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Real-Time Monitoring of Pond Water Quality Parameters with Iot to Determine Optimum Data Using Euclidean Distance Algorithm

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Abstract— *The objective of this research is to develop an Internet of Things (IoT) system that is capable of monitoring shrimp pond water quality in real-time, with a focus on three main parameters: temperature, pH, and dissolved oxygen (DO).The system integrates hardware in the form of sensors and microcontrollers, as well as cloud-based software for data processing and visualization. The collected data underwent analysis using the Euclidean Distance and Weighted Euclidean Distance methods to calculate the distance between data, followed by a filtering process to filter relevant data based on proximity.The findings of the study demonstrate that the IoT system is capable of measuring water quality parameters with good accuracy and of automatically transmitting data to the cloud platform for further monitoring and analysis.The Weighted Euclidean Distance method provides more optimal results than standard Euclidean Distance, because it considers the weight of each parameter. It is hoped that this system can provide an innovative solution to support more efficient, data-based and sustainable shrimp pond management.*
Index Terms— Internet of Things, water quality, shrimp ponds, Euclidean distance, weighted Euclidean distance, real-time monitoring.

I. INTRODUCTION

Aquaculture can be regarded as a sophisticated method that has the capacity to alter the manner in which we perceive and utilise aquatic resources[1]. It is important to consider the potential of a world in which the production of fish, shrimp and shellfish can be carried out in a controlled environment, with a positive impact on both the economy and environmental sustainability[2]. In the context of intensive shrimp cultivation, the quality of the water is a pivotal factor. The quality of the water in shrimp farming activities is subject to constant fluctuation over time [3]. It is imperative that shrimp farmers prioritise the maintenance of stable cultivation water quality, ensuring it meets the threshold values for water quality standards stipulated for shrimp cultivation activities. The Internet of Things (IoT) architecture is a complex framework that integrates sensors, actuators, communication protocols, cloud services, and various layers, working together to create a cohesive IoT network system [4]. The system being discussed typically consists of several layers that allow administrators to assess, monitor, and ensure the system's stability. Like any system design approach, it also necessitates a strategy for integration with the organization's current infrastructure and systems. The use of Euclidean distance in optimization is predicated on the fact that it is frequently employed in clustering techniques to group data based on the distance between data points [5]. The grouping of similar data allows the model to focus more effectively on patterns within specific groups. The identification of outlier data points, characterised by a significant Euclidean distance from other points in the dataset, is a crucial step in the process. The

removal or treatment of outliers with care has been shown to enhance the accuracy of a prediction model. The incorporation of the Euclidean distance as part of the optimisation process ensures that the data processed by the model is distributed in homogeneous groups or exhibits similar characteristics. This, in turn, enables the model to learn more effectively and improve prediction accuracy.

A. The Design and Architecture of IoT Systems

The integration of Internet of Things (IoT)-based platforms into aquaculture infrastructure facilitates the optimisation of data communication pathways between microcontrollers, sensors and servers[6]. The Internet of Things (IoT) is a technology that uses sensors to monitor water conditions in real-time. This technology is employed for the purpose of monitoring pond water quality [7]. The Internet of Things (IoT) is a system that employs sensors to monitor and assess water conditions in real time. This technology is employed for the purpose of monitoring pond water quality [8]. The architectural design methodology can be explained as follows:

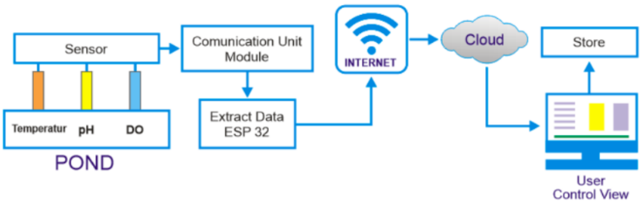

Fig. 1. Architectur Internet of Things

B. IoT Network Testing

The IoT circuit trial was conducted as an inaugural stage prior to the implementation of the system in shrimp ponds. This stage was undertaken to ensure that all components, including microcontrollers, sensors, communication modules and cloud services, functioned correctly and were optimally integrated[9]. Tests are conducted in conditions that emulate real-world settings to ascertain the precision of temperature, pH, and dissolved oxygen (DO) sensors in measuring water quality parameters [10]. Furthermore, the testing process involves transmitting data in real time over the Internet to a monitoring platform, such as Google Sheets, aiming to verify the accuracy and reliability of the received data. The outcomes of this trial will be utilised to identify potential enhancements and to adjust the system configuration prior to its implementation on actual shrimp farms.

