Application of Support Vector Machine (SVM) for Water Quality Analysis in Tilapia Cultivation

Tazkiah Kamilah Aulia[1]*, Willdan Aprizal Arifin[2], Mad Rudi[3]
Universitas Pendidikan Indonesia, Bandung, Indonesia
Email: tazkiahkaulia@upi.edu[1], willdanarifin@upi.edu[2], madrudi@upi.edu[3]

***Keywords**:*
Classification, Machine Learning, Pond, Radial Basis Function, Support Vector Machine

Abstract
Water quality is a key factor that determines the success and desirability of tilapia cultivation. Inappropriate water parameters, such as temperature or chemical content, can cause physiological stress, reduce growth rates, and even cause fish death. This condition makes water quality monitoring a very crucial and urgent aspect in cultivation practices. This study aims to model the classification of water quality feasibility using the Support Vector Machine (SVM) algorithm combined with the Radial Basis Function (RBF) kernel. The RBF kernel is a mathematical function that allows SVM to map non-linearly separated data into a higher-dimensional space, so that classification patterns become more visible. Numerical data were obtained from eight water quality parameters: temperature, pH, total dissolved solids (TDS), dissolved oxygen, nitrite, nitrate, phosphate, and ammonia. Furthermore, the data was classified into two categories: feasible and unfeasible, based on predetermined biological thresholds. The model was built using a supervised learning approach and evaluation through accuracy matrix and confusion matrix. The test results showed that the SVM model with the RBF kernel produced an accuracy of 82%, with precision and recall values reaching 100% in the "unfeasible" category. This shows that the model is very good at identifying risky water conditions, making it a potential solution for monitoring cultivation water.

INTRODUCTION

In general, fish are aquatic organisms that show high diversity of species, forms, and ecological roles [1]. Tilapia (Oreochromis niloticus) is one of the freshwater fishery commodities that is included in the category of superior cultivated fish in various countries, including Indonesia. Tilapia is introduced to developing countries and cultivated at subsistence levels to meet local protein needs [2]. Based on the data listed in BPS (2021), the export value of tilapia over the past 3 years, 2018-2020 experienced an increase of 17.13%. In 2020, tilapia exports reached a volume of 12.29 tons per year, generating an export value of approximately USD 78.44 million [3].

Decreased water quality can cause a decrease in the immunity of organisms, making them susceptible to disease attacks [4]. Aquaculture must be developed in accordance with the times. Freshwater fisheries have quite promising prospects, this is because freshwater fisheries can produce various forms such as fresh fish and processed fish. In carrying out the fish farming process, it is highly expected that the fish can grow well [5]. As a maritime country with a wide coastline and abundant water resources, Indonesia has a great opportunity to develop the fisheries sector, including freshwater cultivation. The characteristics of tilapia fish which are easy to cultivate, adaptive to the environment, and can be maintained in high densities make it very potential to be developed [6].

However to support the productivity of tilapia cultivation, integrated and technology-based management is needed. One of the fundamental aspects in cultivation is the quality of pond water. Water quality is a major determinant of growth. Parameters such as water temperature, acidity, dissolved oxygen levels, ammonia concentrations, nitrites, nitrates, phosphates, and total dissolved solids have a direct impact on the physiological and metabolic conditions of fish. Decreased water quality can cause acute and chronic stress in fish, leading to decreased growth, increased mortality, and decreased production efficiency [7].

Practice in the field, water quality management is often still carried out conventionally and unsystematically. This is exacerbated by human activities that also pollute the cultivation environment. Based on research conducted by Rina et al. (2025), it shows that tilapia that have good water quality do not experience death and the movement of the operculum runs normally. This study can be used as an illustration that water pollution will damage aquatic biota and cause death [8].

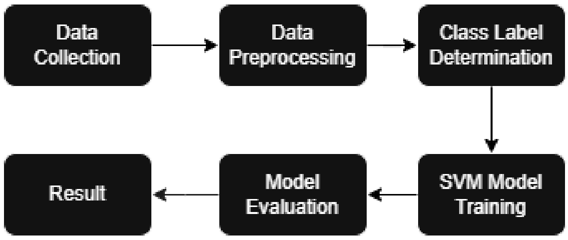
Another study conducted by Khoirunisa (2022) in Menggoro Village, Temanggung Regency, Central Java, evaluated the suitability of pond water quality for tilapia cultivation with research results showing that poor water quality, especially that polluted by household waste, can cause tilapia stress which is characterized by slow growth and can cause death [7].

