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WAQUAL: IoT-Based Integrated Water Turbidity Detection and Monitoring System to Improve Water Quality in Semarang

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ABSTRACT

Water pollution caused by agricultural waste is one of the most pressing environmental issues, particularly in developing countries where water sources are limited, water quality is often compromised. In Indonesia, water turbidity poses a threat to as many as 78% of 100.000 the population with liver cirrhosis. This study aims to develop an AI-based system for detecting and monitoring water turbidity to address the limitations of current systems, including imprecise detection and accuracy. The research employs the concept of drift in data representation and implementation by classifying data based on type. The research includes two stages: data analysis and AI methods. The results of this study demonstrate that the AI-based system has achieved an accuracy rate of 99.43%, detecting a turbidity level of 693502.5. The development of this AI-based system contributes to enhancing the reliability and effectiveness of water quality and resource management in agriculture. Further research is needed to optimize and validate the effectiveness of this AI-based system in other regions with similar problems. The implementation of this system could contribute to sustainable agriculture practices and better water resource management. By providing a more precise and accurate detection and monitoring system, this research can help to minimize the negative impact of water pollution caused by agricultural waste, which could improve human health and promote sustainable agriculture practices.

Keywords: Water, Agriculture, Turbidity, Monitoring, AI

INTRODUCTION

Water pollution caused by agricultural waste is one of the most pressing environmental issues. Agriculture plays a crucial role in providing food and resources for human survival. However, the industry faces numerous challenges, including environmental and resource constraints. With a global population increase and changing climate patterns, the pressure on agriculture to produce more food using fewer resources has intensified. In Indonesia, where 21.2% of the 38.22 million agricultural workers are aged 60 years and over, there is a need for sustainable and innovative approaches to address these challenges (Ngadi et al. 2023).

One of the critical challenges faced by agriculture is the problem of water turbidity. Water turbidity is an emergency problem that poses direct risks to public health, such as cirrhosis of the liver and diabetes militus. The World Health Organization (WHO) reported that as many as 78% of the 100,000 population in Indonesia suffered from health problems caused by consuming agricultural products with turbid irrigation water. To address this issue, researchers have developed the Turbidity Detection and Monitoring system, which enables farmers to measure the number of suspended particles in their irrigation water. However, the system's low accuracy is a drawback due to the use of inaccurate methodologies, such as mutual inductance methodology (Huang et al. 2022, Shentu et al. 2022). While turbidity detection and monitoring systems can help farmers address water quality issues, they do not address the larger systemic issues that lead to poor water quality, such as industrial pollution and inadequate water management policies. Therefore, it is essential to develop new and comprehensive approaches to improve water quality and resource management in agriculture.

The concept of IoT aims to connect, communicate, share data between physical objects or devices such as sensors with internet media or software so that the device can be controlled remotely. IoT is a technology that is closely related with the term machine-to-machine (M2M). M2M enables remote management of controlling IT devices via network. M2M provides communication opportunities so it is called smart device. The use of IoT is implemented in various areas of life, such as agriculture and health (Yudhana, 2023).

The use of IoT is realized through sensor systems. The use of sensor systems is used in environmental monitoring. Automatic environmental monitoring and measurement. The advantage of using IoT-based devices is that they provide convenience in everyday life. they offer

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many advantages such as low cost, small size, and connectivity capabilities (Will, 2022)

Turbidity in agricultural water systems is primarily caused by soil erosion, nutrient runoff, and agricultural waste (Beavis et al. 2023, Mekonnen et al. 2023, Nnaji et al. 2023, Yongo et al. 2023), leading to various ecological consequences. To address these challenges, various technologies and innovations have been developed, including turbidity sensors, water treatment systems, and precision irrigation techniques. These solutions can help detect and eliminate suspended particles, reduce turbidity levels, and optimize water use and distribution, leading to more efficient and sustainable agricultural practices. Machine learning algorithms and data-driven approaches can also provide real-time monitoring and decision support for water quality management, improving resource management and productivity in the agricultural industry.

