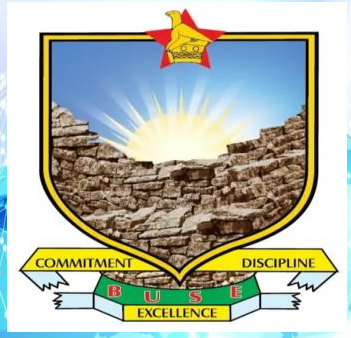
BINDURA UNIVERSITY OF SCIENCE EDUCATION

FACULTY OF SCIENCE AND ENGINEERING

DEPARTMENT OF COMPUTER SCIENCE



Research Project topic: A Hybrid Framework Approach for SMART Water Quality Monitoring and Predictive Analysis Using Internet of Things, and Random Forest Algorithm

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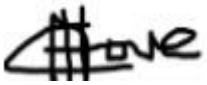
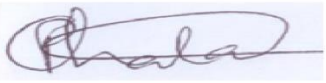
Approval form

The undersigned certify that they have supervised the student **Frank Matope (B211132B)** dissertation entitled, **"A Hybrid Framework Approach for SMART Water Quality Monitoring and Predictive Analysis Using Internet of Things, and Random Forest Algorithm"** submitted in partial fulfilment of the requirements of the **Bachelor of Science Honors degree in Network Engineering at Bindura University of Science Education**.

Supervisor - Mr D. Hove 

Chairperson - Mr P. Chaka 

Student – Frank Matope 

Dedication

This dissertation is dedicated to my dad, Mr. C Matope, my mother, Mrs. E Matope, and my big sisters for all the prayers, encouragement, and love they gave me over the years for my education and intellectual development.

Acknowledgements

I would like to thank and praise God the Almighty for the gift of life. A further acknowledgement goes to my family for the unconditional love and support throughout the journey. I would also like to express my gratitude to my supervisor, Mr. Hove, for his support, encouragement, and direction in the course of the research.

Abstract

This research presents a hybrid framework for SMART water quality monitoring and predictive analysis, integrating Internet of Things (IoT) technologies with the Random Forest algorithm. As water quality degradation poses significant risks to public health, agriculture, and ecosystems, timely and accurate monitoring is essential. The proposed framework employs IoT sensors to collect real-time data on critical water quality parameters such as pH, turbidity, and dissolved oxygen. These data streams are processed through a Random Forest algorithm to predict contamination events and detect anomalies, enabling proactive resource management. The study evaluates the system's performance through case studies and simulations, demonstrating high accuracy in predictions and efficient data processing. By merging IoT and machine learning, this framework addresses existing gaps in conventional monitoring methods, providing a scalable solution that supports sustainable water management and aligns with global health and environmental objectives.

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Abbreviations

IoT - Internet of Things
ML - Machine Learning
SMART - Specific, Measurable, Achievable, Relevant, Time-bound
UN - United Nations
WHO - World Health Organization
TDS - Total Dissolved Solids
DO - Dissolved Oxygen
BOD - Biochemical Oxygen Demand
MAE - Mean Absolute Error
RMSE - Root Mean Square Error
SVM - Support Vector Machines
LSTM - Long Short-Term Memory
CNN - Convolutional Neural Network
PCA - Principal Component Analysis
API - Application Programming Interface
WQI - Water Quality Index
NB-IoT - Narrowband Internet of Things
LoRaWAN - Long Range Wide Area Network

CHAPTER 1: INTRODUCTION

1.0 Introduction

Technological progress has fundamentally reshaped strategies for confronting global water quality challenges. With rising pollution concerns impacting public health, agriculture, and ecosystems, this domain demands urgent attention. This research introduces a hybrid SMART framework for water quality surveillance and contamination prediction, merging Internet of Things (IoT) sensors with Machine Learning (ML) to enable proactive resource management. This chapter details the study's context, problem statement, objectives, methodology, hypotheses, scope, limitations, and terminology.

1.1 Background of the Study

As a vital resource for life, industry, and agriculture, water quality degradation from urbanization, industrialization, and climate change poses severe risks (UNESCO, 2020). Conventional monitoring—reliant on manual sampling and lab analysis—proves inefficient for real-time data acquisition due to delays and expense (Chen et al., 2019).

IoT-ML integration offers transformative potential: Sensor networks continuously track parameters (pH, turbidity, temperature, dissolved oxygen), while ML algorithms detect anomalies and forecast contamination events (Zhang et al., 2021). This synergy promises sustainable, efficient water management.

1.2 Problem Statement

Water pollution triggers global health crises, ecological harm, and economic strain. Legacy systems reactively identify contamination post-occurrence—a critical shortfall in resource-limited regions needing immediate intervention (WHO, 2021).

Existing IoT deployments prioritize data collection but lack predictive capacity. Standalone ML models use historical data without real-time IoT integration. This gap impedes proactive water safety measures, necessitating an integrated IoT-ML solution.

1.3 Research Aim

This study develops and validates a hybrid IoT-ML system (using Random Forest) for SMART

water quality assessment, enabling real-time monitoring, contamination forecasting, and proactive resource governance.

1.4 Research Objectives

1. Design an IoT architecture for real-time tracking of pH, turbidity, dissolved oxygen, and temperature.
2. Develop ML models for contamination prediction and anomaly detection using live/historical data.
3. Assess system efficiency in water management via case studies and simulations.