The term "information systems" the broad and dynamic interactions between between people, algorithms, data, and technology [9]. In the era of Industry 4.0, advancements in information technology, aquaculture analytics, and the Internet of Things have created new opportunities for managing the aquaculture sector, enabling improvements in quality and efficiency [10]. One of the relevant approaches to be applied in water quality analysis is Support Vector Machine (SVM). SVM is a machine learning method that is included in the supervised learning group, and is widely used for classification purposes. SVM can work well on relatively small to medium datasets, which are common in aquaculture water quality research, where the amount of data is limited.

Several studies have also shown that SVM is able to classify water quality conditions with high accuracy, such as in the study of Tingting Li et al. (2022) which stated that SVM can predict water quality parameters such as dissolved oxygen, pH, ammonia, nitrate, and nitrite with a correlation coefficient of up to 0.99, outperforming other methods such as Back Propagation Neural Network (BPNN) and Radial Basis Function Neural Network (RBFNN) [11].

In addition, research conducted by Salma et al. (2023) is also an important reference in the use of the SVM method for water quality classification. In their research, the SVM method with the One-Versus-One (OVO) approach was used to test the classification performance of water quality data. The results showed that SVM with the RBF kernel and optimal parameters $C = 1000$ and $\gamma = 4$ was able to achieve an accuracy of 100%. Meanwhile, the polynomial kernel had high accuracy and the sigmoid kernel was only 60%. These results indicate that the selection of the right kernel and parameters greatly affects the performance of the SVM model in water quality classification [12]. The difference in this study lies in the water samples used, the study conducted by Salma et al. (2023) used data from Perumda Tirta Pase for the suitability of drinking water, while this study used tilapia fish farming water quality data from Dinas Perikanan dan Peternakan Purwakarta. In addition, Salma et al. (2023) split the data by 80:20 for training data:test data, but in this study they split the data by 60:40 for training data:test data.

Based on the description above, it can be concluded that the SVM-based approach has great potential to be applied in monitoring the water quality of tilapia fish farming. Therefore, this study aims to develop a classification information model for tilapia fish farming pond water quality based on the SVM algorithm that is able to process water parameter data and produce informative classifications. The advantage of SVM is its ability to handle irregular and complex data efficiently [13]. This is used to support the decision-making process in managing fish farming efficiently and based on data. The results of this study are expected to contribute to the development of information systems in the cultivation sector, as well as encourage the digitalization of sustainable tilapia fish farming management.



METHODS

This study uses a quantitative approach that focuses on the analysis of numerical data in classifying the water quality of tilapia fish farming ponds using the SVM algorithm. The data used in this study is data obtained from Dinas Perikanan dan Peternakan Purwakarta which includes a number of water quality parameters such as water temperature, acidity, dissolved oxygen, total dissolved solids, nitrite, nitrate, phosphate, and ammonia. All of these data are analyzed computationally using the SVM algorithm with the RBF kernel to identify patterns and relationships between parameters that contribute to the classification of water quality eligibility.

The selection of the RBF kernel in the SVM algorithm is based on its ability to handle non-linear data, which is commonly found in aquaculture environmental systems. The model training process is carried out through a cross-validation technique (5-Fold Cross Validation) to measure the consistency and generalization ability of the model. In addition, an analysis of the confusion matrix is conducted to evaluate the classification performance, including accuracy, precision, recall, and f1-score. This approach allows the identification of water quality parameters that have the most influence on the suitability status of pond water, so that the results of the study can be the basis for managerial decision making in tilapia cultivation activities.

The complete flow of research implementation is presented in Figure 1 in the form of a flowchart to provide a clearer picture of the process carried out from start to finish.

Figure 1. Research Flow

A. Data Collection

In conducting data collection, this study used several main tools needed to obtain water quality parameter data. The tools used include test reagents with certain brands and specifications, as well as measuring instruments such as pH meters, DO meters, and TDS meters to obtain accurate water quality parameter data. The following is a complete list of tools and brands used presented in Table 1.