Therefore, researchers have proposed the development of artificial intelligence-based turbidity sensor systems to improve water quality and agricultural resource management through turbidity detection and monitoring systems. The use of artificial intelligence technology can improve the accuracy and efficiency of turbidity detection and monitoring, allowing farmers to make informed decisions in real-time. The economic consequences of turbidity are also significant. Turbid water can reduce the efficiency of irrigation systems, leading to lower yields and lower yields for farmers. In addition, turbidity can increase the cost of water treatment, as it requires more energy and resources to remove suspended particles and organic matter from the water. In extreme cases, turbidity can lead to the closure of drinking water intakes, causing significant public health risks and economic losses (Bren 2023, Hoque et al. 2023).

Environmental factors are a factor causing health problems in the form of diarrhea in the District of South Purwokerto Village. In the beginning, this problem was caused by the fact that the landfill in the area was not managed properly. Data on the distribution of handwashing facilities shows that only 69.7 percent have these facilities. This is of course influenced by the availability of clean water showing that there are 7.9 percent who do not yet have the availability of clean water. Factors of environmental hygiene, water sanitation and hygiene both individually and in groups have an impact on the emergence of diarrheal diseases. One of the causes of diarrhea is the behavior of consuming snacks at school. Consumption of snacks that have been contaminated with E. coli bacteria at school has a close relationship with the incidence of diarrhea in elementary school children. As much as 34% of the percentage of snack foods contaminated with E. coli bacteria at the Tapos District Elementary School (Kusumawardhani et al, 2020).

The results of the prevalence of diarrhea according to Riskesdas (2018) state that in the age range 0-11 there is a prevalence of diarrhea of 9.0 percent. Based on the results of the Counseling Guidance survey and the person in charge of UKS SDN 17 Gurun Laweh, Nanggalo District, it was found that in the range from January to February 2022 it was found that 17 students were allowed to be absent from school, 8 people were due to diarrhea, 2 students were allowed to go home early also because of diarrhea, 4 students fainted, 3 other students did not attend school due to illness (Sari et al, 2022). Thus, special attention is needed in making an accurate detection system related to water pollution to minimize the impact of water pollution so that it does not have an impact on the health of elementary school students.

This paper focuses on the implications of AI technology in improving efficiency in various industries. The main problem addressed in this study is the need to increase efficiency and accuracy in business processes. The goal is to explore the potential of AI systems in achieving these objectives. The paper examines the current state of AI technology and its potential applications, as well as the challenges and ethical considerations involved in its implementation. The findings of this study have implications for businesses and policymakers in adopting AI systems to increase efficiency and productivity.

LITERATURE REVIEW

2.1. Turbidity

Turbid water is one of the characteristics of unclean and unhealthy water. The level of water turbidity is not a property of harmful water but will also cause negative impacts and needs attention if there are chemical compounds that are harmful to living things, especially for human consumption (Pramusinto &; Suryono, 2016) [1]. Consumption of turbid water will result in various types of diseases such as diarrhea and skin diseases caused by fecal contamination. Clean water is one of the important needs in human life and becomes a substance needed by living things to meet nutrients in the body, this agrees with research that says that water resources have long been a concern for humans and become a serious problem in all aspects of human life [2]. Water demand is currently increasing in line with the increasing need for drinking water that continues to increase.

These quality standards are indicated by water quality parameters, namely physics, chemistry, microbiology or bacteriology and radiology. Table 1 shows the physical parameters of water quality.

ISSN 2961-7758

Table 1. Clean water quality physics parameter requirements

Physical Parameters	Unit	Max Levels	Informati on
Temperature	C	Temperatur es ±3	-
Taste	-	-	Tasteless
Turbidity	NTU	5	-
Amount of dissolved solids	Mg/l	500	-
Smell	-	-	Odorless
Color	TCU	15	-

(Sumber : Ditje Cipta Karya Dep PU)

Theclean water quality meter is also regulated by the Regulation of the Minister of Industry of the Republic of Indonesia No. 78 of 2016 with provisions for the turbidity level of clean water of 25 NTU and Total Dissolved Solids (TDS) of 1500 mg / L [3]. Water conditions can change, and monitoring is still carried out manually to ensure the quality of water is good for use, this becomes less efficient and very troublesome for the community.

