Predicting Catfish Growth and Feed Efficiency in Using Decision Tree and Support Vector Regression

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ABSTRACT

Catfish farming has a key part in maintaining the economy of Poris Plawad Utara, Cipondoh, Tangerang where many farmers depend on it as their primary source of income. However, poor feed management creates considerable obstacles as overfeeding leads to higher expences and enviromental issues while underfeeding inhibits fish growth. Traditional methods for identifiying ideal feed amounts rely on manual observation, which often leads in irregular growth rates and feed loss. Despite the necessity of effective feed utilization, there is a paucity of powerful predictive techniques available to enable farmers accurately forecast feed demands and fish growth. There, we employ machine learning approaches including Decision Tree and Support Vector Regression (SVR), to predict catfish development and feed efficiency based on several environmental parameters such as water temperature, pH levels, and oxygen concentration. The algorithm we used was trained using data acquired from catfish farm in Poris Plawad Utara, comprising 3 month of feeding and growth records. The results of the analysis demonstrate that while Support Vector Regression (SVR) and Decision Trees perform well in stable environments, they have trouble handling environmental changes. Accuracy is impacted by feed management and environmental stability. More variables and an intricate machine learning strategy are required for better performance. While SVR works well in stable systems, complicated dynamics require adaptations. These results show that feed efficiency and fish development may be grately increased by incorporating machine learning into catfish farming operations. This methodology provides farmers with data-driven solutions that maximizes the efficiency of aquaculture and sustainability.

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1. INTRODUCTION

1.1 Background

Catfish farming has already been one of the important sectors of regional economy in Poris Plawad Utara, Cipondoh Tangerang. Being one of the most popular food sources of protein in Indonesia, the market for catfish is increasing, locally and nationally[1]. In Poris Plawad Utara, the catfish farming sector has provide a significant economic opportunity for the local community, especially for the small farmers who make the business their livelihood. With a relatively low cost of capital and fast production cycle, catfish farming is capable of providing a stable income for many families in Poris Plawad Utara, Cipondoh Tangerang who choose catfish farming as their main income. The development of this industry as one of the main pillars of the local economny has also been assisted by the infrastructure support and training given by the local goverment [2]. Catfish farming in Poris Plawad Utara still confornts a number of challenges that could prevent it form expanding despite its enormous potential. Managing resources efficienly is one of the biggest issues, particulary when it comes to using feed for catfish [3]. The cost of feed accounts for the majority of production expenses and the profitability of aquaculture operations is significantly impacted by feed efficiency [4].

Excessive or incorrect feed utilization can cause waste and hurt farmers if not adequately handled [5]. The Poris Plawad Utara community will benefit economically from improved production outcomes and increased feed provision, which should be optimized based on fish requirements and enviromental factors. Catfish farmers in Poris Plawad Utara, Cipondoh Tangerang are dealing with serious issues with fish growth and feed efficiency. More than 60-70 % of the overall production expenditures in catfish farming operations are incurred by fish feed [6]. Large amounts of waste can results from inefficient feed provision such as overfeeding of underfeeding [7]. Overfeeding can lead to water pollution and a decline in the pond's enviromental quality which in turn impacts the fish's growth and health in addition to increasing expenses [8]. Conversely, if fish are feed insuffienct amounts, they will not acquire enough nourishment, which will stunt their growth and lenghten the harvest cycle [9]. This will lead to decrase in productivity and profitability for the farmers.

A number of parameters including the water's temperature, pH, oxygen content, and fish density in the pond have significant impact on catfish growth [10]. Farmers must constantly check and modify the amount of feed to meet the changing needs of the fish which adds complexity to the management of farming duet to enviromental fluctuation [11]. In conventional practice, feed modifications are frequently accomplished using approximations or experience neither is consistently reliable [12]. A major obstacle to catfish production optimization is the lack of precision in predicting feed requirements form enviromental data and fish growth pattrens [13]. Catfish farmer's in Poris Plawad Utara frequently employ a number of traditional tactics to address issues with feed efficiency and fish development. Manually monitoring and adjusting the amount of feed given based on firsthand observation and expertise is one such method [14]. The best frequency and amount of feed are usually detemined by farmers by keeping an eye on the health of the fish and any changes in their feeding habits [15].

