Development of Euclidean Distance Algorithm for ANFIS Optimization in IoT-based Pond Water Quality Prediction

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***Abstract*—Pond water quality is a pivotal factor that influences the productivity and health of biota in aquaculture systems. The monitoring and prediction of water quality parameters, including temperature, pH, and dissolved oxygen (DO) levels, are imperative for maintaining optimal environmental conditions. The objective of this research is to develop the Euclidean Distance algorithm as an optimization method in adaptive neuro-fuzzy inference system (ANFIS) modeling to enhance the accuracy of internet of things (IoT)-based pond water quality prediction. Water quality parameter data is collected in real-time using IoT sensors connected to an ESP32 microcontroller and transmitted to a cloud storage platform for analysis. Subsequently, the data undergoes a series of processing steps, including min-max normalization and feature selection based on Euclidean distance. This process aims to generate a more representative and relevant subset of data for the subsequent model training process. The ANFIS model was trained using the optimized data and evaluated using MSE, MAD, MRSE and MAPE metrics. The training process involving four data sharing scenarios demonstrated a reduction in error when compared to the model that lacked optimization, specifically: The following proportions were determined: 50% versus 50% (0.11824 versus 0.15536), 70% versus 30% (0.18666 versus 0.19454), 80% versus 20% (0.17843 versus 0.18833), and 90% versus 10% (0.22477 versus 0.22859). The findings indicate that the incorporation of the Weighted Euclidean Distance algorithm within the IoT-based prediction system can markedly enhance the efficiency and precision of the ANFIS model.**

Keywords*—*ANFIS; Weighted Euclidean Distance; Water Quality Prediction; Aquaculture Monitoring; Data Optimization; IoT.

I. INTRODUCTION

Aquaculture plays a vital role in enhancing national fisheries productivity, particularly in shrimp farming [1]. The success of shrimp farming largely depends on the quality of pond water, which is influenced by several environmental parameters such as temperature, pH, and dissolved oxygen (DO) levels [2]. These parameters have been shown to significantly affect shrimp health and growth [3]. Therefore, effective water quality management is essential in aquaculture practices [4], [5]. However, farmers often face challenges in obtaining critical information about these parameters due to limited resources. These limitations can lead to suboptimal aquaculture outcomes and may even result in production failure. The integration of internet of things (IoT) technology in aquaculture presents innovative solutions by enabling real-time monitoring and data collection, thus reducing dependence on manual methods [6], [7]. An IoT system [8], [9], which includes sensors [10]-[12], communication modules, internet connectivity, and a user interface, enables accurate and efficient monitoring of water quality parameters. These sensors are used to measure temperature, pH, and dissolved oxygen (DO). The measurement results are displayed in real time, allowing for the optimization of pond conditions and supporting faster and more informed decision-making.

The adaptive neuro-fuzzy inference system (ANFIS) has become a widely adopted modeling technique for predicting pond water quality, utilizing the analysis of relevant environmental parameters to generate accurate forecasts [13], [14]. Despite its advantages, ANFIS often faces challenges such as overfitting, which limits its ability to generalize to unseen data. To address this limitation, the present study proposes the implementation of a training data selection optimization algorithm based on the Euclidean distance metric. It is hypothesized that this approach will enhance the model's predictive performance and generalization capability [15], [16]. The primary objective of this study is to integrate the Euclidean distance algorithm into IoT-based ANFIS modeling to improve the accuracy of pond water quality prediction. This approach is expected to support aquaculture practitioners in maintaining optimal pond conditions, thereby increasing productivity and promoting the sustainability of shrimp farming. This objective is consistent with previous research aimed at enhancing aquaculture efficiency through improvements in both IoT system performance and the predictive capabilities of ANFIS models. This section provides a comprehensive review of literature related to aquaculture, ANFIS, the Euclidean distance metric, and the internet of things (IoT).

Satra *et al.* [17] Tiger shrimp farming constitutes a significant segment of Indonesia's fisheries industry, contributing substantially to the nation's foreign exchange earnings through the export of fishery products. Nevertheless, this sector continues to confront a range of challenges, particularly those associated with suboptimal yields. The success of tiger shrimp farming is contingent upon the water temperature in the pond, which is a primary factor in the overall outcome. Temperatures that are unstable or outside the ideal range have been shown to inhibit shrimp growth and increase the risk of mortality.

Woźniacka *et al.* [18] Inland freshwater and brackish water aquaculture plays a significant role in global food security. Nevertheless, its rapid growth can have deleterious effects on the environment [19]. Therefore, the future development of the aquaculture industry must be predicated on achieving a balance between the augmentation of food production and the sustainable utilization of natural resources [20]. The prospects for the future expansion of aquaculture are anticipated to be influenced by a variety of factors, including the availability and quality of natural resources [21], particularly freshwater, as well as concerns pertaining to contamination and salinity.

Ouhssain *et al.* [22] the proposed adaptive network developed fuzzy inference system (ANFIS) is presented as a potential alternative to conventional methods due to its capacity to adapt and learn from data, thereby enhancing overall system performance. ANFIS possesses the capability to adapt to a range of operational conditions, facilitating the learning and optimization of its performance. This attribute renders it instrumental in enhancing the effectiveness of control systems [23]. The ANFIS model's capacity to adapt to variations in sensor data and perpetually enhance its performance renders it highly effective in elevating prediction accuracy and facilitating a more precise and responsive decision-making process [24].

Eaysin *et al.* [25] the ANFIS model demonstrates a high degree of predictive capability for response parameters, as evidenced by experimental validation that yields performance exceeding actual measurements. In comparison, the Brute Force algorithm is employed to determine the smallest combination required to attain the optimal parameter configuration. The Taguchi method is also employed to ascertain the most efficient set of process parameters.

Iwata *at al.* [26] the distance between two points is determined through the application of the Euclidean metric. By repeatedly measuring the movement length between two points, the distance distribution about a given set can be determined. When two points are selected uniformly from the set, the distribution is influenced by the geometry of the set. This distribution has been utilized within the framework of shape analysis, playing a pivotal role in various practical techniques based on the Euclidean metric.

Lahari *et al.* [27] the present study concentrates on the development of an electrochemical sensor that can be fabricated expeditiously. The sensor utilizes AuNPs on carbon filaments as working electrodes to detect Cd, Pb, Cu, and Hg ions in water. The findings of the study demonstrate the practical potential of this model, reflected by the satisfactory recovery rates in water samples from three different lakes. Notably, the model exhibited superior performance in the classification of metal ions, as evidenced by its high accuracy, precision, recall, and F1-score values.

The primary contribution of this research is the enhancement of the precision of ANFIS clustering and prediction through the implementation of Euclidean Distance and data normalization to generate a more balanced and informative data representation.