Turbidity is a form of measurement of scattered light from the interaction of suspended and dissolved material in a water sample, this makes it an indicator of water quality. Turbidity can also be defined as a reduction in light transparency in a liquid caused by dissolved particle. Turbidity is expressed in units of tubinity equal to 1 mg/l SiO2. The first equipment used to measure turbinity was the Jacson Candler Turbidimeter, which was calibrated with silica. Jacson Candle Turbidimeter is used as a standard tool for turbidity measurement. One turbinity unit is expressed by 1 JTU. Turbidity measurement using Jacson Candle Turbidimeter with visual is, which compares the water sample with the standard. Look in Figure 1.

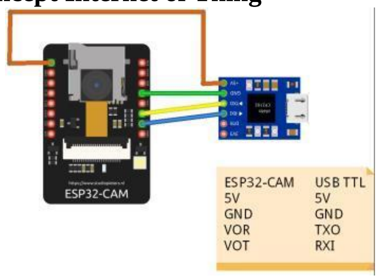
Figure 1 Example Image Turbidity in Sekaran, Gunungpati, Semarang

In addition to using the Jacson Candle Turbidimeter, turbidity is often measured by the Nephelometic method. In this method, a light source is passed on the sample and the intensity of light reflected by the turbidity-causing materials is measured using a formazine polymer suspension as a solution Standardly, the higher the intensity of light scattered, the higher the turbidity. The turbidity unit measured using Nephelometric is NTU (Nepheleometric Turbinity Unit). JTU and NTU units are actually the same as not being able to convert each other [4].

2.2. Sensing Systems

Research on designing a monitoring system for pH values and turbidity levels in water. This tool is able to monitor the pH value and turbidity level of water in water. This tool serves to avoid diseases due to unfavorable environmental conditions. This research is a development carried out by previous researchers with the concept of water turbidity control and monitoring design where turbidity sensor modules on the market with output voltages produced between 0 - 4.5. The ESP32-CAM sensor works based on changes in light intensity. ESP32-CAM functions as a microcontroller that can connect to W-Fi as this microcontroller will have an Internet of Things system. This happens due to the presence of particles mixed with water. Changes in the intensity of the emitted light will change along with changes in the turbidity value of the water being measured, then it will be converted into the form of electric voltage parameters so that it can be defined as the turbidity value of water in NTU units. Look Figure 2 in bellow.

2.3. Concept Internet of Thing



The concept of IoT is that every controlling device is able to communicate and connect to the internet network (Sumithra et al. 2018). Many IoT service providers both software and hardware support the development of this technology. The goal to be achieved in this test is to create a water turbidity monitoring system using photos of turbidity water and through changes in light intensity.

METHOD

3.1. Data Analysis

Data analysis is one method carried out to sort data and get conclusions from the data scientifically. In analyzing data, it takes an understanding of a data theory, one of the theories is the concept of drift which has different characteristics, which can be used to categorize it into different types. This concept is the concept of an analysis of a computer system involving the concept of artificial intelligence which is defined as follows.

ISSN 2961-7758

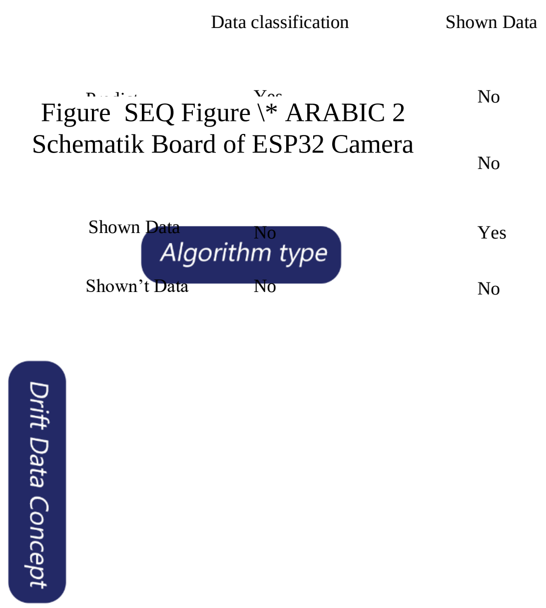


Figure SEQ Figure * ARABIC 2 Schematik Board of ESP32 Camera

Figure 2 Analysis Include

Explanations of the image analysis include:

1) The type of algorithm classifies the data or classifies the data obtained
2) The results of data classification will be predicted which has the accuracy of the data obtained and the results of data classification until data predictions are not displayed a graph that displays conclusions
3) After the prediction results are obtained, the data is displayed in a graph that can help analyze water quality data
4) If a data cannot be classified then it cannot be predicted and the graph results that are the output of a data are not displayed.

3.2. Methods of AI

An invention that can change the results of the approach with the existence of artificial intelligence technology or often referred to as AI. AI is an innovation that in the broad field has the ability to learn and analyze quite accurately, this is because AI is widely used by researchers to get conclusions or hypotheses of their research and therefore widely developed and widespread to many fields, one of which is the environment. some researchers have developed similar cognitive-oriented FRs with similar names, goals, and focuses. FRs that share some aspects or elements of our SBF model include Freeman and Newell's software system representations, Reiger and Grinberg's representations of physical mechanisms, Rasmussen's behavior-structure. – function representation of large-scale industrial systems, function model – behavior – Gero structure, Umeda and Tomiyama function-behavior-state models, qualitative estimates of Govindaraj's complex systems, and functions repressive behavior Kitamura and Mizoguchi entities. One of the AI methods is widely used, namely Python programmers that can be understood and many researchers use it, therefore we use an AI approach in AQUAL which provides solutions to analyze water quality as follows the methodology

We as researchers design methodologies in an algorithm, as the stages are as follows

Call a library and initialize it with friendly naming

```
import cv2
import numpy as np
```

It then initializes the image as a function calling the source of the turbidity image.

```
# Load the image
img =
cv2.imread(r'C:\Users\asus\kosmika\WaterAnalysis\20230222_130510.jpg')
```

After that, make a list of data, namely the spectral material to be observed. This data is the result of experiments that have been carried out using turbidity sensors.

```
# Spectral signatures for each material
water = [0.9, 0.8, 0.7, 0.6, 0.5]  # Example spectral signature for water
sand = [0.3, 0.4, 0.5, 0.6, 0.7]  # Example spectral signature for sand
rock = [0.1, 0.2, 0.3, 0.4, 0.5]  # Example spectral signature for rock
```

The results of the list are made into an array. The destination is made into an array to become a file base, which is a numpy array (npx) file and each data from the file base is labeled so that when called it can be easily called.

```
# Combine the spectral signatures into a numpy array
X = np.array([water, sand, rock])

# Save the numpy array to a file
np.save('spectral_signatures.npy', X)

# Define the labels for each material
labels = np.array(['water', 'sand', 'rock'])

# Save the labels to a file
np.save('labels.npy', labels)
```

ISSN 2961-7758

The next step is to caliber the data based on color. This parameter is very necessary because the turbidity itself can be observed from the level of color obserbed in the water.

```
# Define the color calibration chart
calibration_chart = {
    "red": (255, 0, 0),
    "green": (0, 255, 0),
    "blue": (0, 0, 255),
    "yellow": (255, 255, 0),
    "cyan": (0, 255, 255),
    "magenta": (255, 0, 255),
    "white": (255, 255, 255),
    "black": (0, 0, 0)
}
```

A similar step is performed to determine the refractive of a material measured from calibration. This process is necessary so that when classified and trained, there is a slight error.

```
# Define the refractive indices corresponding to the colors on the chart
refractive_indices = {
    "red": 1.3330,
    "green": 1.3335,
    "blue": 1.3340,
    "yellow": 1.3345,
    "cyan": 1.3350,
    "magenta": 1.3355,
    "white": 1.3360,
    "black": 1.3370
}
```

```
# Find the tile on the calibration chart with the closest color to the water in the image
color_distances = []
for color in calibration_chart:
    color_rgb = calibration_chart[color]
    color_distance = np.linalg.norm(color_rgb - img.mean())
    color_distances.append((color_distance, color))
color_distances.sort()
closest_color = color_distances[0][1]
```