Fig. 2. Test IoT tools

C. Research Location

The collection of research data was conducted in a shrimp pond situated in Pintu Air Village, Pangkalan Susu District, Langkat Regency, North Sumatra Province. This location was selected due to its representation of environmental characteristics conducive to shrimp cultivation, in conjunction with a pond management system that facilitates research on water quality.Pintu Air Village is recognised as a region with considerable fisheries potential, supported by adequate accessibility and a community that is actively engaged in the aquaculture sector. The geographical features and pond ecosystems in this region offer an excellent opportunity to implement Internet of Things (IoT) technology for monitoring essential water quality parameters, including temperature, pH, and dissolved oxygen (DO), which are vital for the success of shrimp farming.

Fig. 3. Location of the pond where the data was collected

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D. Testing IoT Tools at Farm Locations

The testing of IoT tools is conducted in situ at the shrimp pond location. The objective of this activity is to ensure that the IoT tools function effectively in field conditions while collecting pond water quality data. The test was conducted using three types of sensors: a temperature sensor to measure water temperature, a pH sensor to measure acidity levels, and a dissolved oxygen (DO) sensor to determine the level of oxygen available in water[11].

The testing process is comprised of three stages. Firstly, Internet of Things (IoT) devices are installed on the farm. Secondly, sensors are calibrated to produce accurate data. Thirdly, the delivery of real-time data to the monitoring platform via the Internet network is tested. The data obtained from these three parameters is then analysed in order to evaluate the environmental conditions of the pond and assess the reliability of IoT tools in supporting shrimp cultivation management. The results of this trial will also be used as a reference for improving the system before long-term implementation.

Fig. 4. IoT tool testing process at the farm location

Fig. 5. Position of sensor in pond water

Fig. 6.

II. RESEARCH METHODS

A. Euclidean Distance

Euclidian distance is a method employed to calculate the distance between two points in n-dimensional space. In the context of data science, this method is frequently applied to measure the closeness between two data points or to ascertain the level of similarity between attributes in a dataset[12]. Euclidean Distance is calculated based on a geometry formula that measures the length of a straight line between two points. The formula is as follows:

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

Where:

i = index of the attribute
n = amount of data
xi = attribute of data to-i, (i= 1, 2, 3..., ..., n)
yi = attribute of cluster centre to-i, (i= 1, 2, 3, ..., ..., n)

The Euclidean distance method is frequently regarded as a conventional approach that is both straightforward and efficacious for quantifying the distance between two data points in n-dimensional space[13]. The method is predicated on geometric principles that calculate the length of a straight line connecting two points. This provides an intuitive understanding of the closeness or similarity between data[14]. The programme's widespread utilisation can be attributed chiefly to its straightforward implementation and its capacity to deliver expeditious outcomes in a range of data analysis applications.

B. Weighted Euclidean Distance

Weighted Euclidean Distance (WED) represents a refinement of the conventional Euclidean Distance method, whereby the calculation of distance between two data points incorporates a weighting factor [15]. The primary objective of WED is to address scenarios in which each dimension (or feature) of the data possesses a distinct level of importance. By assigning a numerical value to each dimension, WED enables dimensions deemed more significant to exert a greater influence, while dimensions with lesser relevance are assigned a reduced numerical value[16]. The formula for the weighted Euclidean distance is as follows:

$$d_w(x,y) = \sqrt{\sum_{i=1}^{n} w_i.(x_i - y_i)^2}$$

Where:

x_1, y_1 = The value of the to-i feature for data points x and y.

w_1 = Weight for the to-i feature, indicating the importance of that dimension ($wi \geq 0$)

n = Number of dimensions (fitur).

