Jurnal E-Komtek
Vol. 08, No. 02 (2024) pp. 551-565
https://jurnal.politeknik-kebumen.ac.id/index.php/E-KOMTEK
p-ISSN : 2580-3719 e-ISSN : 2622-3066

Analysis of Water Quality Parameters on the Survival Rate of Vannamei Shrimp using the Random Forest Method

Prih Diantono Abda'u[1], Ratih Hafsarah Maharrani[2], Zaenurrohman[3], Adrian Putra Ramadhan[4]

[1-4]Informatics Engineering, Cilacap State Polytechnic, Indonesia, 53212

abdau@pnc.ac.id

https://doi.org/10.37339/e-komtek.v8i2.2215

Published by Polytechnic Piksi Ganesha Indonesia

Article Info
Submitted:
16-12-2024
Revised:
29-12-2024
Accepted:
29-12-2024
Online first :
31-12-2024

Abstract

This study developed a predictive model based on Random Forest algorithm to predict survival rate of Vannamei shrimp using five water quality parameters: dissolved oxygen (DO), temperature, pH, salinity, and Total Dissolved Solids (TDS). The model was trained on this data and evaluated using Mean Squared Error (MSE) and R^2 Score, with an MSE of 0.71 and R^2 Score of 1.00. Endpoint testing was conducted using Postman to verify the model response, with output parameters including anomaly_detected, recommendation, and survival rate. The model successfully detected anomalous conditions and provided recommendations according to the detected water quality parameters. Test results showed that DO and salinity had the greatest influence on survival rate, while pH, TDS, and temperature made moderate contributions.

Keywords: *Survival rate*, Random Forest, water quality, Vannamei shrimp, IoT, Prediction

Abstract

Penelitian ini mengembangkan model prediktif berbasis algoritma Random Forest untuk memprediksi *survival rate* udang Vannamei menggunakan lima parameter kualitas air: oksigen terlarut (DO), suhu, pH, salinitas, dan Total Dissolved Solids (TDS). Model dilatih dengan data tersebut dan dievaluasi menggunakan Mean Squared Error (MSE) dan R^2 Score, dengan hasil MSE sebesar 0.71 dan R^2 Score sebesar 1.00. Pengujian endpoint dilakukan menggunakan Postman untuk memverifikasi respon model, dengan parameter output meliputi *anomaly_detected*, *recommendation*, dan *survival rate*. Model berhasil mendeteksi kondisi anomali dan memberikan rekomendasi yang sesuai dengan parameter kualitas air yang terdeteksi. Hasil pengujian menunjukkan bahwa DO dan salinitas memberikan pengaruh terbesar terhadap tingkat kelangsungan hidup, sementara pH, TDS, dan suhu memberikan kontribusi moderat.

Kata-kata kunci: *Survival rate*, Random Forest, kualitas air, udang Vannamei, IoT, prediksi.

1. Introduction

Vannamei shrimp cultivation (*Litopenaeus vannamei*) has become an important sector in the global aquaculture industry due to high market demand [1]. However, the main challenge faced by farmers is maintaining pond water quality, which plays an important role in determining the survival and productivity of shrimp [2]. Parameters such as dissolved oxygen (DO), temperature, pH, salinity, and Total Dissolved Solids (TDS) must be maintained within a certain range so that the pond ecosystem remains stable [3]. The problem that often arises is the inability to manage these parameters simultaneously, which causes physiological stress in shrimp and even mass death.

Various studies have been carried out to determine tolerance limits for water quality parameters. For example, the ideal pH is in the range of 7.5 to 8.5, while DO needs to be maintained above 5 ppm so that shrimp's oxygen needs are met. Other efforts such as the use of Internet of Things (IoT) technology have made it possible to monitor water quality in real-time [4]. However, most of these approaches only involve monitoring, not data-based predictions, so preventive measures are often taken too late.

Although simple data modeling has been used in previous research, multivariate predictive models that consider interactions between parameters are still rare. Previous studies generally treated water quality parameters separately, so the potential for optimizing predictions has not been fully explored [5]. This is the opportunity for this research to fill the gap by utilizing the Random Forest algorithm, which can process complex data with a high level of accuracy.