In order to maintain an enviromnent that promotes fish growth, many farmers also regularly evaluate the water quality using method like pH, temperature, and oxygen levels [16]. Farmers work to reduce waste and guarantee the best possible growth for fish by modifiying the feed and consistenly enchancing the surrounding [17]. Using an effective feed rotation system and managing feed stocks is another traditional tactic. To provide fish with the nourishment they need at different phases of growth, farmers frequently use feed with varied compositions [18]. In order to cut down on waste, they also use feed management strategies like progressive feeding and leftover feed monitoring [19]. With this method, there is less chance of residual feed contaminating the water because it is given in smaller amounts more frequently [20]. By using this technique, farmers want to strike a balance between the fish's nutritional requirements and the effectiveness of their feed utilization, which ultimately contributes to improving the sustainability and productivity of their catfish farming operations.

The utilization of Decision Tree and Support Vector Regression (SVR) techniques presents a highly efficient means means of addressing the issues related to feed efficiency and catfish growth. The crucial elements affecting catfish growth can be analyzed and comprehended in a structured and understandable way using the Decision Tree approach. The Decision Tree can determine the correlations between fish development rate and enviromental factors by using historical data that includes variables like fish density, pH, temperature and water quality. This model will examine choices made under different circumstances, giving precise insights into how modifications to certain parameters impact fish growth. This enables farmers to optimize fish developments rates by concentrating on the most important variables and making the required modifications.

A factor in the very accurate prediction of feed efficiency is SVR. More precise feed demand estimations are made possible by SVR, which models the intricate link between fish growth outcomes, environmental factors, and feed quantity. SVR can help farmers determinine the best amount of feed to administer under different conditions with the help of complete and representative data, which will save waste and increase efficiency. In this study, routine recordings and direct measurements in the catfish farming pond will provide the data needed to construct the machine learning model. Data on feed consumption and quantifiable fish growth over a given time period, along with information on temperature, pH, oxygen levels, and water quality, are all necessary. This information will be gathered from multiple catfish farming sites in Poris Plawad Utara, Cipondoh Tangerang to guarantee representativeness and diversity. It will then be processed and examined to create a precise and useful machine learning model for farmers. The activities of catfish farmers providing feed can be seen in Figure 1.

Figure 1. Farmer in Poris Plawad Utara Feeding Catfish

The use of machine learning methods to forecast catfish growth and feed efficiency has been studied in a number of studies. Regression-based models were used by Rahmadani et al to forecast fish production, and they showed excellent accuracy in predicting growth trend. Their analysis was limited in its ability to adjust to shifting environmental circumstances, though, because it mostly relied on historical data [21]. Similarly, using machine learning classifiers to evaluate fish malnutrition based on histology indicators, Oliveira et al offered important information on fish health status but did not specially address growth predition [22]. Although Tychenko et al did not test their method on catfish directly, they used genetic algorithms to estimate tilapia productivity, demonstrating successful aquaculture practice optimization [23]. While feed conversion efficiency was not the main focus of the study, Palaiokostas looked at decision tree-based ensemble learning to predict disease resistance in aquaculture species, which can indirectly affect growth efficiency [24]. Mandal and Ghosh concluded their study of artificial intelligence applications in fish farming by emphasizing the ways in which predictive models enhance growth rate estimation and feeding efficiency. Despite being thorough, their research was only theoretical and not used in real life [25]. All of these research show how machine learning can used in aquaculture, but they also show that decision trees and support vector regression are not fully integrated for predicting catfish growth and feed efficiency.

1.2 Problem Statement

The particular problem of inefficient feed distribution that has an immediate effect on catfish growth is the subject of this study. When deciding how much feed to give, catfish producers sometimes rely on antiquated methods that are manual and experience-based [26]. This method frequently results in excessive or unequeal feed distribution, which has an impact on the water quality and eventually the health and growth rate of the fish [27]. In catfish farming, feed accounts for a large amount of operating expenses hence efficiency in feed utilization is crucial [28]. Farmers may see a decline in profitabilly and production as a result of this inefficiency. To maximize feed provision in accordance with fish requirements at each stage of growth a more exact solution is thus required [29].