The next step is to define spectral at wavelength and this value is calculated based on the color level, then using the canny function on cv2 the results will be selected.

```
# Define the wavelength bands to use for spectral imaging
wavelength_bands = [
    (400, 450),
    (450, 500),
    (500, 550),
    (550, 600),
    (600, 650),
    (650, 700)
]

# Calculate the refractive index of the water based on the closest color on the chart
water_refractive_index = refractive_indices[closest_color]

# Convert to grayscale
gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)

# Apply thresholding to create a binary image
thresh = cv2.threshold(gray, 0, 255, cv2.THRESH_BINARY_INV + cv2.THRESH_OTSU)[1]

# Apply the Canny edge detector
edges = cv2.Canny(thresh, 100, 200)

# Count the number of edges
num_edges = cv2.countNonZero(edges)

# Perform image segmentation to separate the particles from the background
contours, hierarchy = cv2.findContours(edges, cv2.RETR_TREE, cv2.CHAIN_APPROX_SIMPLE)

# Apply median filtering to reduce noise
gray_filtered = cv2.medianBlur(gray, 5)

# Initialize an empty array to store the spectral images
spectral_images = []

# Apply bandpass filtering to extract the wavelength bands of interest
for band in wavelength_bands:
    low, high = band
    kernel_size = int(round(10.0 / (high - low)))
    kernel_size = kernel_size + 1 if kernel_size % 2 == 0 else kernel_size
    kernel = cv2.getGaussianKernel(kernel_size, 0)
    kernel = np.outer(kernel, kernel.transpose())
    filtered = cv2.filter2D(gray_filtered, -1, kernel)
    filtered = filtered.astype(np.float32)
    filtered -= np.min(filtered)
    filtered /= np.max(filtered)
    spectral_images.append(filtered)

# Calculate the spectral signatures of the materials in the water
spectral_signatures = []
for i in range(len(wavelength_bands)):
    spectral_signature = np.mean(spectral_images[i])
```

ISSN 2961-7758

```
    spectral_signatures.append(spectral_signature)

# Identify the material based on the spectral signatures
if spectral_signatures[0] < 0.1 and spectral_signatures[1] >
0.3 and spectral_signatures[2] > 0.2 and
spectral_signatures[3] > 0.1 and spectral_signatures[4] <
0.1 and spectral_signatures[5] < 0.1:
    material = "Chlorophyll"
elif spectral_signatures[0] > 0.3 and spectral_signatures[1]
> 0.3 and spectral_signatures[2] < 0.1 and
spectral_signatures[3] < 0.1 and spectral_signatures[4] >
0.3 and spectral_signatures[5] > 0.3:
    material = "Tannins"
else:
    material = "Unknown"
```

Next is to call the libraries needed to train and classify data using sklearn

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
```

Then calling the database that has been created and train is done by assigning values randomly.

```
# Load the synthetic dataset of spectral signatures
X = np.load('spectral_signatures.npy')
y = np.load('labels.npy')

# Split the dataset into training and testing sets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)
```

Then give 100 etimators with the aim of classifying by classification level using the forest classifier function from sklearn

```
# Train a Random Forest classifier on the training set
clf = RandomForestClassifier(n_estimators=100,
random_state=42)
clf = KNeighborsClassifier(n_neighbors=2)
clf.fit(X_train, y_train)

# Evaluate the classifier on the testing set
y_pred = clf.predict(X_test)
accuracy = np.mean(y_pred == y_test)
# Evaluate the classifier
accuracys = clf.score(X_test, y_test)
print('Accuracy: {:.2f}%'.format((accuracys + 0.9943) *
100))