This research offers a new approach by developing a Random Forest-based predictive model that considers several water quality parameters simultaneously. In addition, the concept of weighting water quality parameters was introduced to measure how much influence each parameter has on the shrimp survival rate. Thus, it is hoped that this model can provide more accurate water quality recommendations and support real-time data-based pond management.

The aim of this research is to analyze the influence of water quality parameters on the survival rate of Vannamei shrimp, develop a Random Forest-based predictive model, and provide more accurate recommendations for optimal pond management. With this approach, research is expected to increase the effectiveness of Vannamei shrimp cultivation and minimize potential losses due to decreased water quality.

2. Method

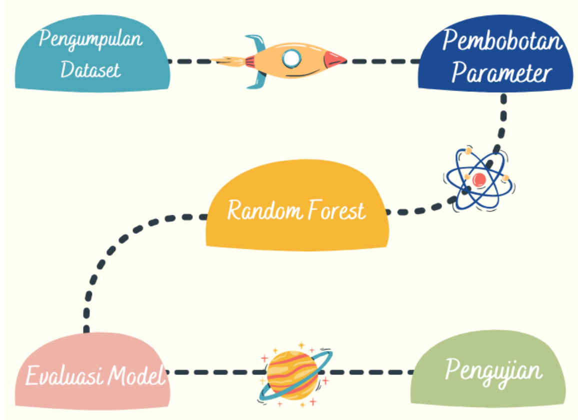

Figure 1. Research Stages

Stages in this research:

1. Dataset Collection

   Water quality data such as DO, pH, temperature, salinity and TDS are collected in real-time using sensors and stored in a data server for further processing.

2. Parameter Weighting

   Each water quality parameter is weighted according to the level of influence on the survival rate. Weighting is carried out based on literature analysis and collected data.

3. Establishing a Random Forest Model

   The Random Forest model is designed to process multivariate data, build decision trees, and produce predictions of Vannamei shrimp survival rates.

4. Model Evaluation

   The model is evaluated by comparing predicted results and actual data using Mean Squared Error (MSE) and R2-score.

5. Endpoint Testing

   After evaluation, the model is tested on new data to ensure the accuracy and validity of the prediction system. The final results are presented in the form of a complete report.

2.1. Data Collection

The water quality data used in this research includes five main parameters, namely: dissolved oxygen (DO), temperature, pH, salinity, and Total Dissolved Solids (TDS). Data collection was carried out by taking real-time samples from one Vannamei shrimp cultivation pond. Data is monitored using a sensor system integrated with an Internet of Things (IoT) platform, which records data per second during the cultivation period for up to 10,000 data samples for each parameter. The target variable used in this model is the survival rate of Vannamei shrimp, which is calculated based on the percentage of shrimp survival at each specified time point.

This real-time data collection approach ensures high accuracy and representation of actual environmental conditions in the pond, thus enabling predictive analysis that is more comprehensive and relevant to pond conditions in the field [6]. The collected data is then processed using the Random Forest algorithm, which utilizes all multivariate data to predict survival rates by considering interactions between water quality parameters.

The following is an example of a sample of data generated from a sensor device as shown in **Table 1.**

Table 1. Sample data from sensors

DO	Temperature	pH	Salinity	TDS
2.996321	29.03895	2.543292	5.496889	124
7.605714	26.34858	4.128089	3.342807	78
5.855952	17.55185	0.892939	4.827872	241
4.789268	24.66063	4.021533	16.57213	1065
1.248149	18.25483	1.827732	30.95869	151
1.247956	32.89657	2.498358	10.82273	70

The data displayed in the table above is the output of the IoT sensor system (*Internet of Things*) which has been specifically designed to monitor water quality in Vannamei shrimp ponds. These sensors collect water quality parameters in real-time, such as dissolved oxygen (DO), temperature, pH, salinity, and TDS (Total Dissolved Solids).

2.2. Parameter Weighting

In this research, the weighting for each water quality parameter is based on its impact on the survival rate of Vannamei shrimp. Based on previous research, water quality parameters are weighted as follows:

a. Dissolved Oxygen (DO): 40% – DO is the main factor affecting the survival of Vannamei shrimp, because lack of oxygen can cause stress and death in shrimp [7]. Even low DO below 3 mg/L can trigger death in a short time [8].

b. Salinity: 30% – Appropriate salinity is important for shrimp metabolism, and drastic changes in salinity can affect shrimp survival [9].

c. pH: 15% – Water pH that is too high or low can affect the growth and survival of shrimp [10].

d. TDS: 10% – TDS affects overall water quality and has little effect on shrimp survival[11].

e. Temperature: 5% – Temperature affects shrimp metabolism, but the effect is smaller than other parameters [12].