Table 1. Data Collection Research Tools

Tools	**Brand**
pH meter	pH TDS EC Temp (4 in 1) Meter EZ9908
TDS meter	HM Digital TDS-3
DO meter	JPB-70A Pen-Shapped Dissolved Oxygen Tester
Ammonia test kit	SERA Ammonium/Ammonia-Test (NH_4/NH_3) 3x15 mL
Nitrate test kit	SERA Nitrate Test (NO_3) 3x15 ml
Nitrite test kit	SERA Nitrite Test (NO_2) 2x15 ml
Phosphate test kit	SERA Phosphate Test (PO_4) 2x15 ml

All tools listed in Table 1 were used in accordance with the procedures during the water sampling process. The use of various tools aims to obtain the required water quality parameter data, so that it can provide a comprehensive picture of the environmental conditions of the waters being studied. The selection of tools is based on suitability with the type of parameters being measured and the availability of resources to support the implementation of this research.

The data obtained through the use of these tools are then used as the basis for the water quality analysis process at the cultivation location. This process aims to ensure that each recorded parameter has high accuracy and relevance to the actual conditions of the pond waters being studied.

As a basis for water quality analysis at fish farming locations, available data is used and includes a number of physical and chemical parameters of water. The following figure presents an excerpt of the initial data processed for the purposes of this study.

```
df.head()
```

	lokasi (kelompok)	Derajat Keasaman (pH)	Temperatur Air (°C)	Total Dissolved Solid (TDS; ppt)	Oksigen Terlarut (DO; mg/L)	Amonia (NH3 NH4; mg/L)	Nitrit (NO2; mg/L)	Nitrat (NO3; mg/L)	Fosfat (PO4; mg/L)
0	warungkadu	7.9	30.0	30	6.1	0.5	0.0	0.0	0.5
1	nagrog 1	8.3	25.0	40	5.5	0.5	0.0	0.0	1.0
2	nagrog 2	7.0	24.1	40	3.0	0.0	0.0	0.0	0.5
3	cilegong 1	7.6	28.3	55	3.3	0.0	0.0	0.0	1.0
4	cilegong 2	8.0	26.5	40	4.0	0.5	0.0	0.0	2.0

Figure 2. Research Data

The figure shows an initial snapshot of a data frame containing water quality data from various farming locations. Each row represents one observation point that includes a number of parameters to assess water quality. This data is the basis for further analysis of the environmental conditions of the waters used in fish farming activities, especially in evaluating the suitability and potential risks to fish survival.

B. Data Preprocessing

At this stage, we build the final dataset from the raw data. There are several parts that will be processed, including data cleaning, data selection, data transformation so that it can be used as input at the modeling stage [16].

C. Class Label Determination

This study presents a two-class classification, namely "Feasible" and "Unfeasible" for the quality of tilapia fish farming ponds.

Water quality parameters with still water pools for tilapia fish based on (SNI 7550)

- Temperature (°C): 25 - 32
- pH: 6.5 - 8.5
- DO (mg/l): min 3
- Ammonia: max 0.02

D. SVM Training Model

The model was developed using data that included key physicochemical parameters such as pH (acidity), water temperature (°C), total dissolved solids (TDS), dissolved oxygen (DO), ammonia (NH3/NH4), nitrite (NO2), nitrate (NO3), and phosphate (PO4). To train the model, the dataset was split into two portions: 60% for training and 40% for testing, utilizing the train-test split method.

E. Model Evaluation

To obtain the optimal of parameters in SVM algorithm with the RBF kernel, optimization was carried out using the Grid Search technique combined with cross-validation.

RESULTS AND DISCUSSION

This study successfully developed a classification model of tilapia fish farming pond water quality using the SVM algorithm with the RBF kernel. The model was trained with data consisting of the main physicochemical parameters, namely acidity (pH), water temperature (°C), total dissolved solids (TDS), dissolved oxygen (DO), ammonia (NH^3/NH^4), nitrite (NO^2), nitrate (NO^3), and phosphate (PO^4). The training process was carried out by dividing the data into two parts, 60% train data and 40% test data, using the train-test split technique. All numeric features were normalized using MinMaxScaler to be in the range [0,1]. The target labels were classified binary based on water quality criteria, namely "Feasible " and " Unfeasible". The resulting model was then evaluated based on classification performance metrics and data visualization.