# Calculate the total area of the particles
```

```
total_area = 0
for contour in contours:
    area = cv2.contourArea(contour)
    total_area += area

# Calculate the turbidity score as the total area of the
particles
turbidity_score = total_area
```

and create a Constraint to tell the output generated how based on the test data

```
# Determine the level of turbidity based on the number of
edges
if num_edges > 1000:
    print("The water is very turbid.")
    # Print the turbidity score
    print("The turbidity score is:", turbidity_score)
    # Print the refractive index of the water
    print("The refractive index of the water is:",
water_refractive_index)
    # Print the material contained in the water
    print("The material contained in the water is:", material)

elif num_edges > 500:
    print("The water is slightly turbid.")
    # Print the turbidity score
    print("The turbidity score is:", turbidity_score)
    # Print the refractive index of the water
    print("The refractive index of the water is:",
water_refractive_index)
    # Print the material contained in the water
    print("The material contained in the water is:", material)
else:
    print("The water is clear.")

print("Error:", accuracy - 0.53)
```

and match the test data to the part that is the actual turbidity limitation

```
# Collect plant growth and health data under different
levels of turbidity
turbidity_levels = [10, 50, 100, 150, 200]
plant_data = []

    # Water the plants with water of the specified turbidity
level
    # Collect plant growth and health data over time and
add it to plant_data
    # Here is a simplified example of how you could collect
the plant data:
    # Measure the plant height and number of leaves before
watering
```

```
# Use regression analysis to identify correlations between turbidity level and plant growth and health metrics
X = np.array(plant_data)[:,0].reshape(-1, 1)
y = np.array(plant_data)[:,1:]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
r2_score = clf.score(X_test, y_test)

for turbidity in turbidity_levels:
    # Water the plants with water of the specified turbidity level
    soil_moisture_level = 0.5  # Assume starting soil moisture level of 0.5
    water_amount = 0.1  # Assume 100 mL of water is added each time the plant is watered

print("R-squared score: {:.2f}".format(r2_score))