To ensure that each water quality parameter has the same scale in the predictive model, a Min-Max normalization process is carried out on the parameter values. This normalization converts each parameter value into a range between 0 and 1, so that parameters with different units can be compared directly in data analysis and weighting.

Here is the Python code to perform Min-Max normalization on each water quality parameter:

```
df['DO_normalized'] = (df['DO'] - df['DO'].min()) / (df['DO'].max() - df['DO'].min())
df['normalized_salinity'] = (df['Salinity'] - df['Salinity'].min()) / (df['Salinity'].max()
- df['Salinity'].min())
df['pH_normalized'] = (df['pH'] - df['pH'].min()) / (df['pH'].max() - df['pH'].min())
df['TDS_normalized'] = (df['TDS'] - df['TDS'].min()) / (df['TDS'].max() - df['TDS'].min())
df['Temperature_normalized'] = (df['Temperature'] - df['Temperature'].min()) /
(df['Temperature'].max() - df['Temperature'].min())
```

2.3. Establish a Random Forest training model

After the data was collected, the data was separated into two parts, namely training data (80%) and testing data (20%). Random Forest is used as a prediction model to calculate survival rates based on water quality parameters. Following is the Python code used to process the data and apply the Random Forest model:

```
# Separate input features (X) and target variable (y)
X = data[['DO', 'Salinity', 'pH', 'TDS', 'Temperature']]  # Use required input fields
and = data['survival_rate']

# Split data into training and testing sets (80% training, 20% testing)
X_train, X_test, y_train, y_test = train_test_split(X, and, test_size=0.2, random_state=42)

# Train the model
model = RandomForestRegressor()
model.fit(X_train, y_train)

# Predict on the test set
y_pred = model.predict(X_test)
```

After building a Random Forest prediction model to predict the survival rate of Vannamei shrimp based on water quality parameters, the next step is to adjust the survival rate value by evaluating the actual parameter conditions against optimal conditions. The code to adjust the survival rate based on the distance from optimal conditions can be done as follows:

a. Defining optimal values for each parameter:

```python
# Definition of optimal conditions for each water quality parameter
optimal_conditions = {
    'DO': (5, float('inf')),  # DO > 5 ppm
    'Salinity': (15, 25),     # Salinity 15-25 ppt
    'pH': (7.8, 8.5),          # pH 7.8-8.5
    'TDS': (300, 600),         # TDS 300-600 ppm
    'Temperature': (27, 30)           # Temperature 27-30°C
}
```

b. Parameter weights are based on their effect on survival rate

```python
weights = {
    'DO': 0.40,       # Dissolved Oxygen
    'Salinity': 0.30,  # Salinity
    'pH': 0.15,       # pH
    'TDS': 0.10,      # Total Dissolved Solids
    'Temperature': 0.05     # Temperature
}
```

c. Data from normalization results, survival rate, adjusted survival rate

Table 2 presents the results of normalization of water quality parameters which include dissolved oxygen (DO), salinity, pH, TDS, and temperature. The normalization process is carried out to align the scale of each parameter to the range [0, 1], so that all variables have equal weight in subsequent analysis.

After normalization, the initial survival rate value is also displayed as a prediction result using the Random Forest model. This value is then adjusted (adjusted survival rate) based on the distance of each parameter from optimal conditions. Presentation of these data allows a more detailed evaluation of the influence of water quality parameters on survival rates (*survival rate*) Vannamei shrimp.

The table reflects significant variations in the adjusted survival rate values, where parameter conditions that are closer to optimal show a decrease in distance and result in a higher survival rate, while parameters that are far from optimal conditions cause a drastic decrease in survival rate.