There is also the difficulty of bridging the gap between conventional fish farming methods and the predictive advantages provided by machine learning. The conventional methods depends on manual evaluations that aren't always reliable for estimating feed needs or gauging enviromental elements that impact fish development [30]. However, by utilizing past data and enviromental factors machine learning based techniques like Support Vector Regression and Decision Tree can produce more precise forecasts about fish growth rates and feed requirements. Machine learning can help farmers make more accurate data-driven decisions by providing deeper analytical skills. This can improve feed efficiency and support optimal fish growth.

2. RESEARCH METHOD

The initial stage of this research is determining the primary concerns about feed efficiency and catfish growth in Poris Plawad Utara, Cipondoh Tangerang. The research's objective is to use a machine learning model to maximize feed usage and improve fish growth. Data collection from the catfish farming pond is the initial step. This involves, gathering information on crucial parameters including water temperature, pH, dissolved oxygen levels, feed intake, and fish development. After that, the gathered data will be appropriately normalized and transformed to handle problems like outliers and missing data. Afterwards, feature selection techiniques will be employed to pick pertinent characteristic making sure that only significant variables are included in the analysis.

To evaluate the data, two models will be emlployed : Decision Tree and SVR. Decision Tree will be used to determine the main parameters impacting fish development, and SVR will be used to forecast feed eficiency. The parameters of this model will be assessed using metrics like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). It will be trained using training data and tested using test data. To improve the productivity and sustainability of catfish farming in the area, the model's output will be interpreted to offer guidance on how to best supply feed and promote fish growth. The research method that will be conducted can be seen in the Figure 2.

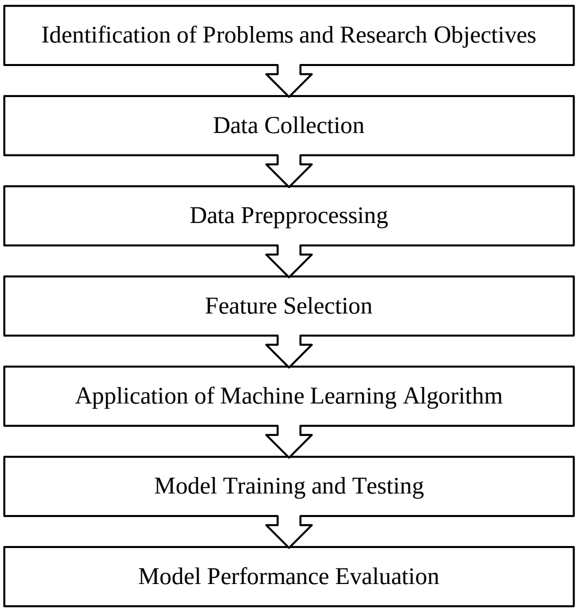

Figure 2. Research Methodology

2.1 Identification of Problems and Research Objectives

Like many other parts of Indonesia, Poris Plawad Utara, Cipondoh Tangerang has subtansial obstacles in the form of feed efficiency and fish growth when it comes to catfish farming. Insufficient food frequently leads to fish development that is not ideal, high operating costs and resource waste [31]. Feed is one the biggest expenses in fish farming, and inefficient use of it can have a direct negative influence on the company's profitabillty [32]. Prognostications regarding fish development and feed efficiency are futher complicated by unpredictability of enviromental element including water temperature, water quality, and pond conditions [33]. The goal of this study is to better estimate feed efficiency and identify important parameters impacting catfish growth by using machine learning models, particulary Decision Tree and SVR to address the problem.

2.2 Data Collection

To guarantee the quality and completeness of the data required to construct the machine learning model, the research's data collection procedure was conducted methodically. A number of significant factors that effect catfish growth are included in the data was gathered, such as fish growth size, daily feed comsuntion, dissolved oxygen levels, pH, and water temperature [34]. The fish' reaction to feeding and changes in the surrounding environment are recorded through routine measurements taken at regular intervals. Several catfish farming pond in Poris Plawad Utara are chosen for sampling based on differences in environmental conditions and management techniques using a representative approach in the field. Temperature, pH, and dissolved oxygen levels are measured by digital sensors to determine the quality of the water; dialy records kept by the farmers provide information on fish development and feed intake. Afterwards, the gathered information is arranged into a structured dataset, which will be the source of future analysis for machine learning models.

