller or larger than most of the observations (Cousineau dan Chartier 2010). Examination of outliers is carried out using boxplots and percentiles. Data that lies outside the whisker is outlier data. The boxplot for the feed column data is shown in Figure 4, and the boxplot for the fish column data is shown in Figure 5.

Figure 4. Boxplot for data in the fish_food column

Figure 5. Boxplot for data in the fish_weight column

From Figure 4 and Figure 5, there are outliers for both fish_weight and fish_food. Outliers are located at the top of the data. To check for outlier values, percentiles are used. The outlier value is determined from a value that is greater than the upper limit or smaller than the lower limit. In this case, only values are greater than the upper limit. The upper limit value is obtained from P95 (95th percentile). Using Python, the upper limit value for the fish_food column is 10.53, while the upper limit value for the fish_weight column is 185.35. The outlier data is presented in Figure 6. There are six outlier data. Thus, the current amount of data becomes 100 data.

	aquarium_week	fish_food	fish_weight
16	B8	10.68	213.6
17	B9	10.68	213.6
41	E8	11.12	185.4
42	E9	11.12	185.4
104	L8	11.67	194.4
105	L9	11.67	194.4

Figure 6. The outlier data

The next stage in data preprocessing is data split. Data split divides the data into training data and testing data. The size of the testing data in this study is 1/3 of the data. Python splits this data process using the Scikit-learn (Sklearn) module. The line of code used is presented in Figure 7.

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test =
train_test_split(X, y, test_size = 1/3, random_state = 0)
```

Figure 7. The line of code for data split process

The next stage is the training model. This process extracts patterns from the training data using a linear regression algorithm. This algorithm looks for the relationship between independent variables and dependent variables. In this case, fish_food is the independent variable, and fish_weight is the dependent variable. A linear regression algorithm is selected based on the data distribution in Figure 8.

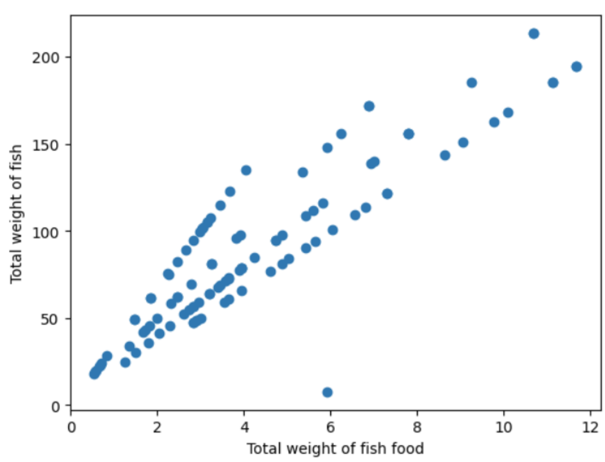

Figure 8. Distribution of data_nila

From Figure 8, it can be seen that the data is spread in a shape similar to a straight line. Such data is suitable for modeling with linear regression. The model training process is carried out in a Jupyter notebook using the program code presented in Figure 9. This process uses the LinearReggression ( ) function available in the sklearn module. Next, predictions are made on the test data (Figure 10). This prediction generates 34 data.

```
# Fitting Linear Regression (Training model)
from sklearn.linear_model import LinearRegression
regresi = LinearRegression()
regresi.fit(X_train, y_train)
```

```
▾ LinearRegression
LinearRegression()
```

Figure 9. The Model training process for linear regression

```
# Predict Data Test results
y_pred = regresi.predict(X_test)
y_pred.shape
```