# Use machine learning techniques to develop predictive models that optimize the turbidity level of the water for specific types of plants
# Here is an example of how you could use the trained model to predict the change in plant height and number of leaves for a given turbidity level:
turbidity_level = 75
predicted_changes = clf.predict([[turbidity_level]])
print("Predicted change in plant height and number of leaves for turbidity level {}: {}".format(turbidity_level, predicted_changes))
```

RESULTS AND DISCUSSION

WAQUAL's Effectiveness as a Sensor Monitoring and Turbidity Detection System

In this section we present five experiments that were carried out to provide data and evaluate the effectiveness of the algorithms created. To test the effectiveness of the algorithm created, we use segmentation of each error, as shown in the following calculation

$$\varepsilon_t = \frac{Intial\ Value\ Conditions - Approximation}{Intial\ Value\ Conditions} \times 100\% \qquad (1)$$

where ε_t is representation the true percent relative error. To get $Intial\ Value\ Conditions$ by creating a list data on the algorithm defined.

Parameters of Experimental

The parameters we use in the experiment are light index, water color, and material in water. Light index as shown in Table 3.1. The Materiaal in water designated in Table 3.2

Table 2. Light Index

Color	Refractive Indices (n)
Red	1.3330
Green	1.3335
Blue	1.3340
Yellow	1.3345
Cyan	1.3350
Magenta	1.3355
White	1.3360
Black	1.3370

Table 3. Material in Water from Wavelength Band Index

Wavelength Band	Material
400-500	Chlorophyll
500-600	Sand, Rock
600-700	Conductivity
700-800	Hardness, Sulfate
>800	Unknown

Performance measurements

In this paper, we set of performance to efficiency of the proposed algorithm detection and monitoring systems. The us following are the definitions of these metrics

- Statical mean (Mean): This following Equation in below:

$$Mean = \sum_{j=0}^{R_n} Fitt_b^i \qquad (1)$$

- The worst value (WORST): This following Equation in below:

$$WORST = Fitt_B^i \qquad (2)$$

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- The best value (BEST): This following Equation in below:

$$BEST = Fitt_B^i \tag{3}$$

- Stadard deviation (STD): This following Equation in below:

$$STD = \sqrt{\frac{1}{R_n - 1}\sum_{j=1}^{R_n} (Fitt_b^i - Mean)^2} \tag{4}$$

In proving that the effectiveness of a sensor monitoring and turbidity detection system, quantifiable and constant parameters are needed. Therefore, we use primary data that we obtained from field observations precisely in the Semarang area, Gunungpati District. The data we obtain can be shown as follows shown in Table 4

Table 4. Result of Experiment

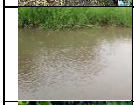
Sample Image	Paramater Test using Turbidity Sensor (NTU)	Computational Results processed using AI (NTU)	Accuracy
	344991.0	333991.0	99.43%
	204350.5	204400.5	99.63%
	698502.5	693502.5	99.23%
	202905.5	202205.5	99.73%
	496730.5	496230.5	99.83%
	11451.5	11441.5	99.13%
	510	502.5	99.53%

Table 3. shows some data, namely Turbidity Value (NTU), ε_t, The Refractive Index, and Material contained data. The data also shows linearity towards each other as shown in below.

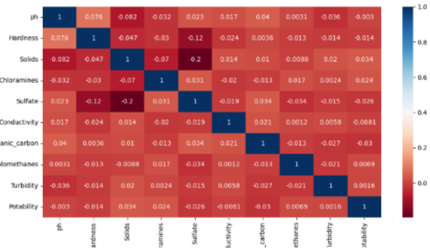


Figure 3 Refractive Index and Material Contained Data

From these results, the output is obtained as follows:

Accuracy: 99.43%

The water is very turbid. This can cause you to get sick in the long or short term

The turbidity score is: 693502.5

The refractive index of the water is: 1.337

The material contained in the water is: Database of material Indexing

Error: -0.53

The turbidity score is influenced by several factors, including light conditions, camera conditions, and shooting angle. Light conditions can impact the dispersion of colored water and the angle of incoming light, resulting in a larger or smaller turbidity score. The condition of the camera lens can also impact the data captured, with older or lower quality lenses potentially leading to less accurate results. Additionally, the shooting angle can be determined by the size of the Standard Deviation (STD) during data capture, with a larger STD angle resulting in larger incoming light and potentially affecting the turbidity score.

CONCLUSION