The model was tested on 40% of the test data and produced a classification accuracy of 82%. The following table summarizes the model performance metrics.

Table 2. Precision and Recall Values

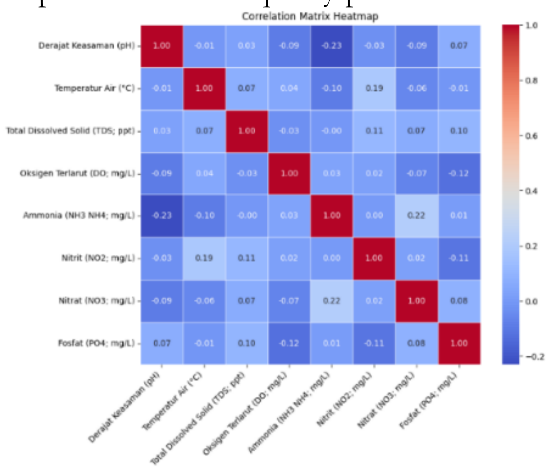
Class	Precision	Recall	F-1 Score	Support
Feasible	0.75	1.00	0.86	18
Unfeasible	1.00	0.62	0.77	16
Accuracy	-	-	0.82	34
Macro Average	0.88	0.81	0.81	34
Weighted Average	0.87	0.82	0.82	34

The model successfully classified all “Suitable” water quality data correctly, resulting in a recall of 100%. This shows that the model has high sensitivity to water conditions suitable for cultivation. On the other hand, predictions for the “Unsuitable” class have a precision of 100%, meaning that every “Unsuitable” prediction generated truly reflects poor water conditions, with no misidentification of water that is actually suitable.

To understand the relationship between input variables, a Pearson correlation analysis was performed, which is shown in the following heatmap:

Figure 3. Heatmap Correlation

The correlation heatmap generated from the data analysis shows the strength and direction of the relationship between water quality parameters used in the classification model. Classification can be used for various cases as a rule-making for a dataset. One of the most relevant correlations seen is the negative relationship between water temperature and dissolved oxygen levels, which supports the scientific principle that the higher the water temperature, the lower the solubility of oxygen.



This is important in the context of fish farming because dissolved oxygen is a crucial factor for the metabolism and survival of tilapia. In addition, there is a positive correlation between pH and ammonia levels, indicating that increasing pH tends to increase the concentration of free ammonia which is toxic to fish.

Some variables show low or near-zero correlation, such as between "TDS" and "pH" (0.03), or between "Nitrite" and "Phosphate" (0.02), indicating that the relationship between these parameters is relatively linearly independent. However, the non-linear relationship that may occur can still be handled effectively by the SVM algorithm with the RBF kernel which is indeed designed to recognize complex patterns in data that are not always linear. Overall, the numbers in this heatmap provide scientific justification that the parameters used in the model are indeed interrelated in a biological and chemical context. Therefore, this correlational relationship supports the validity of feature selection in the development of a machine learning-based water quality classification system.

Confusion matrix is one of the main evaluation tools in measuring the performance of a classification model, because it provides a detailed picture of how the model predicts each class compared to the actual labels. Confusion matrix helps in evaluating model performance by presenting information about the extent to which the model is able to identify and classify data. From the elements contained in it, we can calculate several crucial evaluation metrics, including accuracy, precision, recall (sensitivity), F1-score, and others [17]. The classification performance for each testing method was evaluated using a Confusion Matrix, which provides results in terms of accuracy, precision, and recall. The Confusion Matrix serves as a tool to assess how effectively the model distinguishes between imbalanced classes [18].

Data derived from the Confusion Matrix can be utilized to compute evaluation metrics such as accuracy, precision, and recall. Accuracy reflects how correctly the model identifies relevant data in comparison to the total amount of actual relevant data. Meanwhile, precision indicates the model's ability to correctly classify instances, calculated by comparing the number of correct predictions to the total number of predictions made. Meanwhile, recall measures the proportion of positive data that is successfully recognized correctly by the model from all existing positive data.

Figure 4 shows the results of the confusion matrix for water suitability classification.