2.3 Data Pre-Processing

Before conducting additional analysis using machine learning models, the preprocessing stage of the data is crucial for ensuring the accuracy and consistency of the data. Preprocessing in this research starts with addressing missing data, where missing values are replaced using imputation techniques based on the distribution of data that is currently available. The next step involves identifying and removing outliers that could compromise the model's accuracy. After that, the data was standardized using the min-max scaling technique to make sure that all sure features fall into a similar range, which improved the model's ability to forecast. To prepare the dataset for the model's ensuing training and assessment procedure's, data conversion is also performed to convert raw data into a format that is appropriate for the Decision Tree and SVR techniques.

2.4 Feature Selection

The purpose of the selection step is to enhance the machine learning model's performance by choosing the variabels that are most pertinent to fish growth and feed efficiency. This process starts with a correlation analysis to find the relationship between the goal variable, fish growth and independent factors including feed consumption, pH, dissolved oxygen, and water temperature. The most important characteristic are then repeatedly removing using automatic techniques like Recursive Feature Elimination (RFE), leaving only the features that have the greatest impact on the accuracy of the model. Modeling fish development and feed efficiency becomes more accurate and efficient when this approach is followed to guarantee that the model is only constructed using the most pertinent features.

2.5 Application of Machine Learning Algortihm

The research employs machine learning methods, specifically Decision Tree for determining the primary parameters impacting catfish growth and SVR for predicting feed efficiency. The Decision Tree is employed due to its capacity to generate and unambiguos hierarchical framework that facilitates the identification of crucial factor including water temperature, pH, and feed intake along with their impact on fish development. However, using a few chosen input variables SVR is used to create a precise predictive model for forecasting feed efficiency. The combination of these two techniques yields accurate estimates for the effective utilization on feed in addition to enabling a thorough understanding of the variables impacting fish growth.

2.6 Model Training and Testing

Splitting the dataset into training and testing data which are used to train the model and assess its performance, respectively is how the model training and testing procedure is carried out [35]. Utilizing a train-test split approach with 80% of the data being training and 20% of the data being testing [36]. This study made sure the model could adapt well to new data. A more reliable assessment of the model's performance was also obtained by applying k-fold cross-validation with k=5 which reduced overfitting [37]. The model is frequently trained and tested on different data subsets using this method, which leads to a more accurate assessment of the Decision Tree and SVR model's predictive abilities in modeling fish growth and feed efficiency.

2.7 Model Performance Evaluation

Metrics like MAE, RMSE, and prediction accuracy are used to assess the model's performance[38]. By calculating the average absolute difference between expected and actual values. The MAE provides a general picture of the magnitude of prediction mistakes [39]. To calculate the root mean square of the discrepancies between expected and actual values one uses RMSE a more outlier-sensitive method that emphasizes larger errors. The percentage of accurate predictions in relation to the actual values is also shown using prediction accuracy [40]. The evaluation's findings give a through picture of how well the model predicts fish growth and feed efficiency. When a model's prediction accuracy is high and its MAE and RMSE values are low, it its deemed successful since it can produce reliable and accurate forecasts [41].

3. RESULTS AND ANALYSIS

3.1 Data Collection and Preprocessing

The information utilized in this research came from catfish farms in Poris Plawad Utara, Cipondoh Tangerang. Concentrating on the element that affect feed efficiency and growth. The data source is a 90-day period of daily recordings that contain environmental characteristics like pH, and water temperature in addition to biometric information about the catfish such as initial and end weights and the amount of feed given. Fish age, feed type, and feeding frequency are among the characteristics that are gathered. The data is preprocessed before analysis, which includes normalization to make sure all variables fall into the same range and data cleaning to remove outliers and missing values. In order for the predictive model that is produced to produce more accurate and trustworthy outcomes, this technique seeks to improve the quality of the data. The dataset table used in the research can be seen in table 1.