II. Research Methodology

In the context of model training, data optimization refers to a set of techniques and methodologies used to prepare, modify, and structure data in a way that supports the model's learning process and improves its predictive accuracy [28]. The primary goal of this process is to enhance the quality of the data, streamline the training phase, and enable the model to more effectively identify and learn patterns. Specifically, in the training of models such as the adaptive neuro-fuzzy inference system (ANFIS) [29], [30], data optimization involves not only preprocessing the data before training but also optimizing how the data is presented to the model. This comprehensive approach ensures a more efficient learning process and contributes to the generation of more accurate prediction results [31].

A. Euclidean Distance Algorithm

In the context of optimization processes, the Euclidean distance metric is commonly used in clustering techniques, such as the K-Means algorithm, to group data points based on their relative distances from one another [32]-[34]. Grouping similar data points allows the model to focus more effectively on identifying patterns within each cluster [35]-[39]. Moreover, Euclidean distance is a valuable metric for detecting outliers-data points that significantly deviate from the majority of values in the dataset [40]. Proper handling of these outliers, whether through removal or adjustment, can improve the predictive accuracy of the model. By incorporating Euclidean distance into the optimization process, the resulting dataset tends to exhibit more uniform characteristics, thereby enabling the model to learn more effectively and produce more accurate predictions. The formula used is as (1):

$$d(x, y) = |x - y| \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{1}$$

B. Weighted Euclidwean Distance Algorithm

Weighted Euclidean distance (WED) represents an enhancement of the traditional Euclidean distance metric by incorporating a weighted calculation of the distance between two data points [41], [42]. This improvement can offer greater analytical value, particularly in specific applications such as predicting pond water quality using ANFIS modeling. The core idea behind WED is to modify the standard Euclidean distance by assigning distinct weights to each dimension or feature during the distance computation. By doing so, WED enables more flexible and accurate analysis, especially when certain variables in the dataset carry different levels of importance. Essentially, weighted Euclidean Distance integrates variable weights to reflect their individual contributions to the overall distance measurement. being used. The following formula outlines the calculation of weighted Euclidean distance in (2).

$$WED = \sqrt{\sum_{i=1}^{n} wi.(x_i - y_i)^2} \quad (2)$$

C. Min-Max Normalization

Min-max normalization is a data scaling technique that transforms values into a specific range, typically between 0 and 1 [43]. The process involves subtracting the minimum value of the dataset from each data point and then dividing the result by the data range, which is defined as the difference between the maximum and minimum values [44], [45]. By standardizing the scale of datasets with attributes that may vary significantly in range, min-max normalization ensures that all features are represented on a uniform scale [46]. This technique is especially important in modeling processes such as ANFIS, which are sensitive to differences in the scale of input data [47]. The formula employed for this process is as (3):

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (3)$$

D. ANFIS Structure

The ANFIS structure is composed of five interconnected layers [48]-[57], each of which fulfills a distinct function in the modeling process, as shown in Fig. 1.

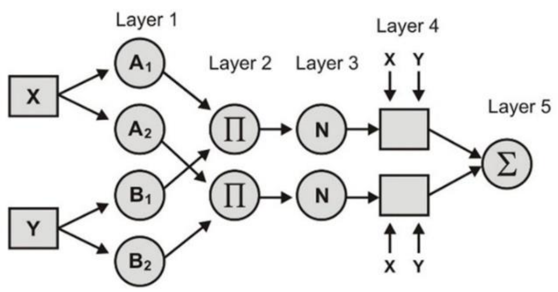


Fig. 1. ANFIS Structure

The neuro-fuzzy system comprises five layers with interconnected functions and characteristics. The ensuing section provides an exposition of these systems:

- Layer 1: designated as the "fuzzyfication layer," is characterized by the following definition. Let O1,i denote the output of each node in layer 1. Each node i in this layer is an adaptive node with node function O1,i = μAi(x) for i = 1, 2; or O1,i = μBi(y) for i = 1, 2, where x is the input to node i and Ai is the linguistic label (small, large, etc.) corresponding to this node function. In certain cases, the bell-shaped membership function O1,i Bell-shaped membership function is defined as follows: where A1 and its membership degree are specific to a given x, adequately quantifying Ai. Among the most commonly used types of membership functions are bell-shaped and Gaussian functions.

$$f(x, a, b, c) = \frac{1}{1 + \frac{x - c^{2b}}{a}} \quad (4)$$

The parameter b is generally positive, while c indicates the center of the curve. The Gaussian fit function is defined as (5):

$$A(x) = e^{\frac{(x-c)^2}{2a^2}} \quad (5)$$

- Layer 2: This layer utilizes the t-norm (multiplication) operator to integrate the signals from Layer 1. The process entails the multiplication of all inputs, resulting in the production of an output. The formulation for this process is as (6):

$$O_{2,i} = \mu A_i(x).\mu B_i(y) = W_i \quad (6)$$

In this layer, each node represents the strength of a rule, and its output serves as a weight in the inference process.

- Layer 3: The nodes in this layer normalize the weights produced by the previous product layer. The normalized output is calculated using the (7):

$$O_{3,i} = \frac{W_i}{w_1 + w_2} \quad (7)$$

- Layer 4: The nodes within this layer exhibit an adaptive nature, and the defuzzified output is computed using the (8):

$$O_{4,i} = O_{3,i}(\alpha_{4,i} = O_{3,i}(\alpha_i x) + \beta_i y + Y_{i)} \quad (8)$$

It is important to that αi, βi, and γi is imperative to delineate the linear parameters that are derived from the activation strength of the node i.

- Layer 5: The total output layer is a component of the information processing system that functions by synthesizing the information transmitted from the fourth layer and returning the total output. This process is governed by a predetermined function that is implemented within the layer:

$$O_{5,i} = \frac{\sum w_i\, y_i}{\sum w_i} \quad (9)$$

E. Model Evaluation

In the field of model evaluation, particularly within the framework of regression or prediction, variety of methodologies are utilized to evaluate the model's capacity to produce precise predictions. Commonly used evaluation metrics include Mean Absolute Deviation (MAD), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The subsequent section will delineate the precise formulae for each of these metrics.

$$MAD = \frac{\sum |A_t - F_t|}{n} \quad (10)$$

$$MSE = \frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n} \quad (11)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}} \quad (12)$$

$$MAPE = \frac{\sum_{t=1}^{n} \frac{|A_t - F_t|}{A_t}}{n} x100\% \tag{13}$$

In the development of predictive models, including ANFIS, the evaluation stage is of paramount importance. This stage is essential for testing the extent to which the model functions effectively. This stage involves the implementation of rigorous procedures to ascertain the efficacy of the model, both in terms of its performance on existing training data and its capacity to generate accurate results when confronted with novel data or data that has not been previously encountered by the model.

F. Research Framework

The stages in this research are meticulously arranged and implemented as a systematic guide for researchers, ensuring that the results achieved are congruent with the objectives that have been formulated, as shown in Fig. 2. These steps are meticulously designed to address and resolve the problems that are the focal point of the research.