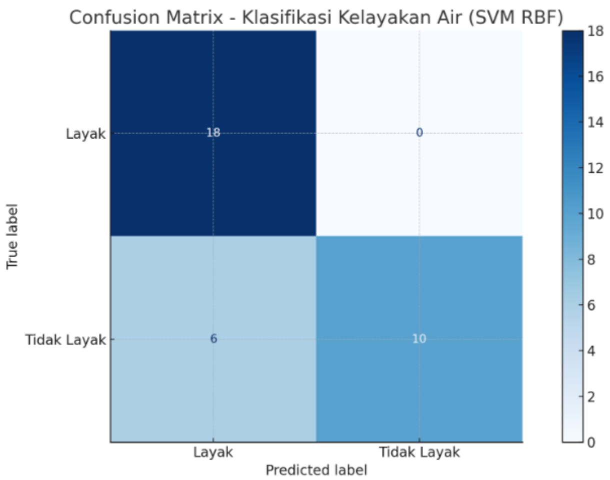


Figure 4. Confusion Matrix

In the context of this study, the confusion matrix presents the classification results of two classes, namely "Suitable" and "Unsuitable" for the water quality of tilapia fish farming ponds. The confusion matrix shows the details of the classification results between the two classes tested. The matrix shows that the model produces 18 true positives (TP) for the "Suitable" class, with no misclassifications (false negatives = 0). For the "Unsuitable" class, the model produces 10 true negatives (TN) and 6 false negatives (FN), with no false positives. In other words, no "Suitable" data is misclassified as "Unsuitable", indicating full confidence in the water being classified as good enough. The class stated as "Unsuitable" comes from data that has high concentrations of ammonia and phosphate.

The confusion matrix visualization shows that the model is conservative, meaning it tends to only classify water as "Suitable" if it truly meets the criteria. This approach is useful in the context of an early warning system because it can prevent the risk of stress or fish death due to poor water conditions that are not detected. The high accuracy in detecting "Unsuitable" conditions makes the model very feasible to be applied as a decision support system in the management of aquaculture ponds.

To obtain the best combination of parameters in the SVM algorithm with the RBF kernel, optimization was carried out using the Grid Search technique combined with cross-validation. The visualization of the results of this process is presented in the form of a heatmap, which describes the average value of cross-validation accuracy for each combination of C and gamma (γ) parameters.

After normalization, the data is partitioned into 60% training data and 40% test data. The SVM model is trained using the RBF kernel, with the ideal parameters of the grid search results:

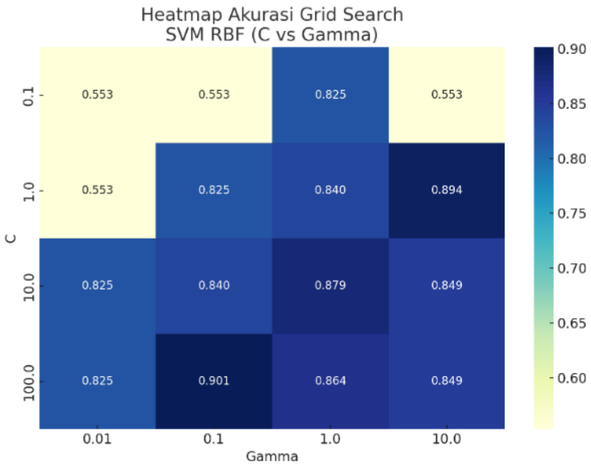


Figure 5. *Heatmap Grid Search*

Based on Figure 5, the heatmap shows that the combination of parameters C = 10 and gamma = 0.1 produces the highest accuracy value, which is around 85.75%, on the training data. This combination forms an optimal decision boundary, flexible enough to capture non-linear relationships between water quality variables without causing overfitting. Conversely, at gamma values that are too high (e.g. gamma = 10), accuracy decreases, indicating that the model is too sensitive to local variations and less able to generalize.