This approach has been demonstrated to offer certain advantages over the conventional Euclidean Distance method. The former is characterised by its increased flexibility and adaptability in the context of datasets comprising features that exert differing influences on the analysis process. The incorporation of weights into the WED framework has been shown to facilitate the calculation of more relevant distance results, a particular benefit that is evident in scenarios where feature priorities are imbalanced, such as in classification, clustering, and model optimisation. This attribute of WED signifies its status as a more sophisticated and effective methodology when compared with the conventional Euclidean Distance approach[17].

In the context of Weighted Euclidean Distance, a weight is assigned to each dimension or data parameter, thereby signifying the relative importance of each parameter in the calculation of distance. The purpose of this weight determination is to ensure that parameters deemed more significant receive greater influence, thereby ensuring that the calculated distance more accurately reflects the relevance between data in the context of analysis.

The weights are determined on the basis of the expert's understanding or experience regarding the importance of each parameter in the context of the analysis. For example, if dissolved oxygen (DO) is considered more important than temperature in determining pond water quality, then DO is given greater weight.

C. Data Filtering

Following the calculation of the distance between the data using the Euclidean distance formula, the subsequent step is to implement a filtering process. This involves arranging the distance calculation results in ascending order, from the smallest to the largest distance. The objective of this sorting process is to identify data that exhibits the greatest similarity or proximity to a reference point.

It is evident that data with a smaller distance indicates a higher level of similarity or closeness in comparison to other data. Consequently, the ascending sorting process facilitates the selection of the most relevant data for subsequent analysis, such as classification, clustering, or decision-making. This filtration process is a pivotal step in ensuring that only data with significant characteristics is utilised in the ensuing process, thereby enhancing the accuracy and efficiency of the analysis.

III. RESULTS AND DISCUSSION

This section presents the findings of research conducted through data testing and analysis, along with a discussion of the interpretation of these findings.The results displayed include data generated during the research process, such as measurements of water quality parameters, performance of IoT tools, and evaluation of the implemented system.The discussion is conducted to assess the accuracy and effectiveness of the methods used, as well as to relate the results to theory and previous research. The analysis also includes an explanation of the factors that influence the results, as well as their implications for technology development and sustainable management of shrimp ponds.

A. Data Collection with Sensors

The data collection process is conducted through the utilisation of an Internet of Things (IoT) device that has been meticulously engineered to monitor water quality parameters in shrimp ponds in real time[18]. The data collection process is conducted through the utilisation of an Internet of Things (IoT) device that has been meticulously engineered to monitor water quality parameters in shrimp ponds in real time.

The data generated by sensors is automatically transmitted via the internet network to a cloud-based monitoring platform, facilitating convenient access and analysis. The data collection process is conducted periodically to ensure the consistency and accuracy of the information obtained, as well as to support the evaluation of the IoT system in a real operational environment. The following section presents the results of data collection from ponds using IoT sensors:

TABLE I. SAMPLE DATA COLLECTING

Terperatur (mg/L)	pH	Dissolved Oxygen (°C)
29.50	8.30	6.77
29.50	8.40	6.92
29.50	8.30	6.96
29.50	8.40	7.03
29.50	8.50	7.07
29.50	8.70	5.60
29.50	8.70	6.04
29.50	8.70	6.22
29.50	8.80	6.19
29.50	8.50	6.37
30.50	8.70	4.35
30.50	8.90	4.38
30.50	8.90	4.30
31.00	8.80	4.24
32.50	9.00	4.30
33.00	9.00	4.42
33.50	8.80	4.60
33.50	8.80	4.49
33.50	8.70	4.49
32.00	9.00	4.53
28.50	8.80	5.70
28.50	9.20	5.63
28.50	8.80	5.89
28.50	8.50	5.96
28.50	8.70	5.89
28.50	9.20	5.96
28.50	8.80	5.96
28.50	8.80	6.04
28.50	9.00	6.07
28.50	8.70	6.01

B. . Data Capture Chart

The following graph presents the results of real-time data collection on water quality parameters in shrimp ponds, obtained from Internet of Things (IoT) devices. The data displayed includes three main parameters: water temperature, pH and dissolved oxygen (DO), which were recorded at certain time intervals[19]. The graph is intended to provide a visual representation of the fluctuations in water conditions that were observed during the specified period.