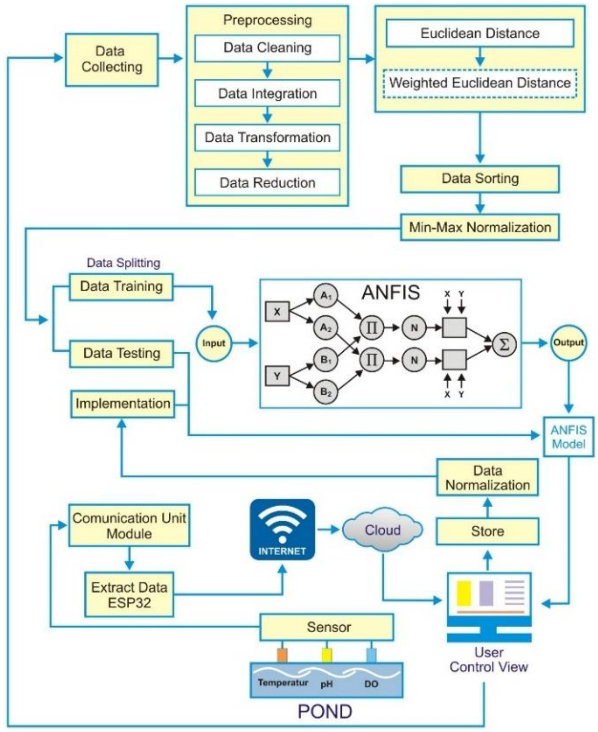


Fig. 2. Research framework

G. Data Collecting

The initial phase of this research entails the aggregation of pertinent, high-quality data from multiple sources. This study used 1,000 data, which after going through the selection process resulted in 100 data used as training data and test data on the ANFIS model in Table I. The data was obtained from the Marine and Fisheries Service of North Sumatra Province, Indonesia. This data encompasses historical data, experimental data, and data obtained from sensors. It is imperative to ascertain that the collected data encompasses the variables to be employed in the ANFIS model training. The ANFIS model is to be of a high caliber and representative of the conditions to be analyzed. Moreover, the ANFIS model will predict the water quality parameters that have been ascertained according to the stipulated requirements.

TABLE I. DATA COLLECTING

No	Temperature (°C)	pH	DO (mg/L)	Output
1	27.80	7.70	4.60	4
2	28.00	7.40	4.10	3
3	28.30	7.40	4.70	4
4	28.00	7.50	3.90	3
5	28.00	7.40	3.80	3
6	28.00	7.32	5.20	4
7	28.00	7.00	4.15	3
8	28.00	7.00	4.15	3
9	28.15	6.95	4.52	4
10	27.70	6.97	4.46	4
…	…..	…..	…..	…
60	25.50	7.74	7.40	3
61	31.00	6.80	6.50	4
62	25.50	6.91	1.60	2
63	24.70	7.00	5.80	3
64	31.00	8.47	2.67	3
65	25.00	7.00	2.30	2
66	31.00	6.05	5.61	4
…	…..	…..	…..	…
100	21.00	6.60	5.98	3

H. ANFIS Implementation

Fig. 3 shows the implementation of the ANFIS model in this study was carried out using MATLAB version R2024a with the Sugeno structure [58]-[62]. the Sugeno structure is known to have good nonlinear mapping capabilities in prediction systems. The model has been developed for the analysis and prediction of pond water quality parameters. The model utilizes three primary input variables: temperature pH. and dissolved oxygen (DO) levels [63], [64]. The selection of the ANFIS method with the Sugeno structure is predicated on its demonstrated efficacy in the management of complex systems characterized by elevated degrees of uncertainty. in addition to its capacity to exhibit adaptability in the face of variations in data patterns [65], [66]. This methodology enables the model to employ historical data for the purpose of learning. Thereby enhancing the precision of predictions.

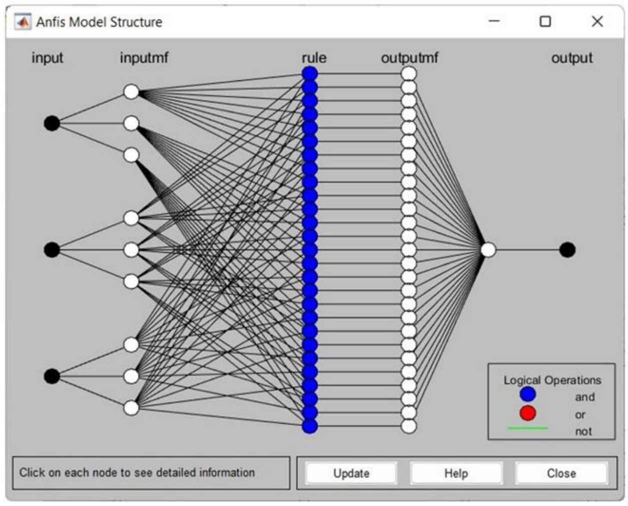


Fig. 3. ANFIS model structure

III. RESULTS AND DISCUSSION

The ANFIS training process is initiated with the input of pond water quality parameters. including temperature pH. and dissolved oxygen (DO) levels. as input data. into the system. These parameters then undergo a fuzzification stage. wherein each input value that remains in the numeric value is converted into a collection value in a previously determined fuzzy set. The fuzzification process employs a membership function that is designed to evaluate the extent to which an input value belongs to a particular fuzzy set.

The objective of determining the weight of each parameter in ANFIS data pre-processing with Weighted Euclidean Distance is to ensure that the contribution of each feature to training is proportional and informative. Parameters that exert a greater influence on the output are assigned higher weights, while those that are redundant or exhibit high variance are assigned lower weights. Consequently, the weights are indicative of the true contribution of each parameter, thereby enhancing the accuracy and representativeness of ANFIS training.

A. Normalization of Euclidean Distance

In the K-means clustering algorithm, Euclidean distance (ED) is used to measure the distance between each data point and the cluster centroid based on a specified metric. This calculation helps evaluate the similarity between the collected data and a predefined reference. Afterward, the data is sorted in ascending order and normalized to equalize the scale of different variables, ensuring fair and direct comparison. Normalization transforms all variables into a consistent range, such as 0 to 1 or -1 to 1, depending on the method applied, as shown in Table II.