After obtaining the best parameters through optimization, the next step is to evaluate the model performance in more depth using the Receiver Operating Characteristic (ROC) curve. This evaluation aims to be a measuring tool to what extent the model can distinguish between two target classes, namely "Suitable" and "Unsuitable", at various classification thresholds. the receiver operating characteristic curve is a visual method commonly used in machine learning to assess the overall ability of a classification model. In this study, ROC is used to assess the reliability of the SVM RBF model in classifying the water quality of tilapia fish farming ponds. In addition, the Area Under Curve (AUC) value is calculated as a numerical indicator of the model's discriminatory ability. The following figure presents the results of the receiver operating characteristic curve obtained from testing the model on the test data:

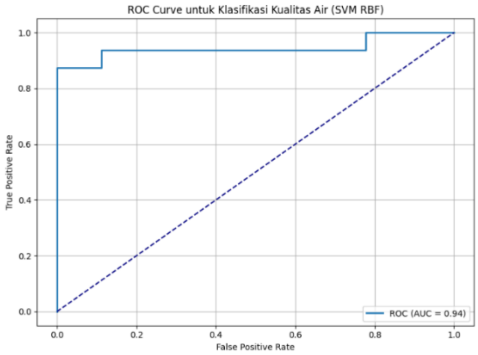


Figure 6. ROC Curve

The ROC Curve displayed illustrates the effectiveness of the SVM classification model with an RBF kernel in differentiating between the "Suitable" and "Unsuitable" categories using the test dataset. The blue line represents the correlation between the True Positive Rate (TPR) and the False Positive Rate (FPR) across multiple classification thresholds. A curve positioned well above the diagonal baseline (dashed line) suggests that the model demonstrates strong classification performance. The shape of the ROC curve that approaches the upper left corner of the graph indicates that the model has a high TPR with a low FPR, meaning that the model can accurately identify “Suitable” data while minimizing errors in classifying “Unsuitable” data. The Area Under Curve (AUC) value = 0.94 further confirms that the model has excellent discriminatory ability. An AUC value close to 1 indicates that the model is statistically very effective in distinguishing two classes consistently at various decision thresholds.

Based on the results of parameter optimization through grid search and model performance evaluation using ROC Curve, it can be concluded that the SVM algorithm with RBF kernel is able to classify the water quality of tilapia fish farming ponds accurately and efficiently. The combination of parameters C = 10 and gamma = 0.1 is proven to provide the highest accuracy and AUC, indicating an optimal balance between model complexity and generalization ability. These findings prove that the integration of machine learning methods in water quality monitoring has great potential to support more efficient, accurate, and sustainable fish farming management.

To assess the effectiveness of the water quality classification model, this research employed the 5-fold Cross Validation technique. The dataset was split into five equal segments, with each segment serving as the test set in turn over five separate training cycles. This process helps to determine whether the model has good performance and prevents overfitting or underfitting [19]. This technique was chosen because it is able to provide a more accurate estimate of model performance and reduce bias that may arise due to uneven distribution of training and test data. The stratification approach is applied so that the distribution of classes (“Suitable” and “Unsuitable”) remains proportional in each fold, so that the model is tested fairly against the entire variation of the data.

The results of the 5-Fold Cross Validation process on the SVM RBF model show the level of accuracy in each fold as follows:

Table 3. 5-Fold Cross Validation Values

Fold	**Accuracy**
1	88.24%
2	75.76%

3	87.88%
4	96.97%
5	90.91%

From these results, an average accuracy of 88% was obtained, indicating that the model is able to classify water quality with a high level of accuracy and consistently across various data subsets. It is concluded that the SVM RBF model has excellent predictive capabilities. This makes it feasible to be applied as a tool in decision-making related to the management of water quality in tilapia fish farming ponds.

Figure 7 below will display a visualization of 5-Fold Cross Validation in the form of a graph. This graph clearly illustrates the variation in accuracy across the five folds, providing a visual representation of the model's performance consistency.

The visualization not only highlights which fold yielded the highest and lowest performance, but also emphasizes the overall stability of the SVM model with RBF kernel. Such consistency is essential for applications in aquaculture, where reliable classification of water quality is critical for maintaining optimal fish health and production outcomes. Thus, the graphical summary presented in Figure 7 reinforces the findings from numerical results and supports the viability of the model for real-world deployment.