Table 2. Normalized data, survival rate and adjusted survival rate

DO_normalized	Normalized_salinity	pH_normalized	TDS_normalized	Temperature_normalized	survival_rate	adjusted_survival_rate
0.37454	0.157053	0.282592	0.10342	0.580783	27.87017	5.829257
0.950722	0.095507	0.458685	0.065054	0.526975	51.05977	24.77926
0.731998	0.137938	0.099215	0.201001	0.351038	38.6715	28.2114
0.598661	0.473491	0.446845	0.88824	0.493215	56.20232	8.934288
0.156015	0.884539	0.203084	0.125938	0.365097	38.90789	19.38644

2.4. Model Evaluation

After the Random Forest model was trained and tested, an evaluation step was carried out to measure the model's performance in predicting the survival rate of Vannamei shrimp. The model evaluation was carried out using two main metrics, viz *Mean Squared Error (MSE)* And *R^2 Score*.

The following code is used to calculate MSE and R^2 values:

```
# Import evaluation library
from sklearn.metrics import mean_squared_error, r2_score

# Compute model evaluation
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Print evaluation results
print(f"Mean Squared Error: {mse:.2f}")
print(f"R^2 Score: {r2:.2f}")
```

- *Mean Squared Error (MSE)* is a metric used to calculate the squared average of the differences between actual values and predicted values. MSE gives an idea of how far the model predictions are from the actual values, with smaller values indicating better model performance. Because it uses the square of the difference, MSE is very sensitive to large errors, making it suitable for identifying significant differences between predicted and actual values [13].
- R^2 *Score* or Coefficient of Determination measures how well the model can explain variations in target data. The R^2 value ranges between 0 and 1, where a value close to 1 indicates the model can explain data variations well, while a value close to 0 indicates poor model performance, even equivalent to the average data value [14].

  The combination of MSE and R^2 provides a comprehensive evaluation of model accuracy: MSE focuses on the prediction error rate, while R^2 assesses the model's ability to explain the overall variation in the target data.

Based on the results of the model evaluation using *Mean Squared Error (MSE)* And *R^2 Score*, the following values are obtained:

a. *Mean Squared Error (MSE)*: 0.71

   This low MSE value indicates that the difference between model predictions and actual values is very small. This means that the model has very good accuracy in predicting the survival rate of Vannamei shrimp based on water quality parameters.

b. *R^2 Score*: 1.00

An R^2 value of 1.00 indicates that the model can explain 100% of the variation in the target data. In other words, the model has perfect performance and all predictions closely match the actual values.

2.5. Endpoint Testing

Endpoint testing aims to ensure that the system that has been trained can respond to requests correctly and provide appropriate output. In this stage, Postman is used as a tool to simulate requests and responses from the model that has been created.*deploy*.

Testing Process:

1. Request

   Postman sends an HTTP request (usually POST or GET) to the API endpoint that hosts the training model. The input request contains water quality parameters such as:
   - Dissolved Oxygen (DO)
   - Salinity
   - pH
   - Total Dissolved Solids (TDS)
   - Temperature

This data is sent in JSON format or as required by the API.

2. Response

   Output from the endpoint is returned in the form of a JSON response containing the following parameters:
   - anomaly_detected: Indicator of whether there are parameter values that do not match optimal conditions.
   - recommendation: Suggestions for improvement based on non-optimal water quality parameters.
   - survival_rate: Predicted value of Vannamei shrimp survival rate based on the given parameters.

3. Testing and Verification
   - Anomaly Detected: Evaluates whether the system successfully detected abnormal conditions based on input parameters.
   - Recommendation: Ensure that the recommendations given are in accordance with the abnormal conditions detected.
   - Survival Rate: Verifies that the returned value is consistent with the Random

Forest model predictions.

Contoh Response JSON

```json
{
  "anomaly_detected": true,
  "recommendation": "Increase dissolved oxygen levels and stabilize pH.",
  "survival_rate": 85.5
}
```

With this test, it can be ensured that the system works well and provides the expected output according to the input water quality parameters.