The graph displays the dynamic changes in parameter values, which reflect the response of the pond environment to external factors such as weather, pond management activities, or daily cycles. The parameters displayed are water temperature (in degrees Celsius), pH (in acidity scale) and DO (in milligrams per litre (mg/L)[20].

This graph enables the observation of trends, patterns or anomalies in water quality data during the collection process. This information is useful for the identification of critical conditions that require immediate action, as well as for the evaluation of the effectiveness of IoT tools in the real-time monitoring of water parameters[21]. The utilisation of data visualisation techniques has been demonstrated to facilitate further analysis, thereby supporting optimal and sustainable pond management.

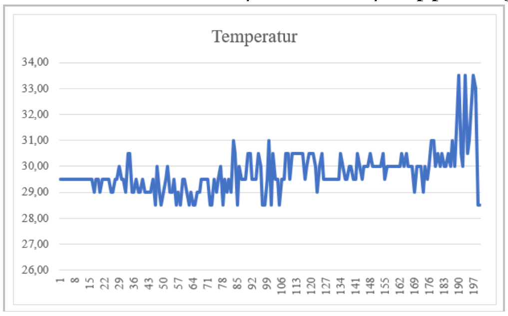

Fig. 7. Water temperature data retrieval poses graph

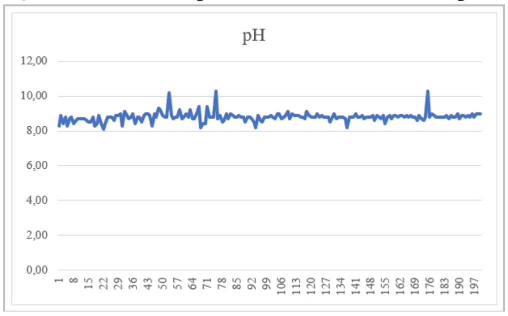

Fig. 8. Water pH data retrieval poses graph

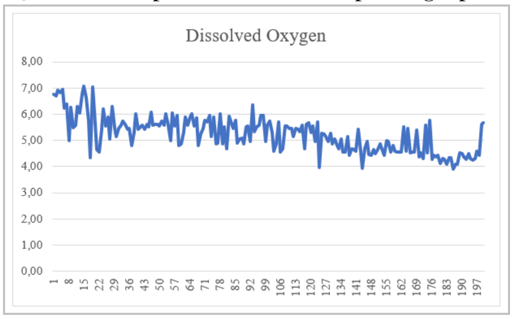

Fig. 9. Water DO data retrieval poses graph

C. Euclidean Distance Results

The calculation of the distance between the data has been performed, utilising the Euclidean distance method. This calculation was conducted with the objective of measuring the closeness between the observation data and a reference point[22]. The results of this calculation yield distance values that reflect the level of similarity between data in n-dimensional space, based on observed parameters such as temperature, pH and dissolved oxygen (DO)

A reduced distance value signifies that the data possesses characteristics that are more analogous to the reference point, whilst an augmented distance value denotes a more substantial discrepancy. The calculated data is subsequently arranged in an ascending order to facilitate further analysis processes, such as the identification of pertinent data groups or the determination of the closest data for the purpose of classification.

The findings of this study provide a valuable foundation for subsequent phases, including data filtration and predictive modelling. These subsequent phases are designed to enhance the precision of analytical processes and to facilitate decision-making processes in the context of farm management.