TABLE II. NORMALIZATION EUCLIDEAN DISTANCE

No	Temperature	pH	DO	Output
1	0.5900	0.74215	0.4185	4
2	0.6150	0.70852	0.4301	4
3	0.6000	0.70852	0.3607	3
4	0.6075	0.65807	0.4092	3
5	0.6000	0.71973	0.3376	3
6	0.6000	0.66368	0.3665	4
7	0.6000	0.66368	0.3665	4
8	0.5850	0.66031	0.4023	3
9	0.5850	0.66031	0.4023	3
10	0.5700	0.68610	0.3838	4
11	0.6000	0.77578	0.3491	3
12	0.6000	0.70852	0.3260	3
13	0.6050	0.66368	0.4647	3
14	0.6000	0.69955	0.4879	3
15	0.6000	0.66368	0.4751	3
16	0.6000	0.66368	0.4751	3
17	0.6000	0.67489	0.4879	3
18	0.6350	0.67040	0.4254	3
19	0.6000	0.80942	0.4647	3
20	0.6350	0.66031	0.4520	3
21	0.6350	0.66031	0.4520	4
22	0.6200	0.71300	0.3052	2
23	0.5650	0.68610	0.3376	3
24	0.6200	0.72085	0.5110	3
25	0.5500	0.73094	0.4069	4
26	0.6400	0.73094	0.4763	4
27	0.6100	0.65247	0.4994	3
28	0.5500	0.71973	0.3838	3
29	0.6100	0.63453	0.3283	3
30	0.6500	0.71973	0.3723	3

B. Normalisasi of Weighted Eeuclidean Distance

The calculation of data distance with weighted Euclidean distance (WED) entails the estimation of the distance between two points in a multidimensional space. with consideration given to the weights assigned to each dimension. These weights serve to reflect the relative importance of each dimension in the distance calculation. a process that is frequently executed based on statistical characteristics such as variance or standard deviation. Subsequent to this. the data is arranged in an ascending sequence. and then it undergoes normalization through the implementation of the Min-Max Normalization method. The application of this method ensures that the dataset is transformed into a new one. where all values have been successfully converted to the desired range. The outcome of this process is a dataset in which each element is now on a uniform scale. thereby facilitating further analysis and enhancing the utilization of machine learning algorithms that are sensitive to variations in scale between features. The normalized dataset is then prepared for the subsequent steps in the data analysis or processing process as shown in Table III.

TABLE III. NORMALIZATION WEIGHTED EUCLIDEAN DISTANCE

No	Temperature	pH	DO	Output
1	0.5900	0.74215	0.4185	4
2	0.6000	0.70852	0.3607	3
3	0.6150	0.70852	0.4301	4
4	0.6000	0.71973	0.3376	3
5	0.6000	0.66368	0.3665	4
6	0.6000	0.66368	0.3665	4
7	0.6075	0.65807	0.4092	3
8	0.6000	0.70852	0.3260	3
9	0.6000	0.69955	0.4879	3
10	0.5850	0.66031	0.4023	3
11	0.5850	0.66031	0.4023	3
12	0.6000	0.77578	0.3491	3
13	0.6050	0.66368	0.4647	3
14	0.6000	0.66368	0.4751	3
15	0.6000	0.66368	0.4751	3
16	0.6000	0.67489	0.4879	3
17	0.5700	0.68610	0.3838	4
18	0.6200	0.71300	0.3052	2
19	0.6200	0.72085	0.5110	3
20	0.6000	0.80942	0.4647	3
21	0.6100	0.65247	0.4994	3
22	0.6350	0.67040	0.4254	3
23	0.5850	0.66592	0.3029	4
24	0.6000	0.65247	0.5110	3
25	0.6000	0.65247	0.5110	3
26	0.6100	0.63453	0.3283	3
27	0.6250	0.68610	0.5087	4
28	0.5650	0.68610	0.3376	3
29	0.5750	0.71525	0.5225	3
30	0.5800	0.71525	0.5341	4

C. Model Training

The training simulation employed in this study utilized the MATLAB R2024a software [67]. The ANFIS model training was conducted in two stages to identify the effect of data optimization on model performance and its accuracy level. In the first stage. the data underwent no additional optimization. and the distance between data points was calculated using only the Euclidean distance (ED) method. without considering special weighting for each parameter. In the second stage. the ANFIS model training used data that had undergone an optimization process using the weighted Euclidean distance (WED) method. Weighted Euclidean Distance-based optimization necessitates the weighting of each pond water quality parameter. including temperature. pH. and DO. The training dataset was partitioned into distinct segments using various combinations of training and test data. ensuring variability in the utilization of both sets. The compositions employed included 50%:50%. 70%:30%. 80%:20%. and 90%:10%. The ANFIS model training dataset. comprising a 70% and 30% composition of the 100 data sets. utilized a training dataset of 70 data sets. The results of the distance calculations employing the Euclidean distance (ED) metric are presented in Table IV.

TABLE IV. MODEL TRAINING DATASET (ED)

No	Temperature	pH	DO	Output
1	0.5900	0.21204	0.1237	4
2	0.6150	0.20243	0.1271	4
3	0.6000	0.20243	0.1066	3
4	0.6075	0.18802	0.1209	4
5	0.6000	0.20564	0.0998	3
6	0.6000	0.18962	0.1083	3
7	0.6000	0.18962	0.1083	3
8	0.5850	0.18866	0.1189	4
9	0.5850	0.18866	0.1189	4
10	0.5700	0.19603	0.1134	3
11	0.6350	0.18866	0.1336	4
…	……..	……..	……..	..
…	……..	……..	……..	..
69	0.2500	0.17681	0.1708	3
70	0.9400	0.19603	0.0348	2

The ensuing findings. derived from the training of the ANFIS model. demonstrate that when the number of epochs is set to 100. the resulting error value is 0.19454. Fig. 4 shows the training result curve provides a visual representation of the model convergence process during iteration. wherein the error progressively diminishes until it attains the final value.

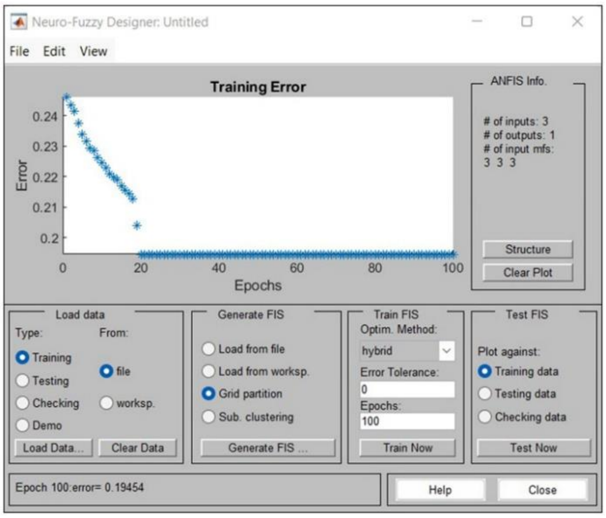


Fig. 4. ED training yield curve

The display of FIS test results functions as an indicator of the conformity between actual values and predicted results in Fig. 5. The closer the distance of the asterisk to the empty circle the superior the ANFIS model produced.

The following dataset is comprised of the ANFIS model training set in Table V. which is composed of 70% and 30% of 100 data sets. as well as the results of calculations with WED. The shape of the ANFIS model training result curve after optimization with an error value of: 0.18666, as shown in Fig. 6.