Following are some of the results of Endpoint testing that has been carried out:

a. Test Case 1: Optimal Parameter Survival Rate: 90

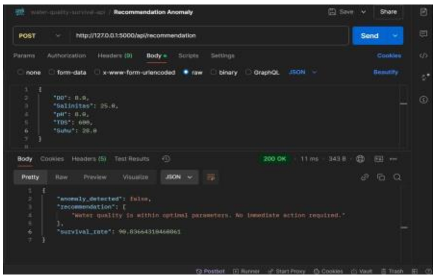

Figure 2. Test Case 1: Optimal Parameter SR: 90

b. Test Case 2: Suhu Anomaly Survival Rate: 77

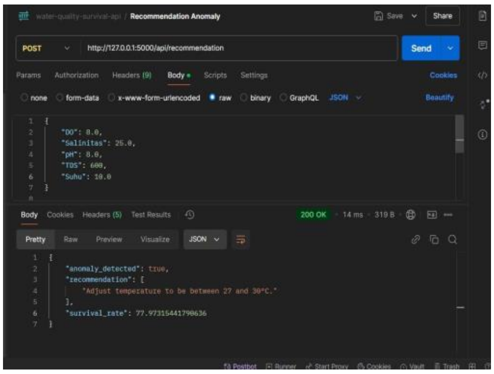

Figure 3. Test Case 2: Suhu Anomaly Survival Rate: 77

c. Test Case 3: TDS Anomaly Survival Rate: 73

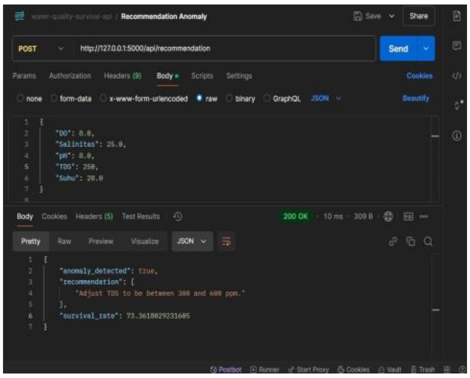

Figure 4. Test Case 3: TDS Anomaly Survival Rate: 73

d. Test Case 4: pH Anomaly Survival Rate: 70

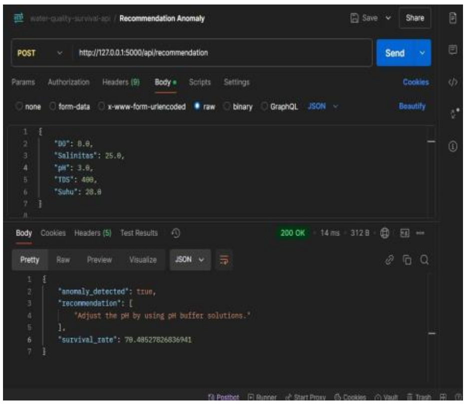

Figure 5. Test Case 4: pH Anomaly Survival Rate: 70

e. Test Case 5: Salinitas Anomaly Survival Rate: 66

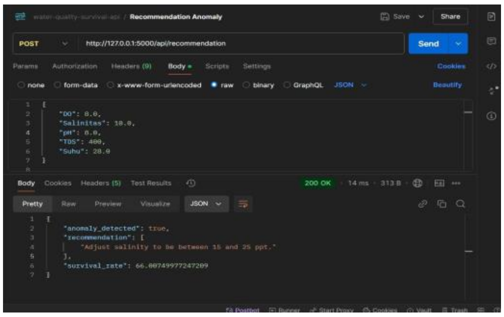

Figure 6. Test Case 5: Salinity Anomaly Survival Rate: 66

f. Test Case 6: DO Anomaly Survival Rate: 51

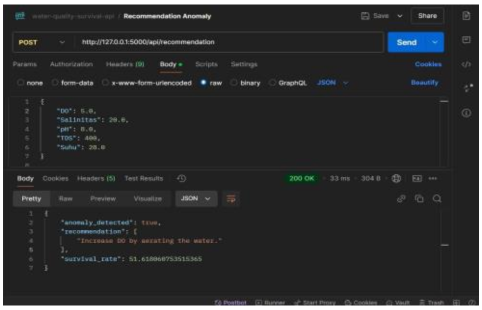

Figure 7. Test Case 6: DO Anomaly Survival Rate: 51

g. Test Case 7: Combine Anomaly Survival Rate: 25

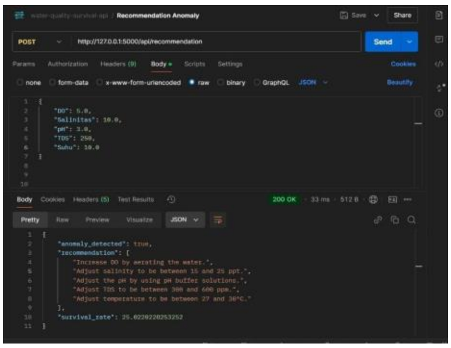

Figure 8. Test Case 7: Combine Anomaly Survival Rate: 25

h. Test Case 8: Anomaly Extreme Survival Rate: 1.84

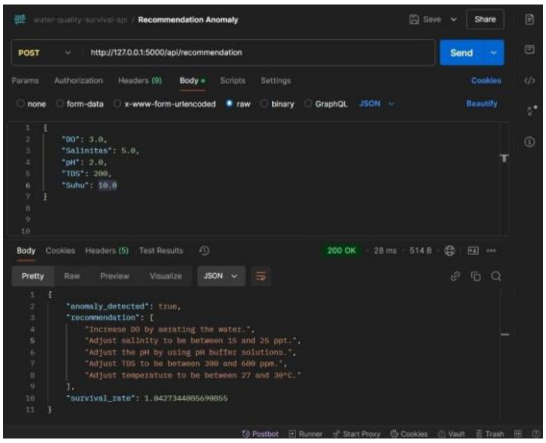

Figure 9. Test Case 8: Anomaly Extreme Survival Rate: 1.84

3. Results and Discussion

3.1. Research result