TABLE II. EUCLIDEAN DISTANCE RESULTS

Temperatur	pH	Dissolved Oxygen (mg/L)	Euclidean Distance

29,50	8,30	6,77	2,83760
29,50	8,40	6,92	2,98847
29,50	8,30	6,96	2,98614
29,50	8,40	7,03	3,07668
29,50	8,50	7,07	3,14253
29,50	8,70	5,60	2,21211
29,50	8,70	6,04	2,46141
29,50	8,70	6,22	2,57978
29,50	8,80	6,19	2,60693
29,50	8,50	6,37	2,59964
29,50	8,50	5,41	2,02078
29,50	8,40	4,82	1,77831
29,50	8,40	5,23	1,89549
29,50	8,50	5,26	1,95720
29,50	8,40	5,00	1,82017
29,50	8,40	4,64	1,75464
29,50	8,30	4,35	1,70696
29,50	8,30	5,45	1,94549
29,50	8,30	5,52	1,98304
29,50	8,20	5,34	1,85533
29,50	8,20	5,15	1,77981
29,50	8,20	4,82	1,68594
29,50	8,10	4,56	1,61670
29,50	8,60	5,05	1,93887
29,50	8,40	5,45	1,98870
29,50	8,40	5,38	1,95861
29,50	8,40	5,00	1,82017
29,50	8,70	5,49	2,16058
29,50	8,60	6,27	2,56422
29,50	8,80	6,41	2,75119

D. Weighted Euclidean Distance Results

The calculation of the distance between the data has been performed using the Weighted Euclidean Distance method. This method measures the closeness between data by considering the weight of each dimension (or parameter). The method provides different levels of influence on each water quality parameter, such as temperature, pH, and dissolved oxygen (DO), according to their level of importance to the analysis.

The calculation results in a distance value that reflects the relative similarity between the data and the reference point. Parameters with higher weights contribute more to the distance results, thus ensuring that more important dimensions receive greater attention in the analysis. The calculated data is then sorted in ascending order to identify the data with the closest distance as the most relevant candidates.

This approach has been demonstrated to produce more accurate and relevant results than traditional methods, especially in situations where parameters have different influences on the analysis results. The results of these calculations form the basis for the process of data selection, classification, or subsequent evaluation steps, which in turn support more effective pond management.

TABLE III. WEIGHTED EUCLIDEAN DISTANCE RESULS

Temperatur	pH	Dissolved Oxygen (mg/L)	Weighted Euclidean Distance
29,50	8,30	6,77	0,08184
29,50	8,40	6,92	0,12813
29,50	8,30	6,96	0,17390
29,50	8,40	7,03	0,56932
29,50	8,50	7,07	0,39428
29,50	8,70	5,60	0,32939

29,50	8,70	6,04	0,37782
29,50	8,70	6,22	0,20938
29,50	8,80	6,19	0,61756
29,50	8,50	6,37	0,87468
29,50	8,50	5,41	0,69178
29,50	8,40	4,82	0,68412
29,50	8,40	5,23	0,79301
29,50	8,50	5,26	0,95637
29,50	8,40	5,00	1,08494
29,50	8,40	4,64	0,59301
29,50	8,30	4,35	0,55946
29,50	8,30	5,45	0,64364
29,50	8,30	5,52	0,72566
29,50	8,20	5,34	0,87468
29,50	8,20	5,15	0,99484
29,50	8,20	4,82	0,78875
29,50	8,10	4,56	0,59553
29,50	8,60	5,05	0,62448
29,50	8,40	5,45	0,79301
29,50	8,40	5,38	0,61418
29,50	8,40	5,00	0,28002
29,50	8,70	5,49	0,31928
29,50	8,60	6,27	0,30485
29,50	8,80	6,41	0,27454

E. Filtering Euclidean Distance Results

Proses filtering dilakukan setelah perhitungan jarak antar data menggunakan metode Euclidean Distance[23]. Filtering dilakukan dengan menyusun hasil perhitungan jarak secara ascending, dimulai dari jarak terkecil hingga terbesar. Hasil ini memungkinkan identifikasi data yang paling dekat atau paling mirip dengan titik acuan (reference point).

Data with minimal distance is indicative of a higher level of similarity or closeness, and as such is prioritised for further analysis. Conversely, data with a greater distance demonstrates significant disparities from the reference point, and can be utilised for the purposes of grouping or other evaluations. This filtration process is of paramount importance in the selection of pertinent data and the reduction of analytical complexity, particularly in circumstances involving voluminous data sets. The outcomes of this filtration process will serve as the foundation for subsequent stages, including classification, clustering, and model validation, thereby enhancing the accuracy and efficiency of data analysis in supporting pond management.