The display of FIS test results functions as an indicator of the conformity between actual values and predicted results. The closer the distance of the asterisk to the empty circle. the superior the ANFIS model produced, as shown in Fig. 7.

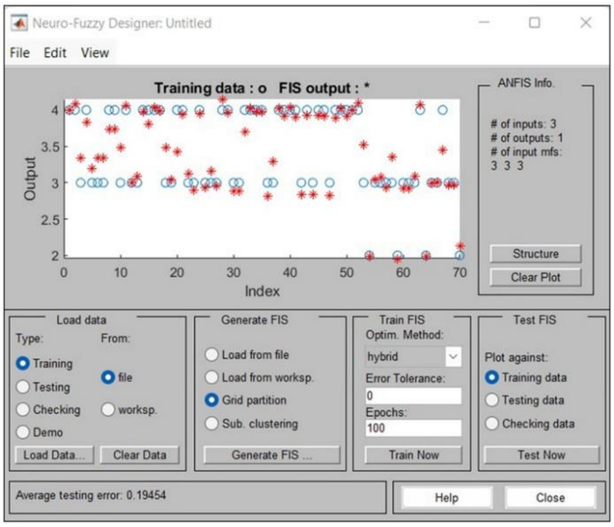


Fig. 5. FIS Euclidean distance test results

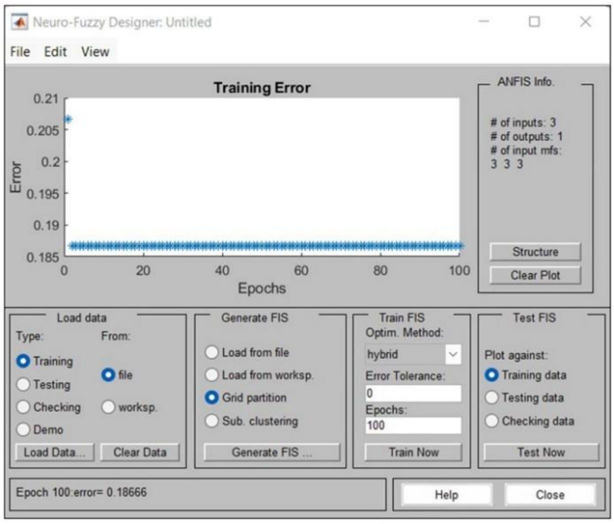


Fig. 6. WED training yield curve

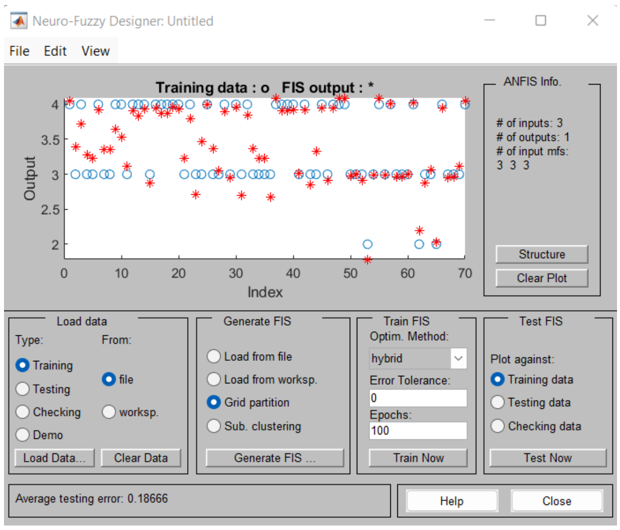


Fig. 7. FIS weighted Euclidean distance test results

TABLE V. MODEL TRAINING DATASET (WED)

No	Temperature	pH	DO	Output
1	0.5900	0.2120	0.1237	4
2	0.6000	0.2024	0.1066	3
3	0.6150	0.2024	0.1271	4
4	0.6000	0.2056	0.0998	3
5	0.6000	0.2024	0.0963	3
6	0.6000	0.1999	0.1442	4
7	0.6000	0.1896	0.1083	3
8	0.6000	0.1896	0.1083	3
9	0.6075	0.1880	0.1209	4
10	0.5850	0.1887	0.1189	4
11	0.5650	0.1960	0.0998	3
…	……..	……..	……..	..
…	……..	……..	……..	..
69	0.4350	0.2015	0.1804	3
70	0.7500	0.1640	0.1756	4

The subsequent section delineates the outcomes of the ANFIS model training. Encompassing the preliminary stages in addition to the post-optimization phase of the data. which was achieved through the implementation of two distinct methodologies: the Euclidean distance (ED) and weighted Euclidean distance (WED) algorithms, as shown in Table VI. Optimization is a process that is carried out with the objective of increasing prediction accuracy. This process occurs during the filtration and adjustment of data distribution stages prior to the training of a model.

The evaluation of model performance is achieved through the implementation of training procedures that encompass a range of scenarios and data sets. Each scenario encompasses four training sessions. each comprising a distinct composition of training and test data. This approach was adopted to ascertain the extent to which data optimization affects prediction outcomes and the stability of the model under diverse conditions. Consequently. this study not only appraises the efficacy of the optimization method employed but also quantifies the reliability of the ANFIS model in generating more precise predictions.

TABLE VI. TRAINING RESULT ERROR VALUES

Model	Split Data	Training Data	Error Value
ED	50%:50%	50 dataset	0.15536
	70%:30%	70 dataset	0.19454
	80%:20%	80 dataset	0.18833
	90%:10%	90 dataset	0.22859
WED	50%:50%	50 dataset	0.11824
	70%:30%	70 dataset	0.18666
	80%:20%	80 dataset	0.17843
	90%:10%	90 dataset	0.22477

The most substantial error reduction was observed in the 50%: 50% composition. suggesting that WED optimization is more efficacious when the training and testing data are balanced. In general, WED optimization enhances model accuracy. though the extent of improvement diminishes in compositions with minimal testing data (e.g. 90%: 10%). The 50%: 50% composition emerges as the optimal choice to ensure model performance. as evidenced by the error results depicted in the ensuing graph.

The ensuing discussion will focus on a comparison of the results of the ANFIS model training. Both before and after optimization, shown in Table VII. The training was carried out using two different methods: the first method involved the use of only Euclidean distance (ED) to calculate data distance and the second method involved the use of weighted Euclidean distance (WED) to calculate data distance. The ensuing comparison illustrates the outcomes of the ANFIS model training. Both prior to and following the optimization stage, as shown in Fig. 8.

TABLE VII. DIFFERENCE IN TRAINING RESULT ERROR VALUES

Split Data	Number of training data	Before optimization (ED Error)	After optimization (WED Error)	Difference in Error value
50%:50%	50 dataset	0.15536	0.11824	-0.03712
70%:30%	70 dataset	0.19454	0.18666	-0.00788
80%:20%	80 dataset	0.18833	0.17843	-0.00990
90%:10%	90 dataset	0.22859	0.22477	-0.00382

Fig. 8. Illustration of error values from training results

As illustrated in Table VII which presents a comparison of training results before and after data optimization. The findings can be interpreted as follows:

1) Composition 50%:50%

The application of WED data optimization techniques resulted in a substantial decrease in error values from 0.15536 to 0.11824, exhibiting an error difference of -0.03712, as shown in Fig. 9. This outcome signifies a notable enhancement in the model's performance for this particular composition.