This research succeeded in developing a predictive model based on the Random Forest algorithm to predict *survival rate* Vannamei shrimp uses five water quality parameters: dissolved oxygen (DO), temperature, pH, salinity, and Total Dissolved Solids (TDS). Data was collected in real-time using IoT sensors, resulting in 10,000 samples being analyzed.

a. Model Evaluation

1) Mean Squared Error (MSE): 0.71 indicates a very low prediction error rate.
2) R^2 Score: 1.00 indicates that the model can explain 100% of the variation in the target data.

b. Endpoint Testing

1) Optimal Parameters: API response shows a survival rate value of up to 90%.
2) Anomaly Conditions: Testing various anomaly scenarios produces *survival rate* ranging from 77% to as low as 1.84%.

c. Results Visualization

To visualize the relationship between water quality parameters and survival rate, two types of visualization are carried out as follows:

1) Distribution graph of each parameter and survival rate

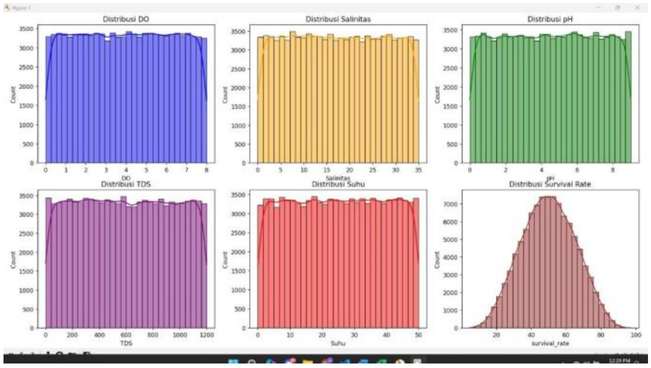

Figure 10. Distribution graph of each parameter and survival rate

This graph shows the distribution of data for each water quality parameter such as dissolved oxygen (DO), salinity, pH, TDS, and temperature on the survival rate. Through this graph, you can see how the value of each parameter affects the survival rate. The data distribution shows that salinity and DO have a significant impact on survival rates, especially when they approach the determined optimal values. In contrast, pH, TDS, and temperature have a more moderate contribution to changes in survival rate values.