Table 1. Research Dataset

Pond_id	Day	Water Temperature (Celcius)	pH	Dissolved Oxygen (mg/L)	Feed Consumption (g/Day)	Fish Density (kg/m3)	Fish Growth (g/Day)
1	1	27.38	6.95	5.67	565.86	22.16	12.00

Pond_id	Day	Water Temperature (Celcius)	pH	Dissolved Oxygen (mg/L)	Feed Consumption (g/Day)	Fish Density (kg/m3)	Fish Growth (g/Day)
1	2	28.61	7.12	6.11	506.50	24.23	13.33
1	3	29.11	6.94	5.78	571.30	22.59	14.00
1	4	29.26	7.18	5.89	552.71	22.86	12.53
1	5	27.88	6.84	5.76	560.58	20.41	13.86

3.2 Model Development

Decision trees and Support Vector Regression (SVR), which are predictive techniques for catfish growth and feed efficiency, are used in the model generation process in this research. The decision tree was selected because it can provide models that are simple to comprehend and analyze, facilitating a more transparent examination of the variables impacting growth. The model's parameters include the splitting criteria, minimum samples for splitting, and tree depth. However, SVR was selected because of its superior accuracy in regression predictions, its capacity to handle non-linear data, and its increased complexity. The primary SVR parameters are the tolerance margin regulation epsilon parameter, the regularization parameter, and the kernel to be utilized. Choosing these two models is intended to provide a more thorough understanding of the most efficient prediction techniques for this study by contrasting how well they function in the particular setting of catfish farming.

3.3 Growth Prediction Results with Decision Tree Method

There are multiple reasons for the discrepancy between the expected and observed outcomes in these three ponds. The first is the unpredictability of the surrounding environment, which can vary from pond to pond and includes variations in water temperature, pH, and dissolved oxygen. The model can identify patterns in ponds with more stable circumstances more readily, which leads to more accurate forecasts. Second, erratic feed management may play a significant role. Thirdly, in certain ponds the link between the input factors (temperature, pH, oxygen, feed consumption) and the output variables (fish growth) can be more complex and dynamic than in others. The analysis's findings indicate that, in a number of ponds with more stable conditions, the Decision Tree approach may predict development reasonably well; but, there are still issues with capturing environmental dynamics and more variable management. These ponds' discrepancies reveal that the accuracy of the model is highly dependent on variables like feed management, environmental stability, and parameter fluctuation in the water quality. The results of the comparison between predictions and actuals on fish recovery can be seen in figure 3.

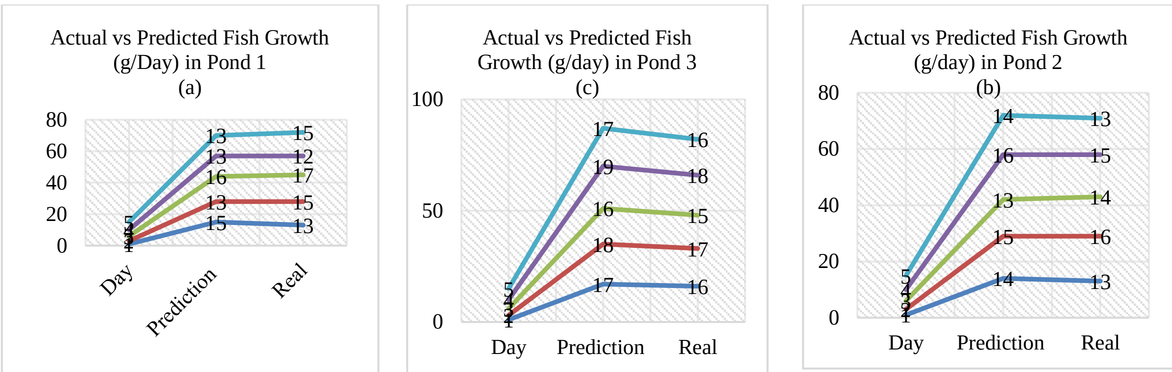

Figure 3. Actual vs Predicted Fish Growth (g/Day)

3.4 Feed Efficiency Analysis with SVR Method

Several important factors can be used to explain why the SVR model's predicted ability varied between the ponds. The model can anticipate growth more correctly in Pond 2 and Pond 3 due to the environmental parameters' greater stability, as opposed to Pond 1, which had a notable surge on the second day. In Pond 1, higher prediction errors may result from abrupt changes in feeding habits or variations in water conditions that are not taken into consideration by the model. Second, how well the model performs can be influenced by how complicated the relationships are among the input variables. Pond 1 may have more complex or non-linear relationships between input variables, such as water temperature, pH, dissolved oxygen, and feed consumption, which makes it challenging for the SVR model to forecast precise results. The relationship between the input and output variables in Ponds 2 and 3, however, appears to be more linear, which makes it simpler for the model to capture growth trends. According to the analysis results, in Ponds 2 and 3, where the cultivation circumstances are more steady, the SVR method seems to produce quite accurate forecasts. However, in Pond 1, where growth fluctuates suddenly, the model is unable to account for these variations, which are probably caused by factors not fully represented by the input variables. SVR can accurately forecast fish development in systems with strong environmental stability overall. The results of the actual and predicted comparison of feeding on catfish can be seen in Figure 4.