2) Composition 70%:30%

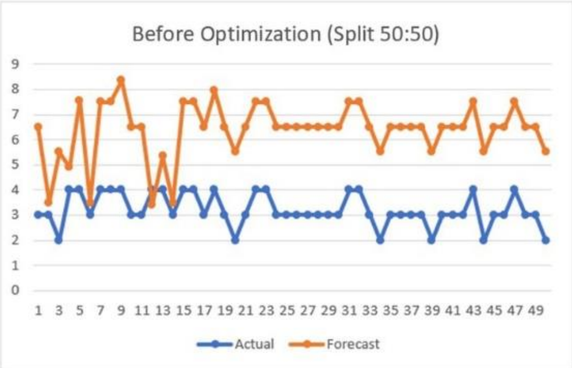
Following the implementation of the optimization process. the error value underwent a reduction from 0.19454 to 0.18666, exhibiting an error difference of -0.00788, as shown in Fig. 10. The error reduction observed in this composition is less pronounced in comparison to the 50%:50% composition

3) Composition 80% :20%

The result of the optimization process was a decrease in the error value from 0.18833 to 0.17843, with a difference of -0.00990, as shown in Fig. 11. Although not very significant. an increase in model performance is visible.

4) Composition 90%:10%

In this composition. optimization reduces the error from 0.22859 to 0.22477, with an error difference of -0.00382, as shown in Fig. 12. This indicates that optimization is less effective when the test data is severely limited.



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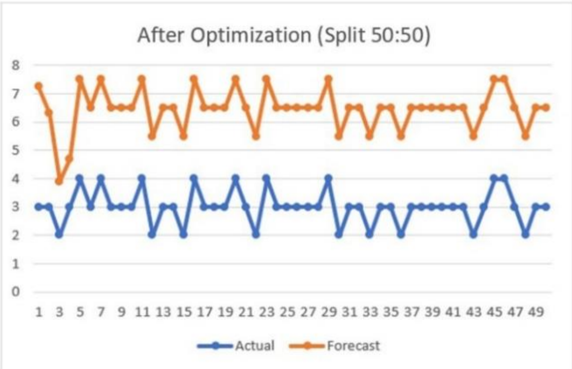

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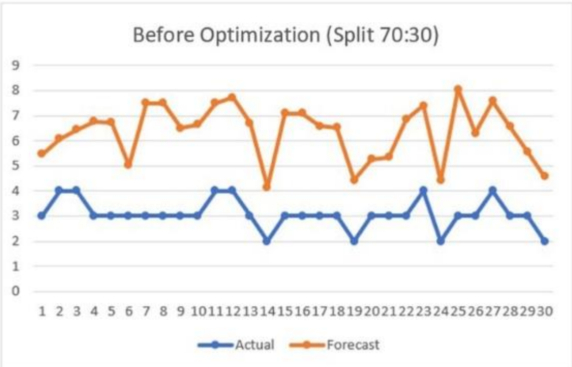
Fig. 9. Comparison chart of ED and WED split 50:50



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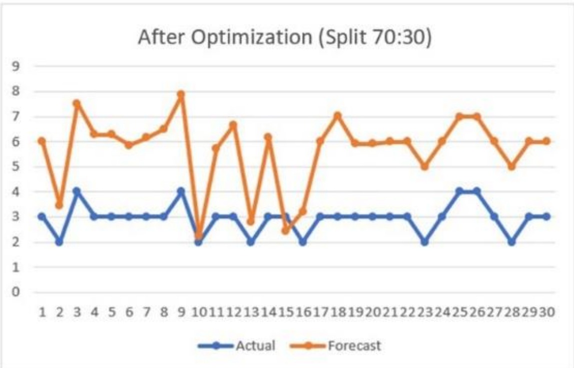

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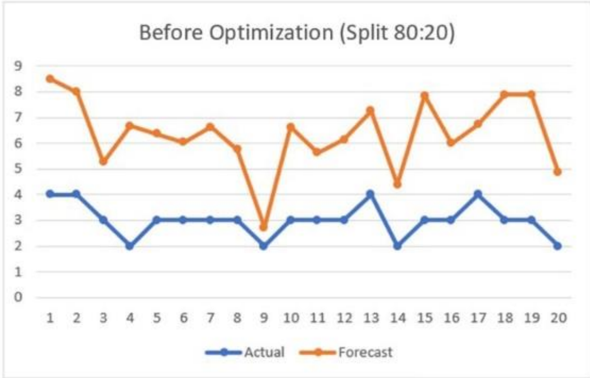
Fig. 10. Comparison chart of ED and WED split 70:30



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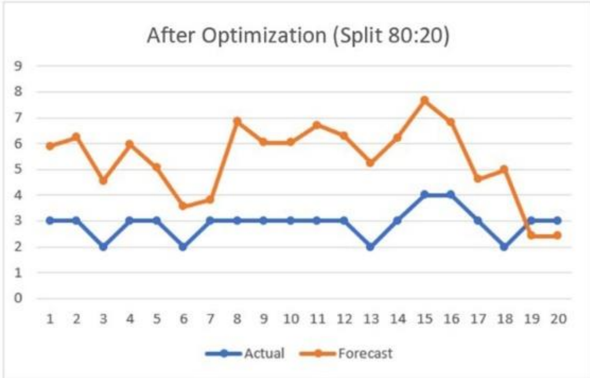

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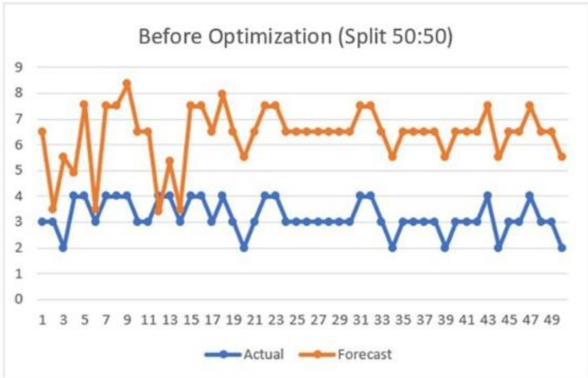
Fig. 11. Comparison chart of ED and WED split 80:20



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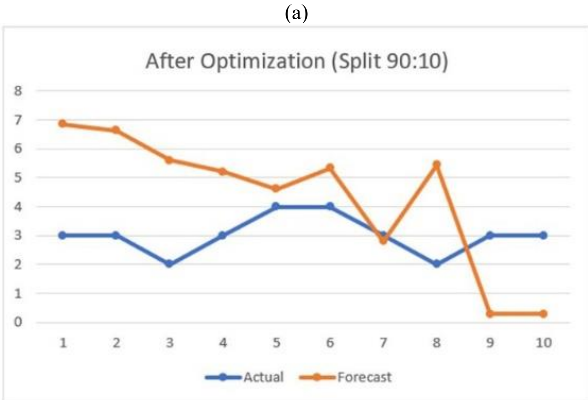

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Fig. 12. Comparison chart of ED and WED split 90:10

D. Model Testing

Model testing constitutes a critical phase following the training process. With the objective being the evaluation of the model's efficacy in predicting output based on test data that was not utilized during the training procedure. This stage is designed to assess the model's generalization capability in handling novel data and to ensure that the model does not experience overfitting.