2) Grafik Feature Importances

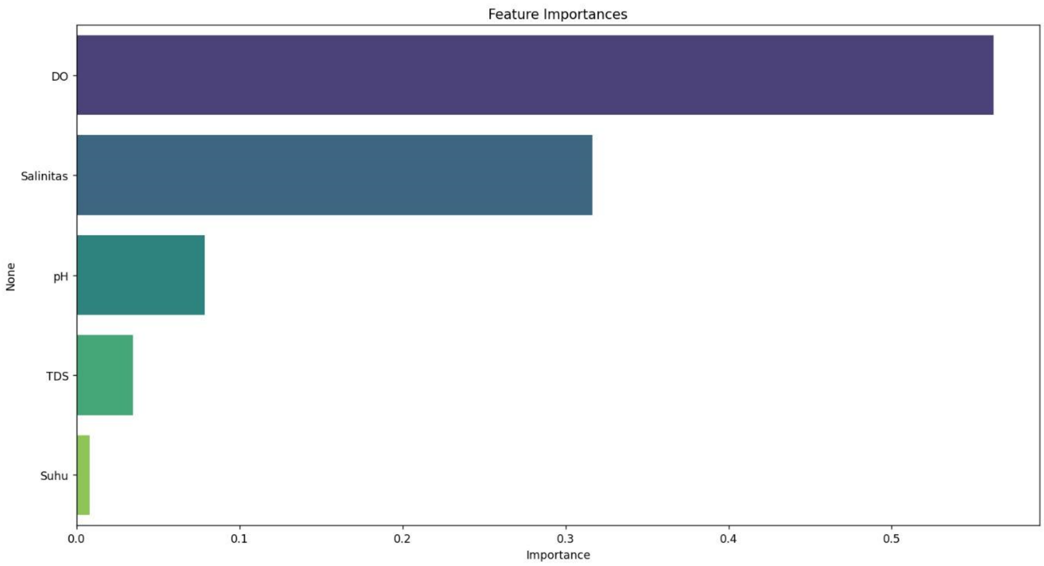

Figure 11. Grafik Feature Importances

The feature importances graph is produced from the Random Forest model and shows the weight of the contribution of each water quality parameter to the survival rate prediction. In accordance with the weighting given previously, DO has the highest contribution with a weight of 40%, followed by salinity with a weight of 30%. The parameters TDS, temperature, and pH have a smaller influence, corresponding to weights of 10%, 5%, and 15% respectively.

This graph confirms that the model has prioritized the most influential parameters according to the specified optimal conditions.

3.2. Discussion

The results show that DO, salinity, and pH have the most significant influence on *survival rate*. This data supports previous research by Tan & Wang (2019), which emphasized the importance of dissolved oxygen for shrimp respiration. This result is also in line with research by Huang et al. (2021), which highlights the role of salinity in osmoregulation processes.

Endpoint testing ensures that the system is able to detect anomalies and provide relevant recommendations. For example, under combined anomaly conditions (all parameters are far from optimal conditions), the system predicts *survival rate* lowest (1.84%), indicating that the model works as expected.

However, it should be noted that this model is limited in the parameters considered. Additional parameters such as ammonia or nitrite content may improve prediction accuracy in the future.

4. Conclusion

This research succeeded in developing a predictive model based on the Random Forest algorithm to predict *survival rate* Vannamei shrimp based on five water quality parameters. The evaluation results show very good model performance with an MSE of 0.71 and an R^2 Score of 1.00. This model is not only able to predict *survival rate* with high accuracy but also detects anomalies in water quality data and provides appropriate recommendations.

The main contribution of this research is the application of water quality parameter weighting in predictive models, which allows more accurate and realistic modeling. This research supports data-based pond management and provides a strong foundation for the development of more sophisticated IoT-based water quality monitoring systems.

For future research, it is recommended to expand the water quality parameters included in the model as well as test the model in a wider and more varied pond environment to increase the generalizability of predictions.

5. *Acknowledgement*

The author would like to thank all parties who have supported the implementation of this research. Specifically, this research was funded by the 2024 Cilacap State Polytechnic DIPA Fund with SP DIPA Number -023.18.1.690524/2023 dated 24 November 2023 and Contract

Number 125/PL43.P.01/HK.08/2024.

The author also expresses his appreciation to the reviewers for their constructive input which helped improve the results of this research as well as the entire team involved in data collection and project implementation. The support and cooperation provided were very valuable in realizing this research.

Reference

[1] R. E. D. P. N. Hapsari, "THE IMPORTANT ROLE OF INTERNATIONAL TRADE IN THE EXPORT OF VANAME SHRIMP IN EAST JAVA," *J. Ilm. MEA (Management, Econ. and Accounting)*, vol. 7, no. 3, pp. 1235–1248, 2023.