TABLE IV. WEIGHTED EUCLIDEAN DISTANCE RESULTS

Temperatur (°C)	pH	Dissolved Oxygen (mg/L)
29,50	8,10	4,56
29,50	8,20	4,82
29,50	8,30	4,35
29,50	8,40	4,64
29,50	8,40	4,82
29,50	8,20	5,15
29,50	8,40	5,00
29,50	8,40	5,00
29,00	8,80	5,31
29,50	8,50	4,86
28,50	8,80	5,70
28,50	8,50	5,96
29,00	8,60	5,60
29,50	8,20	5,34

29,00	8,80	5,38
28,50	8,50	6,01
29,00	8,80	5,41
28,50	8,80	5,78
29,50	8,60	4,86
29,50	8,40	5,23
28,50	8,70	5,89
29,50	8,70	4,56
29,50	8,70	4,56
29,50	8,70	4,60
29,50	8,70	4,68
29,50	8,70	4,68
29,50	8,60	5,05
28,50	8,90	5,75
28,50	9,00	5,63
29,50	8,30	5,45

F. Filtering Weighted Euclidean Distance Result

Following the calculation of the distance between the data using the Weighted Euclidean Distance method, the subsequent step is to carry out filtering by sorting the calculation results in ascending order, starting from the smallest distance to the largest[24]. The objective of this process is to ascertain the data that exhibits the greatest proximity to a reference point, a task accomplished by evaluating the weights that have been assigned to each parameter.

It is evident that data with minimal distance is indicative of a higher level of similarity or relevance. This is due to the fact that parameters with greater weights exert a dominant influence on the calculation of distances. Conversely, data with larger distances demonstrates more significant disparities and can be utilised for pattern analysis or other groupings.

This filtration process offers the advantage of selecting the most pertinent data for subsequent analysis, while ensuring that the final results are more aligned with the predetermined parameter priorities. The results of the Weighted Euclidean Distance filtration process are a vital foundation for subsequent stages, such as classification, clustering, or model validation, thereby supporting pond management more effectively and based on accurate data[25].

TABLE V. WEIGHTED EUCLIDEAN DISTANCE RESULTS

Temperatur (°C)	pH	Dissolved (mg/L)	Oxygen
29,50	8,30	6,77	
29,50	8,90	6,71	
29,50	8,40	6,92	
29,50	8,80	6,82	
29,50	8,30	6,96	
29,50	8,70	6,22	
29,50	8,80	6,41	
29,50	8,40	5,00	
29,50	8,60	6,27	
29,50	8,70	5,49	
29,50	8,70	5,60	
29,50	8,70	6,30	
29,50	8,70	6,04	
29,50	8,60	6,77	
29,50	8,50	7,07	
29,50	8,50	6,63	
29,00	8,80	5,75	
29,50	8,30	4,35	
29,50	8,40	7,03	
29,00	8,90	5,67	

29,50	8,40	4,64
29,50	8,10	4,56
29,50	8,40	5,38
29,50	8,80	6,19
29,00	8,80	5,56
29,00	8,80	5,89
29,50	8,60	5,05
29,50	8,90	6,30
30,00	8,90	5,49
29,50	9,00	5,15

CONCLUSION

The objective of this research was to develop and test an Internet of Things (IoT) system for the real-time monitoring of water quality parameters in shrimp ponds. The integrated system incorporates three primary parameters: temperature, pH, and dissolved oxygen (DO). The experimental results demonstrate the system's capacity to measure water quality parameters in real-time and automatically transmit data via the internet network to a cloud-based monitoring platform.

The utilisation of the Euclidean distance and weighted Euclidean distance methods in data analysis has been demonstrated to facilitate the identification of patterns and proximity between data with a satisfactory degree of accuracy. The implementation of ascending sorting has been shown to enhance the filtration of the most pertinent data for subsequent analysis. Weighted Euclidean distance has been empirically substantiated to yield more representative results by taking into account the weight of different parameters according to their level of importance.

The development of the Internet of Things (IoT) system has demonstrated considerable promise in facilitating efficient, data-driven shrimp pond management. The implementation of this system is anticipated to enhance pond productivity, mitigate the risk of losses attributable to variations in water quality, and promote the sustainable cultivation of shrimp.