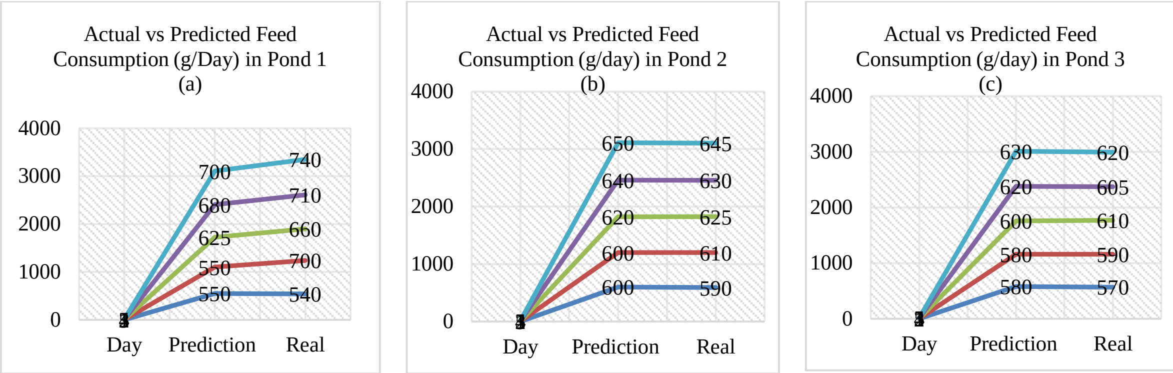

Figure 4. Actual vs Predicted Feed Consumption (g/Day)

3.5 Model Performance Evaluation

3.5.1 Evaluation of SVR Model Performance

The SVR model performed exceptionally well in predicting the amount of feed consumed by catfish in three ponds over a three-month period. Each pond had an R2 value greater than 1. The model in Pond 1 produced findings that were superior than the baseline model and explained all of the variability in the data, with an MAE of 38.26 and an RMSE of 63.29, and a R^2 of 1.097. Pond 2's R2 value of 1.039 indicates that the model is capable of accurately capturing feed consumption patterns, despite the fact that the MAE of 169.70 and RMSE of 192.36 point to a higher quality of error. Pond 3 continues to have a R^2 of 1.037, indicating that this model can correctly depict the dynamics of feed consumption, even with an MAE of 220.93 and an RMSE of 254.03. According to the evaluation results, SVR was successful in predicting feed consumption in each of the three ponds, and its R2 value demonstrated how well it could explain data variability. Despite the rather high error rates in Ponds 2 and 3, the model's overall performance shows that it is capable of being used in this situation. This indicates that SVR has the potential to be a useful predictive tool for feed consumption. The measurement results can be seen in the figure 5.

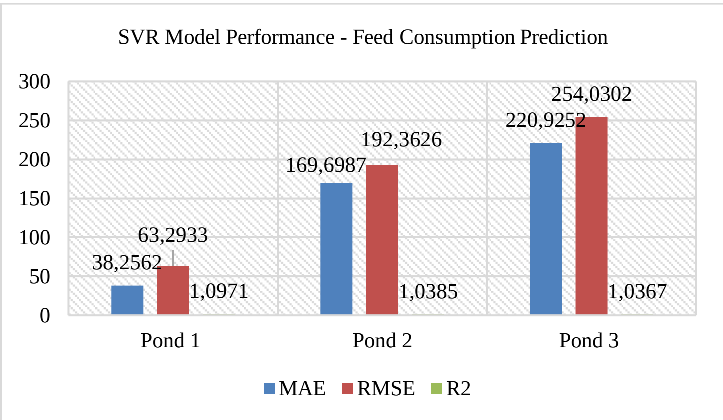

Figure 5. Measurement Results Feed Consumption Prediction

3.5.2 Evaluation of Decision Tree Model Pefrormance

The diverse results obtained from evaluating the Decision Tree model's efficacy in predicting the growth of catfish in three different ponds indicate the model's applicability in different situational settings. The model in Model 1 yielded an R2 of 0.518, an RMSE of 0.649, and an MAE of 0.506, suggesting that while there is space for improvement in accuracy, the model can explain roughly 51.8% of the data variability. Pool 2 exhibits exceptional performance, with very high prediction accuracy with an MAE of 0.439, RMSE of 0.512, and R^2 of 0.972. This model is able to account for nearly all of the variability in the data. Pool 3's results, which show reduced prediction errors with an MAE of 0.244 and an RMSE of 0.302 (albeit R2 is not shown), imply that the model is also useful in this situation.