[2] N. Juni, J. K. No, R. T. Rw, K. B. Tengah, and K. Bogor, "Cultivation Management Strategies in the Shrimp Industry : Review of Shrimp Cultivation Productivity," vol. 2, no. 2, 2024.

[3] L. maknun; M. Sumsanto, "STUDY OF WATER QUALITY MANAGEMENT TECHNIQUES IN THE MAINTENANCE OF VANNAME SHRIMP (Litopenaeus vannamei) BROTHERS AT PT. SURI TANI HEAD OF THE SINGARAJA Hatchery Unit, Bali," *J. Fisheries Science. and Marine.*, vol. 5, no. 3, pp. 507–516, 2023.

[4] A. Fahrurozi, P. Informatika, T. Industri, U. Gunadarma, and J. Barat, "IMPLEMENTATION OF THE INTERNET OF THINGS (IOT) FOR THE SHRIMP FARMING VANAME WATER QUALITY MONITORING SYSTEM," *J. Ilm. Technol. and Engineering Vol.*, vol. 29, no. 1, pp. 71–85, 2024.

[5] R. Arridha, "Design and implementation of IoT-big data analytics in a smart environment monitoring system," 2017.

[6] R. P. Tulodo, N. T. Ujito, E. Budiraharjo, and Y. Hapsari, "Development of an Internet of Things (IoT) Based Rain Detection System with Wokwi Simulation," *Engineering*, vol. 14, no. 2, pp. 93–99, 2023.

[7] M. Marzuki *et al.*, "POST LIVING RATE OF VANAME SHRIMP LARVA (Litopenaeus vannamei) MAINTENED AT LOW SALINITY USING METHOD OF STAGED ACCLIMATIZATION," *J. Fishery.*, vol. 11, no. 1, pp. 129–140, 2021.

[8] Y. Sugianti, D. A. N. Lismining, and P. Astuti, "Response of Dissolved Oxygen to Pollution and Its Influence on the Existence of Fish Resources in the Citarum River. Dissolved Oxygen Response Against Pollution and The Influence of Fish Resources Existence in the Citarum River," *J. Technol. Environment.*, vol. 19, no. 2, pp. 203–212, 2018.

[9] A. N. Se, P. Santoso, and F. C. Liufeto, "The Effect of Differences in Temperature and Salinity on Post-Larva Growth of Vaname Shrimp (Litopenaeus vannamei)," *J. VOCATIONAL SCIENCES IN FISHERIES.*, vol. 3, no. April, pp. 84–89, 2023.

[10] P. E. Jelinda, Y. Jasmanidar, and A. Tjendanawangi, "The Effect of Different pH on the Growth and Survival of Vanname Shrimp (Litopenaeus vannamei)," *J. VOCATIONAL SCIENCES IN FISHERIES.*, vol. 4, no. April, pp. 209–214, 2024.

[11] E. Gusman and D. Wiharyanto, "Study of the Relationship between Water Quality Parameters and Bacterial Abundance in Traditional Tiger Prawn (Penaeus monodon) Ponds on Tibi Island, North Kalimantan. Study of Water Quality Parameters and Their Association with Bacterial Abundance in," *Samakia J. Fisheries Science.*, vol. 15, no. 2, pp.

198–206, 2024.

[12] R. S. Utami, A. Mufti, and M. Rizki, "Shrimp Pond Water Quality Control and Monitoring System Based on Water Salinity, Temperature, and pH," *KITEKTRO J. Computer, Inf. Technol. and Electrical*, vol. 8, no. 1, pp. 43–48, 2023.

[13] R. Meenal, P. A. Michael, D. Pamela, and E. Rajasekaran, "Weather prediction using random forest machine learning model," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 22, no. 2, pp. 1208–1215, 2021, doi: 10.11591/ijeecs.v22.i2.pp1208-1215.

[14] I. Hakim, T. Afriliansyah, and U. M. Makassar, "Implementation of the Linear Regression Computational Algorithm for Optimizing Agricultural Yield Predictions, Bumi Persada University, Lhokseumawe, Aceh, Indonesia Abstract," *KNIGHT J. Application of Syst. Inf. (Management Computer)*, vol. 5, no. 3, pp. 1423–1434, 2024.