```
(34, 1)
```

Figure 10. Predictions from the test data

Linear regression uses the mathematical equation in (1), which describes the line of best fit for the relationship between *y* (dependent variable) and *x* (independent variable) (Kumari dan Yadav 2018). There are two coefficients in the function *m* and *c*. Coefficient *m* is a slope for the line *y*, and coefficient *c* is the intercept value for the equation. The intercept is the value when the x variable is 0. In this study, the independent variable is fish_food (*x*), and the dependent variable is fish_weight (*y*).

$$y = mx + c \tag{1}$$

The slope and intercept coefficient values from the previous process can be determined using Python in Jupyter Notebook. The slope value is 15.51, and the intercept value is 22.17. Thus the linear regression function equation is obtained as in (2).

$$y = 15.51x + 22.17 \tag{2}$$

The next stage, model evaluation, is a process to measure the model's performance that has been produced in the previous process. In this linear regression algorithm, R-square is used to evaluate the model. R-square, or the coefficient of determination, is the portion of the total variation in the dependent variable that the variation in the independent variable can explain. When R-square is, a perfect linear relationship exists between x and y, i.e., 100% of the variation in y is explained by variation in x. When it is 0< R-square <1, there is a weaker linear relationship between x and y, i.e., some but not all of the variations in y are explained by variation in *x* (Kumari dan Yadav 2018). This study's built linear regression model produces an R-square value of 0.798. The R-square value is close to 1, so the model accuracy is good. With an R-square value of 0.798, it means that around 80% of the data is around the linear regression line.

Visualization plot of training and test data is presented in Figure 11 and Figure 12. The data is visualized using a scatter plot. The X-axis represents the fish_food value, while the Y-axis represents the fish_weight value. Dots on the graph represent Data_nila, while the slanted line on the graph is the regression line.

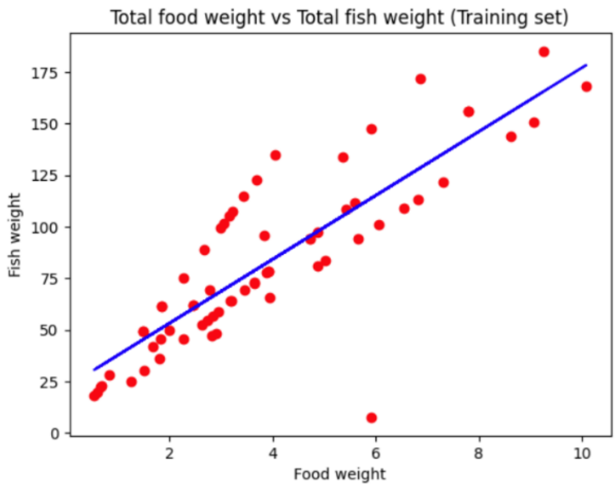

Figure 11. Visualization plot of training data

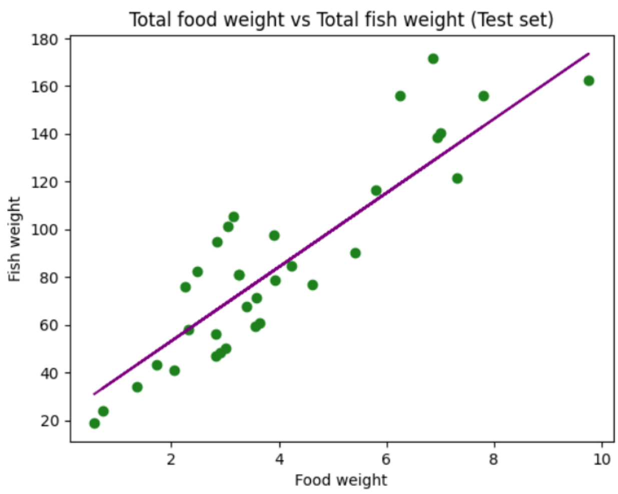

Figure 12. Visualization plot of test data

The final stage is the deployment model. At this stage, the model can be applied. This model can later be applied to red tilapia aquaculture activities. Model scalability must be maintained so that model performance remains good. Red tilapia cultivators can utilize this study's results to produce maximum red tilapia production. At a broader level, this research aligns with higher policy objectives related to public engagement and co-creation with stakeholders as specified in SDG 6 (clear water and sanitation) and SDG 14 (life below water).

4. Conclusions

Red tilapia is an essential fish in world aquaculture production. This fish has thick flesh and good taste. Red tilapia needs to be cultivated optimally. This study predicted the total weight of red tilapia fish based on the amount of feed given. The research data was obtained from cultivating red tilapia for nine weeks in 12 aquariums. The data is processed with a linear regression algorithm to produce a regression equation in (2). The linear regression algorithm was chosen because the distribution of the research data is close to a straight line. This regression model has an accuracy of 0.798 or nearly 80% based on R-square. This model can be applied to red tilapia cultivation activities. Model scalability must be maintained so that model performance remains good. Red tilapia cultivators can utilize this study's results to produce maximum red tilapia production. At a broader level, this research aligns with higher policy objectives related to public engagement and co-creation with stakeholders as specified in SDG 6 (clear water and sanitation) and SDG 14 (life below water).

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