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REFERENCES

[1] S. A. Jayandan, K. Prathibanandhi, A. Sahana, M. B. Agilesh, and D. M. R, “Aquaculture Water Quality Monitoring System,” 2023 Intell. Comput. Control Eng. Bus. Syst., pp. 1–3, 2023, doi: 10.1109/ICCEBS58601.2023.10449172.

[2] S. S. Natva and S. Nannuru, “Denoising and Completion of Euclidean Distance Matrix from Multiple Observations,” 2024 Natl. Conf. Commun. NCC 2024, pp. 1–6, 2024, doi: 10.1109/NCC60321.2024.10485874.

[3] N. A. Mohd Jais, A. F. Abdullah, M. S. Mohd Kassim, M. M. Abd Karim, A. M, and N. ‘Atirah Muhadi, “Improved accuracy in IoT-Based water quality monitoring for aquaculture tanks using low-cost sensors: Asian seabass fish farming,” Heliyon, vol. 10, no. 8, p. e29022, 2024, doi: 10.1016/j.heliyon.2024.e29022.

[4] P. Songpayome et al., “A prototype pond water management system (dissolved oxygen, pH and temperature) for giant freshwater prawn farming in Pak Phanang, Southern Thailand,” Heliyon, vol. 10, no. 10, p. e31231, 2024, doi: 10.1016/j.heliyon.2024.e31231.

[5] F. Cheng, “A Comparative Study of the Performance of Spark-based k-Means Algorithm Based on Euclidean Distance and Manhattan Distance,” Proc. - 2024 3rd Int. Conf. Big Data, Inf. Comput. Network, BDICN 2024, pp. 15–20, 2024, doi: 10.1109/BDICN62775.2024.00010.

[6] R. Ullah, I. Asghar, M. G. Griffiths, C. Stacey, W. Stiles, and C. Whitelaw, “Internet of Things based Sensor System for Vertical Farming and Controlled Environment Agriculture,” Proc. - 2023 6th Conf. Cloud Internet Things, CIoT 2023, pp. 136–140, 2023, doi: 10.1109/CIoT57267.2023.10084913.

[7] I. Essamlali, H. Nhaila, and M. El Khaili, “Advances in machine learning and IoT for water quality monitoring: A comprehensive review,” Heliyon, vol. 10, no. 6, p. e27920, 2024, doi: 10.1016/j.heliyon.2024.e27920.

[8] D. Feng, Q. Han, L. Xu, F. Sohel, S. G. Hassan, and S. Liu, “An ensembled method for predicting dissolved oxygen level in aquaculture environment,” Ecol. Inform., vol. 80, no. August 2023, p. 102501, 2024, doi: 10.1016/j.ecoinf.2024.102501.

[9] C. Jamroen, N. Yonsiri, T. Odthon, N. Wisitthiwong, and S. Janreung, “A standalone photovoltaic/battery energy-powered water quality monitoring system based on narrowband internet of things for aquaculture: Design and implementation,” Smart Agric. Technol., vol. 3, no. May 2022, p. 100072, 2023, doi: 10.1016/j.atech.2022.100072.

[10] A. H. Eneh et al., “Towards an improved internet of things sensors data quality for a smart aquaponics system yield prediction,” MethodsX, vol. 11, no. October, p. 102436, 2023, doi: 10.1016/j.mex.2023.102436.

[11] F. Ahmed, M. H. I. Bijoy, H. R. Hemal, and S. R. H. Noori, “Smart aquaculture analytics: Enhancing shrimp farming in