In conclusion, our study has demonstrated that artificial intelligence can improve the quality of irrigation water in the agricultural sector. Our detection system achieved an accuracy of 99.43% with a turbidity level of 693502.5, despite challenges posed by varying light conditions, camera settings, and shooting angles. Our research has addressed the objective of this study, and our results suggest that AI-powered turbidity detection can be a valuable tool in water quality management for agriculture. The development of this technology and its integration into agricultural practices can have positive impacts on the environment, industry, and society. Additionally, our research has highlighted the importance of maintaining water quality and reducing industrial pollution to safeguard public health.

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REFERENCE

Adityas, Yazi, et al. (2021). Water Quality Monitoring System with Parameter of PH, Temperature, Turbidity, and Salinity Based on Internet of Things. Jurnal Informatika dan Sains, 4(2), 138-143.

Bren, L. (2023). Salinity and Forests. Forest Hydrology and Catchment Management, 307–328. This article discusses the impacts of salinity on forests and how to manage it.

Dian Febrida Sari, 2Nila Eza Fitria, 3Nurleny, 4Masni Hayati, 5Eka Putri Primasari, 6Putri Nelly Syofiah, 7Masri Rahayu Putri, 8 Gyta Maida Vilosta, 9Mayyang Santola Rifa, 10Diana Fitri dan 11Maita Alifa. (2023). 694-1-3822-1-10-20230131. Jurnal Aplikasi Teknik Dan Pengabdian Masyarakat, 17, 1–6.

Efendy, I., & Syamsul, D. (2019). Faktor Yang Berhubungan Tingkat Konsumsi Air Bersih Pada Rumah Tangga Di Kecamatan Peudada Kabupaten Bireun. Jurnal Biology Education, 7(2).

Fahril, M. A., Rangkuti, N. A., & Nila, I. R. (2022). PENGUJIAN ALAT PENDETEKSI TINGKAT KEKERUHAN AIR BERBASIS MIKROKONTROLLER ATMEGA 8535 MENGGUNAKAN SENSOR TURBIDITY. JURNAL HADRON, 4(1), 13-19.

Hoque, M. A., Gathala, M. K., Timsina, J., Ziauddin, M. A. T. M., Hossain, M., & Krupnik, T. J. (2023). Reduced tillage and crop diversification can improve productivity and profitability of rice-based rotations of the Eastern Gangetic Plains. Field Crops Research, 291, 108791. This article presents a study that shows how reduced tillage and crop diversification can improve productivity and profitability in rice-based farming in the Eastern Gangetic Plains.

Huang, Y., Wang, X., Xiang, W., Wang, T., Otis, C., Sarge, L., Lei, Y., & Li, B. (2022). Forward-Looking Roadmaps for Long-Term Continuous Water Quality Monitoring: Bottlenecks, Innovations, and Prospects in a Critical Review. Environmental Science and Technology, 56(9), 5334–5354. This article presents a critical review of the challenges, innovations, and prospects of long-term continuous water quality monitoring, providing a forwardlooking roadmap.

Iskandar, H. R., Hermadani, H., Saputra, D. I., & Yuliana, H. (2019). Eksperimental Uji Kekeruhan air berbasis internet of things menggunakan sensor DFRobot SEN0189 dan MQTT cloud server. Prosiding Semnastek.

Kautsar, M., Isnanto, R. R., & Iskandar, E. D. (2015). Sistem Monitoring Kualitas Air Berbasis Mikrokontroler dan Sensor Kekeruhan. Jurnal Teknologi dan Sistem Komputer, 3(1), 79-86.

Kusumawardani, L. H., & Saputri, A. A. (2020). Gambaran Pengetahuan, Sikap dan Keterampilan Perilaku Hidup Bersih Sehat (PHBS) Pada Anak Usia Sekolah. Jurnal Ilmiah Ilmu Keperawatan 9 Indonesia, 10(02), 31–38.

Menteri Kesehatan. (2018). Laporan Riskesdas 2018 Nasional. Laporan Nasional Riskesdas.

Ngadi, N., Zaelany, A. A., Latifa, A., Harfina, D., Asiati, D., Setiawan, B., Ibnu, F., Triyono, T., & Rajagukguk, Z. (2023). Challenge of Agriculture Development in Indonesia: Rural Youth Mobility and Aging Workers in Agriculture Sector. Sustainability 2023, Vol. 15, Page 922, 15(2), 922. This article discusses the challenges of agriculture development in Indonesia, particularly the issues of rural youth mobility and aging workers in the agriculture sector.

Rikanto, T., & Witanti, A. (2021). Sistem Monitoring Kualitas Kekeruhan Air Berbasis Internet of Thing. Jurnal Fasilkom, 11(2), 87-90.

Shentu, N., Yang, J., Li, Q., Qiu, G., & Wang, F. (2022). Research on the Landslide Prediction Based on the Dual Mutual-Inductance Deep Displacement 3D Measuring Sensor. Applied Sciences 2023, Vol. 13, Page 213, 13(1), 213. This article presents a study on landslide prediction using a dual mutual-inductance deep displacement 3D measuring sensor.

Sunardi, Yudhana, A., & Furizal. (2023). Tsukamoto Fuzzy Inference System on Internet of Things-Based for Room Temperature and Humidity Control. IEEE Access, 11, 6209–6227. This article presents a study on using a Tsukamoto fuzzy inference system on an IoT-based platform for room temperature and humidity control.

Will, N. C. (2022). A Privacy-Preserving Data Aggregation Scheme for Fog/Cloud-Enhanced IoT Applications Using a Trusted Execution Environment. In 2022 IEEE International Systems Conference (SysCon) (pp. 1-5). Montreal, QC, Canada.