A condition in which a model exhibits overfitting to the training data. This results in decreased performance and less accurate predictions when the model is tested with new data with which it has no prior experience. In essence, the objective of model testing is to assess the extent to which the model can adapt patterns from the training data and apply them to new data that has not been previously encountered.

In the context of ANFIS model testing. Previously prepared test data is provided as input to the trained model. The model then generates output based on the processing of the data, which is subsequently compared with the actual target value. The magnitude of prediction error is assessed using suitable evaluation metrics. Including mean absolute deviation (MAD), mean squared error (MSE), root mean squared error (RMSE), and mean absolute percentage error (MAPE). These evaluation metrics offer a thorough assessment of the model's predictive accuracy. enabling the assessment of its effectiveness in making predictions.

The data set under consideration is divided into two parts: 70% is allocated for training and 30% is designated for testing. This division is intended to maintain equilibrium between the training and testing processes. Thereby facilitating the model's recognition and comprehension of the patterns inherent in the data. It is noteworthy that the ANFIS model. once an adequate dataset has been amassed. The model's capacity to discern intricate relationships between inputs and outputs is enhanced.

The utilization of 30% of the data as test data is intended to facilitate an objective evaluation of the model. With the data being drawn from a separate set that is not involved in the training process. This is imperative to assess the model's generalizability. That is. Its capacity to generate precise predictions on unseen data. By allocating a portion of the data for testing. Researchers can obtain a more objective assessment of the model's performance. While circumventing the potential pitfalls of overfitting or underfitting. Which can compromise the accuracy of predictions, as shown in Table VIII.

The ensuing results are derived from the ANFIS model's testing. employing training data that has undergone optimization through WED, as shown in Table IX.

As illustrated in the above graph, a comparison of the results for each scenario is presented in graphical form. The subsequent material will demonstrate the extent to which the model's predicted values correspond to the actual values. The purpose of this visualization is to provide a representation of the extent to which the model aligns with the data. There by facilitating a more profound understanding of the ANFIS model. Each graph contains a pattern of predictions produced by the model compared to actual data. Making it easier to identify areas where the model shows good performance or has weaknesses in capturing complex data patterns.

TABLE VIII. TESTING RESULTS BEFORE OPTIMIZATION

No	Temperature	pH	DO	Forecast
1	0.6500	0.20243	0.0007	2.460
2	0.7500	0.23671	0.0577	2.075
3	0.5500	0.19923	0.0007	2.450
4	0.7500	0.16400	0.1756	3.761
5	0.7500	0.18322	0.1886	3.729
6	0.7500	0.23895	0.0550	2.025
7	0.7850	0.21653	0.1250	4.489
8	0.7850	0.21653	0.1250	4.489
9	0.6950	0.20820	0.2296	3.502
10	0.5500	0.20243	0.2433	3.645
11	0.5500	0.23767	0.2398	3.507
12	0.7500	0.16079	0.1824	3.730
13	0.7500	0.17040	0.1896	3.714
14	0.7000	0.23350	0.0140	2.139
15	0.7850	0.17713	0.1230	4.100
16	0.7850	0.17713	0.1230	4.100
17	0.4750	0.21332	0.2193	3.589
18	0.6500	0.20243	0.0007	2.460
19	0.7500	0.23671	0.0577	2.075
20	0.5500	0.19923	0.0007	2.450
21	0.7500	0.16400	0.1756	3.761
22	0.7500	0.18322	0.1886	3.729
23	0.7500	0.23895	0.0550	2.025
24	0.7850	0.21653	0.1250	4.489
25	0.7850	0.21653	0.1250	4.489
26	0.6950	0.20820	0.2296	3.502
27	0.5500	0.20243	0.2433	3.645
28	0.5500	0.23767	0.2398	3.507
29	0.7500	0.16079	0.1824	3.730
30	0.7500	0.17040	0.1896	3.714

TABLE IX. TESTING RESULTS AFTER OPTIMIZATION

No	Temperature	pH	DO	Forecast
1	0.6550	0.1079	0.1937	3.0000
2	0.4100	0.1989	0.0550	1.4478
3	0.8050	0.1947	0.1257	3.5203
4	0.7850	0.1922	0.0458	3.2781
5	0.7850	0.1922	0.0458	3.2781
6	0.7850	0.1669	0.0687	2.8435
7	0.4050	0.1960	0.1818	3.1636
8	0.8000	0.2088	0.0690	3.4959
9	0.8000	0.2120	0.1715	3.8715
10	0.4300	0.2021	0.0178	0.2074
11	0.3000	0.1960	0.1100	2.7313
12	0.3000	0.1992	0.1373	3.6636
13	0.6500	0.2857	0.3423	0.8023
14	0.3000	0.1960	0.1715	3.1672
15	0.3300	0.2117	0.2426	-0.5627
16	0.8600	0.2505	0.0000	1.2031
17	0.8400	0.1079	0.2040	3.0000
18	0.9000	0.1685	0.1756	4.0248
19	0.2850	0.1954	0.1240	2.9059
20	0.2850	0.1954	0.1240	2.9059
21	0.9350	0.1983	0.1145	3.0000
22	0.9350	0.1903	0.0738	3.0000
23	0.9350	0.1903	0.0649	3.0000
24	0.2500	0.2024	0.1168	3.0000
25	0.2500	0.2120	0.1373	3.0000
26	0.2600	0.2063	0.1988	3.0000
27	0.2500	0.1832	0.1500	3.0000
28	0.9400	0.1960	0.0348	3.0000
29	0.2500	0.1768	0.1708	3.0000
30	0.2500	0.1768	0.1708	3.0000

E. Model Evaluation

The utilization of data analysis techniques is contingent upon the adherence to specific requirements. This necessity stems from the fact that data analysis techniques employed in the forecasting process must adhere to specific criteria to ensure the accuracy of forecasts. Several widely used data analysis techniques in forecasting comprise mean absolute deviation (MAD), mean squared error (MSE), Mean absolute percentage error (MAPE), and root mean squared error (RMSE), as shown in Table X.