Bangladesh through real-time IoT monitoring and predictive machine learning analysis," Heliyon, vol. 10, no. 17, pp. 1–19, 2024, doi: 10.1016/j.heliyon.2024.e37330.
[12] K. Long, B. Xie, Z. Li, G. Xia, and Y. Wang, "A CSI Indoor Positioning Method for Massive MIMO with Reduced Sample Redundancy Based on Euclidean Distance," 2024 9th Int. Conf. Intell. Comput. Signal Process. ICSP 2024, pp. 485–489, 2024, doi: 10.1109/ICSP62122.2024.10743281.
[13] H. Bai, H. Li, W. Yi, and Z. Zou, "Accurate Association of Radar-Vision Measurements Based on Weighted Euclidean Distance," Proc. - 12th IEEE Int. Conf. Control. Autom. Inf. Sci. ICCAIS 2023, pp. 387–392, 2023, doi: 10.1109/ICCAIS59597.2023.10382269.
[14] F. J. Toledo, V. Galiano, J. M. Blanes, V. Herranz, and E. Batzelis, "Photovoltaic single-diode model parametrization. An application to the calculus of the Euclidean distance to an I–V curve," Math. Comput. Simul., vol. 225, pp. 794–819, 2024, doi: 10.1016/j.matcom.2023.01.005.
[15] L. Jiang, W. Wang, S. Zheng, S. Xu, J. Mao, and L. Ding, "A Novel Data Edge Mining Algorithm With Euclidean Distance Weighted Optimization for Integrated Energy Station," ITOEC 2023 - IEEE 7th Inf. Technol. Mechatronics Eng. Conf., vol. 7, pp. 67–71, 2023, doi: 10.1109/ITOEC57671.2023.10291381.
[16] X. An, X. Cui, S. Zhao, G. Liu, and M. Lu, "Efficient Rigid Body Localization Based on Euclidean Distance Matrix Completion for AGV Positioning Under Harsh Environment," IEEE Trans. Veh. Technol., vol. 72, no. 2, pp. 2482–2496, 2023, doi: 10.1109/TVT.2022.3213179.
[17] C. Wulandari, P. Astutik, R. C. Soegito, Y. S. Dharmawan, H. Munawaroh, and T. Bariyah, "Hybrid MCDM Career Recommendation System for Information System Student Using AHP, VIKOR and Weighted Euclidean Distance," Procedia Comput. Sci., vol. 234, pp. 364–372, 2024, doi: 10.1016/j.procs.2024.03.016.
[18] N. F. Mufidah, H. H. Nuha, and N. Anggis, "Monitoring and Prediction of Water Quality in Catfish Biofloc Ponds at SEIN Farm using IoT and Linear Regression," 2023 Int. Conf. Artif. Intell. Blockchain, Cloud Comput. Data Anal. ICoABCD 2023, pp. 13–18, 2023, doi: 10.1109/ICoABCD59879.2023.10390926.
[19] A. P. Gopi and K. J. Naik, "An IoT model for Fish breeding analysis with water quality data of pond using Modified Multilayer Perceptron model," 2022 Int. Conf. Data Anal. Bus. Ind., pp. 1–6, 2022, doi: 10.1109/ICDABI56818.2022.10041617.
[20] A. Quevy, "Data Integrity Analysis of Water Quality Sensors and Water Quality Assessment," IECON 2022 – 48th Annu. Conf. IEEE Ind. Electron. Soc., pp. 1–6, doi: 10.1109/IECON49645.2022.9968643.
[21] D. E. Saputra, D. Suandi, J. W. Sunarto, and P. Michael, "Aerial images and water quality dataset for fishpond's condition monitoring," Data Br., vol. 52, p. 110009, 2024, doi: 10.1016/j.dib.2023.110009.
[22] X. Sha, Z. Ma, S. Sethuvenkatraman, and W. Li, "A new clustering method with an ensemble of weighted distance metrics to discover daily patterns of indoor air quality," J. Build. Eng., vol. 76, no. July, p. 107289, 2023, doi: 10.1016/j.jobe.2023.107289.
[23] T. Ouyang and Q. Li, "Exploiting the Degeneracy of Euclidean Distance Matrix Completion Problem," 2024 7th Int. Conf. Comput. Inf. Sci. Appl. Technol. CISAT 2024, pp. 1164–1169, 2024, doi: 10.1109/CISAT62382.2024.10695191.
[24] X. Liu and F. Li, "Research on Fault Detection Method Based on Improved Euclidean Distance Control," 2022 IEEE 17th Conf. Ind. Electron. Appl., pp. 106–111, 2022, doi: 10.1109/ICIEA54703.2022.10006143.
[25] M. Mahdavi, "Multidimensional Euclidean Distance Calculation using In-Memory Computing," Proc. 2024 IEEE Int. Conf. Comput. Information, Telecommun. Syst. CITS 2024, pp. 1–8, 2024, doi: 10.1109/CITS61189.2024.10608030.