The Decision Tree has shown to be a successful technique for forecasting the growth of catfish; Pond 2 has shown the greatest results. Environmental factors or particular elements impacting fish growth could be the cause of the variance in results between the three ponds. All things considered, this model exhibits considerable promise for use in fish farming applications, particularly in situations where environmental circumstances are more stable and can therefore facilitate more informed management practice decision-making. The measurement results can be seen in the figure 6.

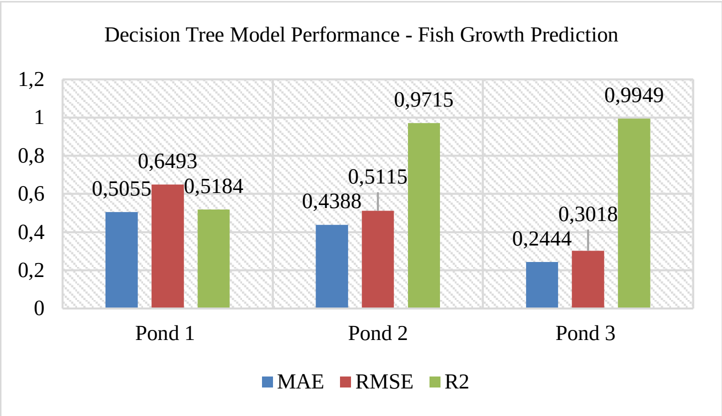

Figure 6. Measurement Results Growth Prediction Results

3.6 Discussion

In terms of forecasting feed consumption and catfish growth, the SVR and Decision Tree Models respective advantages and disadvantages are highlighted by the evaluation. With R^2values greater than 1 in each of three ponds, the SVR model showed a good capacity to forecast feed consumption, which may indicate an overfitting problem or data inconsistencies. The high MAE and RMSE values in Ponds 2 and 3 suggest major mistakes that could impact practical implementation, even if the model did a good job of explaining variability. However, when model modification and data quality enhancements are taken into consideration, SVR's overall performance indicates that it is still a potential tool for predicting feed consumption. However, when it came to forecasting catfish growth in the three ponds, the Decision Tree model showed differing degrees of precision. Pond 1's lower $R^2$of 0.518 indicates that model had trouble adequately capturing growth variability, whereas Pond 2's R^2 of 0.972 indicates good prediction accuracy. Despite the lack of an R^2 score, Pond 3's comparatively lower error levels show some degree of reliability.

Environmental variables, pond conditions, or biological impacts influencing catfish growth could be the cause of the performance differences between ponds. These results indicate that while Decision Tree models may work well in environments with consistens conditions, they may need to be strengthened for resilience by further feature selection or hybrid modeling techniques. Although there is potential for both models to be used in aquaculture, more work is required to increase predicted accuracy and lower mistakes. In aquaculture systems, combining the two methods or adding extra environmental and biological factors may result in more accurate and useful information for maximizing fish development and feed management.

4. CONCLUSION

Significant results are obtained when fish growth and feed efficiency are analyzed using Decision Tree and SVR methods. Deep insights into the most important elements in the cultivation process were obtained by the Decision Tree, which effectively identified the primary factors impacting fish growth, such as ambient conditions and feed management. Even in ponds with strong environmental stability, SVR is used to estimate feed efficiency with a fair degree of accuracy. Support Vector Regression method isn't able to simulate more intricate dynamics, such the abrupt changes in fish growth that were seen in one of the ponds. This study shows how machine learning can be used to efficiently optimize fish farming operations and highlights the significance of feed management and environmental parameter stability in reaching precise forecasts. Future cultivation techniques can be improved with the use of the evaluation's findings to make them more effective and sustainable.

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