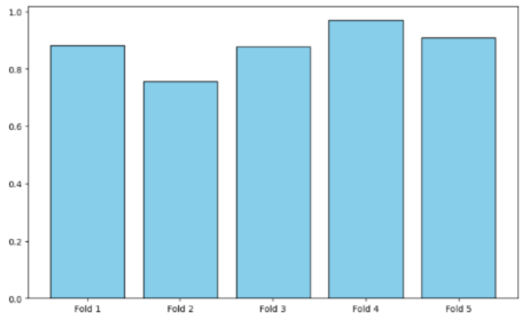


Figure 7. 5-Fold Cross Validation Graph
Visualization of the accuracy of the SVM RBF model on each fold during the 5-Fold Cross Validation process. This graph shows that the model accuracy is quite consistent, with the best performance on Fold 4 (96.97%) and the lowest on Fold 2 (75.76%).

Overall, these results indicate that the SVM model with RBF kernel has quite good stability in predicting data in the cross-validation scenario. Although there is a slight variation between folds, the achieved accuracy remains within an acceptable range, indicating that this model has decent generalization to be used on similar data outside the training data.

CONCLUSION

The water quality classification model based on the Support Vector Machine (SVM) algorithm with the Radial Basis Function (RBF) kernel has been successfully applied to identify the feasibility of water quality in tilapia fish farming ponds. Based on the evaluation results using the Stratified 5-Fold Cross Validation method, the model showed good performance with an average accuracy of 88% which shows the consistency of model performance in various data subsets. In addition, the confusion matrix results show minimal classification errors between the "Feasible" and "Unfeasible" classes, while the precision and recall values from the classification report show good balance between classes. The ROC Curve visualization produces a high AUC value, indicating the model's ability to effectively distinguish the two classes. The parameter tuning process using Grid Search produces an optimal combination of C and gamma values that support increased model accuracy. The class declared "Unfeasible" on average comes from data that has high ammonia and phosphate concentrations. These results can be concluded that the developed SVM RBF model has reliable predictive capabilities and can be used as a tool in making efficient and data-based water quality management decisions.

This research can be further developed by integrating real-time data from IoT sensors to enable automatic and continuous classification. The addition of other environmental parameters such as fish density, rainfall, and feed can also improve model accuracy. In addition, comparisons with other algorithms such as Random Forest or Deep Learning can be a reference for selecting the best method. Trials at different locations and cultivation seasons are also recommended to test the model's adaptability more broadly.

REFERENCE

[1] A. Rahma, D. Sihombing, I. M. Herawati, N. H. Lubis, and W. Aprizal, “Jurnal Sistem dan Teknologi Informasi Indonesia Klasifikasi Harga Ikan Koi Berdasarkan Jumlah Corak dan Ukuran Menggunakan Algoritma K-Nearest Neighbor Classification of Koi Fish Price Based on Number of Patterns and Size Using K- Nearest Neighbor Algorit,” vol. 10, no. 1, pp. 1–8, 2025.

[2] M. I. Dian Eka Ramadhani, Farah Hasna Arafah, Tetty Barunawati Siagian and R. F. A. R. Kurniawinata, Mad Rudi, “The Effect of Ectoparasites on Hatchery Business of Red Tilapia,” 2024.

[3] M. A. Sholahuddin and A. Prayoga, “Development of antioxidant products from Tilapia offal protein hydrolysate with different enzyme concentrations and a review in fulfillment of the halal product assurance criteria,” *J. Halal Prod. Res.*, vol. 6, no. 2, pp. 138–146, 2023, doi: 10.20473/jhpr.vol.6-issue.2.138-146.

[4] A. M. Sabilla, D. Jelita, K. A. Hajijah, and W. A. Arifin, “Optimisasi Produksi Budidaya Perikanan Di Provinsi Nusa Tenggara Timur Melalui Klasterisasi Menggunakan Algoritma K-Means,” vol. 4, no. 2, pp. 71–78, 2024.

[5] A. F. Hasan and H. Prasetyo, “Penambahan Ekstrak Kulit Pisang Kepok (Musa balbisiana) dengan Dosis yang Berbeda Terhadap Pertumbuhan Ikan Nila (Orecheocromis niloticus) Addition Of Kepok Banana Peel Extract (Musa balbisiana) With Different Doses To The Growth Rate Of Tilapia (Orecheoc,” *J. Ilm. Perikan. dan Kelaut.*, vol. 23, no. 1, 2024.