TABLE X. MODEL EVALUATION RESULTS

Model Name	Data Split	ANFIS Model Evaluation Results			
		MSE	MAD	RMSE	MAPE
ED-A	50%:50%	1.5848	0.9049	1.2589	30.46%
ED-B	70%:30%	0.8377	0.7841	0.9152	25.53%
ED-C	80%:20%	1.2079	0.8219	1.0991	30.67%
ED-D	90%:10%	2.7018	1.2286	1.6437	42.71%
WED-A	50%:50%	0.6170	0.6792	0.7855	25.93%
WED-B	70%:30%	0.8196	0.5398	0.9053	20.79%
WED-C	80%:20%	1.9606	0.9495	1.4002	10.26%
WED-D	90%:10%	10.0698	2.6025	3.1733	86.78%

F. *Internet of Things (IoT)*

The practice of pond water monitoring through the implementation of the IoT entails the utilization of sensors [68]-[72]. Which facilitate the real-time and continuous assessment of water quality parameter [73]-[76]. These sensors then transmit the collected data via an internet network for subsequent monitoring and analysis. In this system. three types of sensors will be utilized temperature sensors, pH sensors, and oxygen sensors (DO) [77].

Sensors are of paramount importance in the context of IoT systems. As they are the entities responsible for the collection of data that will subsequently undergo processing [78]-[81]. The utilization of direct data from sensors in research that employs ANFIS to predict or optimize pond water quality constitutes a highly relevant and effective approach [82].

The internet of things (IoT) technology-based approach employed in this study utilizes three types of sensors (i.e. temperature sensors, pH sensors, and dissolved oxygen (DO) sensors) to collect real-time data from ponds. The data generated from these sensors will serve as the primary input for training and testing the ANFIS model. This methodological approach offers distinct advantages and is highly pertinent within the broader context of pond water quality management, as shown in Fig. 13 to Fig. 16.

G. *User Control View*

User control view is a user interface designed to monitor and control IoT systems directly, as shown in Fig. 17. In the context of a pond water quality monitoring system. User control view functions as a conduit between the data collected by IoT devices and the users who require it. This interface enables users to observe data transmitted from temperature, pH, and DO sensors in real-time. Facilitating data-driven decision-making. In this implementation. Sensor data is processed by the ESP32 microcontroller and transmitted to a cloud server over a Wi-Fi network [83]. Subsequently the data is transmitted to a Google Sheet, which serves as the user control view, Google Sheet presents the data in tabular, and graphical formats. offering a comprehensive representation of the pond's water quality conditions.

The user control view in internet of things (IoT) systems serves as the final stage in the IoT workflow. wherein users engage with the data that has been collected. analyzed. and processed by the system. This interface or platform enables users to oversee. regulate. and respond to data generated by IoT devices.

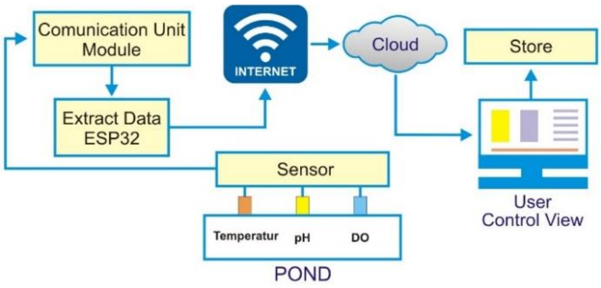

Fig. 13. Internet of things architecture

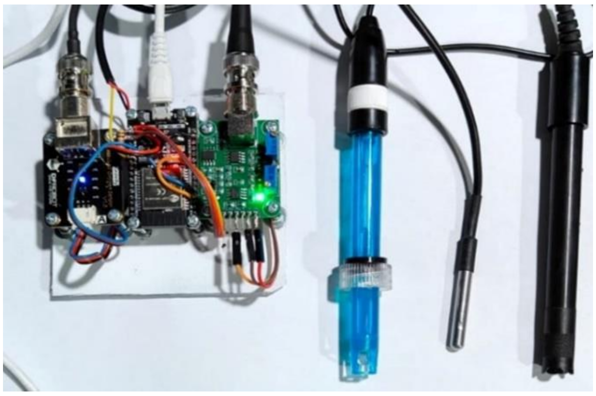

Fig. 14. Internet of things device suite

Fig. 15. Shrimp ponds are utilized for the execution of research endeavors

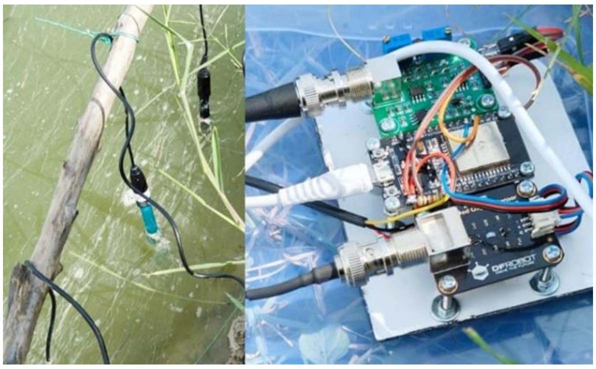

Fig. 16. The process of collecting pond water parameter data

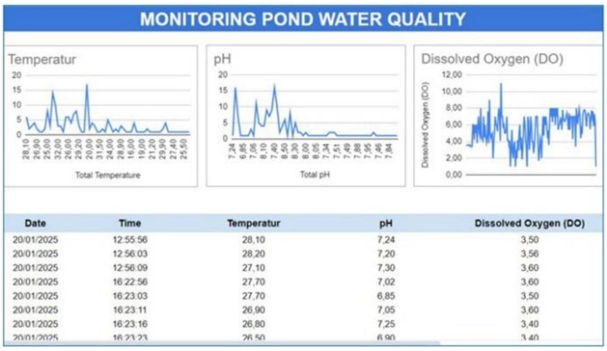

Fig. 17. User control view

IV. CONCLUSION

Following the application of weighted Euclidean distance (WED) optimization, a notable improvement in model performance was observed. The 50:50 data split (WED-A) achieved the lowest error value (0.11824), significantly outperforming the non-optimized counterpart. Similarly, the 70:30 split (WED-B) showed improved accuracy with an error of 0.18666, slightly lower than the original (0.19454). The 80:20 configuration (WED-C) also improved, reducing the error to 0.17843 from 0.18833. Although the 90:10 split (WED-D) showed a modest improvement (0.22477 vs. 0.22859), it still confirmed the benefit of WED optimization.

While WED remained effective across different training proportions, its impact was most pronounced in balanced data splits. The WED-B model, using a 70:30 split, delivered the best overall performance with the lowest MSE, MAD, RMSE, and MAPE values, indicating high accuracy and consistency. Therefore, this model is recommended for ANFIS-based prediction due to its superior ability to capture data patterns efficiently. These results highlight the importance of balanced data division and the strategic use of optimization techniques to enhance predictive model performance.

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