[6] R. Gustiano *et al.*, “The Success of Freshwater Aquaculture Program: Nile Tilapia or ‘Nila’ Culture In Indonesia,” *Zuriat*, vol. 34, no. 2, p. 56, 2023, doi: 10.24198/zuriat.v34i2.50108.

[7] K. Khoirunisa, "Studi Kasus Kesesuaian Kualitas Air Kolam Untuk Budidaya Ikan Nila (Oreochromis Niloticus) Di Desa Menggoro Kabupaten Temanggung Jawa Tengah," pp. 1–104, 2022.

[8] R. Ismawati, "Pengaruh Pencemaran Air Terhadap Gerakan Operkulum Ikan Nila," vol. 8, no. 1, pp. 61–74, 2025.

[9] W. A. Arifin *et al.*, "Bibliometric Computational Mapping Analysis of Publications of Marine Information System Using Vosviewer," *J. Eng. Sci. Technol.*, vol. 18, no. 6, pp. 3018–3028, 2023.

[10] N. S. Fitriasari *et al.*, "IoT-based Knowledge Repository Design for Supporting Knowledge Integration within the Marine Information System Study Program," *J. Phys. Conf. Ser.*, 2021, doi: 10.1088/1742-6596/1811/1/012101.

[11] T. Li, J. Lu, J. Wu, Z. Zhang, and L. Chen, "Predicting Aquaculture Water Quality Using Machine Learning Approaches," *Water (Switzerland)*, vol. 14, no. 18, pp. 1–15, 2022, doi: 10.3390/w14182836.

[12] S. S. Maulina Putri, M. Arhami, and H. Hendrawaty, "Penerapan Metode SVM pada Klasifikasi Kualitas Air," *J. Artif. Intell. Softw. Eng.*, vol. 3, no. 2, p. 93, 2023, doi: 10.30811/jaise.v3i2.4630.

[13] A. R. Hermawan and I. F. Hanif, "Sentiment Classification of Public Perception on LHKPN Using SVM and Naive Bayes," vol. 14, pp. 148–155, 2025.

[14] J. Akbar, M. Ali, and S. Yudono, "Water Level Classification for Detect Flood Disaster Status using KNN and SVM," vol. 13, pp. 298–302, 2024.

[15] A. Hendriana, P. N. Hikmah, A. Iskandar, D. E. Ramadhani, I. Kusumanti, and A. D. Arianto, "Budidaya Ikan Nila Hitam Oreochromis niloticus Studi Kasus Usaha Pembesaran di Tambak H. Umar Faruq Sidoarjo, Jawa Timur," *J. Ilm. Satya Minabahari*, vol. 8, no. 1, pp. 1–11, 2022, doi: 10.53676/jism.v8i1.180.

[16] S. Ariska, D. Puspita, and I. Anggraini, "Comparison Of K-Means and K-Medoids Algorithm for Clustering Data UMKM in Pagar Alam City," *J. Sisfokom (Sistem Inf. dan Komputer)*, vol. 13, no. 2, pp. 193–199, 2024, doi: 10.32736/sisfokom.v13i2.2090.

[17] N. Abdurrahman, B. Rahmat, and A. N. Sihananto, "Perbandingan Performa Klasifikasi Citra Ikan Menggunakan Metode K-Nearest Neighbor (K-NN) Dan Convolutional Neural Network (CNN)," vol. 2, no. 2, pp. 84–93, 2023, doi: 10.33379/jusifor.v2i2.3728.

[18] E. Helmud, E. Helmud, F. Fitriyani, and P. Romadiana, "Classification Comparison Performance of Supervised Machine Learning Random Forest and Decision Tree Algorithms Using Confusion Matrix," *J. Sisfokom (Sistem Inf. dan Komputer)*, vol. 13, no. 1, pp. 92–97, 2024, doi: 10.32736/sisfokom.v13i1.1985.

[19] A. J. Wahidin and T. H. Andika, "Deteksi Dini Stunting Pada Anak Berdasarkan Indikator Antropometri dengan Menggunakan Algoritma Machine Learning," pp. 378–387, 2024, doi: 10.33364/algoritma/v.21-2.2122.