1.5 Research Questions

1. How can IoT devices optimally capture real-time water quality metrics?
2. Which ML models best predict contamination and detect anomalies?
3. How does the hybrid approach outperform traditional methods in accuracy and efficiency?

1.6 Research Justification

This work bridges a critical gap by fusing IoT and ML for pre-emptive pollution response. The system delivers real-time insights and predictive analytics, enabling timely risk mitigation. Aligned with UN Sustainable Development Goal 6 (United Nations, 2020), it addresses escalating water scarcity while advancing public health, ecological conservation, and resource efficiency.

1.7 Literature Review

IoT-ML convergence enables real-time monitoring and predictive analytics. IoT sensors enhance spatial coverage and precision (Wang et al., 2022), while ML models (e.g., SVM, LSTM) outperform traditional methods in forecasting pollution trends (Li & Zhang, 2023). Hybrid ML techniques yield superior accuracy (Kumar & Reddy, 2021).

Integrated frameworks optimize data processing via cloud/edge computing (Ahmad et al., 2023), yet challenges persist: sensor calibration, energy efficiency, and data security require ongoing innovation (Sharma et al., 2022; Li & Zhang, 2023).

1.8 Methodology

A hybrid experimental-simulation approach employs IoT sensors (using LoRaWAN/MQTT) to stream data to cloud platforms. ML models train on historical/live datasets to predict risks. Case studies benchmark system performance against conventional methods in accuracy, scalability, and efficiency.

1.9 Research Hypotheses

- H1: IoT-ML integration significantly enhances monitoring accuracy and speed versus isolated systems.
- H2: ML-driven prediction reduces pollution response time, curtailing public/environmental hazards.

1.10 Scope

Focus: Freshwater bodies (rivers, lakes, reservoirs) monitored for key parameters (pH, turbidity, temperature, dissolved oxygen). Excluded: Water treatment processes.

1.11 Research Limitations

1. Geographical specificity of test sites.
2. Potential scarcity of high-fidelity historical training data.
3. Budget constraints affecting IoT deployment scale. I managed to buy only 2 sensors that is PH sensor and TDS meter sensor.

1.12 Definition of Terms

1. **IoT**: Networked physical devices exchanging sensor data via the internet.
2. **ML**: AI subfield enabling systems to learn from data autonomously.
3. **SMART**: Specific, Measurable, Achievable, Relevant, Time-bound objectives.
4. **Water Quality Parameters**: Indicators (pH, turbidity, etc.) determining water usability.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter synthesizes literature on IoT-ML hybrid frameworks for SMART water monitoring, analysing concepts, technologies, current implementations, and unresolved challenges to establish this study's theoretical foundation.

2.2 IoT in Water Quality Monitoring

IoT revolutionizes environmental sensing by enabling real-time tracking of parameters like pH and turbidity via wireless data transmission (Wang et al., 2022). Low-power protocols (LoRaWAN/NB-IoT) facilitate remote deployment (Sharma et al., 2022), though sensor durability, network stability, and data security remain hurdles (Ahmad et al., 2023).

2.3 ML for Predictive Analysis

ML processes historical/real-time data to forecast water quality and flag anomalies. Supervised models (e.g., SVM) effectively classify parameters, while LSTM networks excel in temporal forecasting (Kumar & Reddy, 2021). Data quality/sparsity critically impacts model robustness (Li & Zhang, 2023).

2.3.1 Previous Studies

ML adoption has expanded in the environmental/energy sectors. Research on supervised learning (including Random Forest) in predictive maintenance informs this study's methodology.

2.3.2 Predictive Maintenance Using Random Forest

Random Forest's proficiency with high-dimensional data makes it ideal for failure prediction. Studies demonstrate >92% accuracy in forecasting wind turbine failures (Chen et al., 2020) and solar panel degradation (Singh & Patel, 2022) when incorporating environmental variables.

A study by Wang et al. (2021), their findings indicated that the model achieved high precision in forecasting maintenance needs, reducing downtime and optimizing resource allocation. The research further emphasized that integrating sensor-based real-time monitoring improved the efficiency of predictive maintenance systems.

Similarly, Chen et al. (2020) implemented Random Forest to predict failures in renewable energy equipment, specifically focusing on wind turbines. Their study involved collecting and processing sensor data to identify potential faults. The authors highlighted the significance of feature selection in enhancing prediction accuracy, suggesting that incorporating environmental and operational parameters further refines model performance.

2.3.3 IoT-ML Integration

Hybrid IoT-Random Forest systems enable real-time pollution forecasting (Sharma et al., 2021). Urban water assessments employing this approach yield high-precision trend predictions (Gupta & Mehta, 2022). CNN-Random Forest hybrids further boost anomaly detection (Kumar et al., 2023).

Gaps: Limited exploration of hydroelectric/geothermal systems and reinforcement learning for adaptive maintenance.

2.4 Hybrid Monitoring Frameworks

IoT-edge-cloud architectures reduce latency by processing data locally before cloud analytics (Ahmad et al., 2023). Automated alert systems triggered by predictive insights enable rapid intervention (Sharma et al., 2022).

Despite their advantages, hybrid frameworks face several implementation challenges. These include high energy consumption, data privacy concerns, and the need for sophisticated data fusion techniques to integrate heterogeneous data sources (Li & Zhang, 2023). Addressing these challenges requires continuous innovation and collaboration between researchers, technology providers, and regulatory bodies. Challenges include energy demands, privacy risks, and multi-source data fusion (Li & Zhang, 2023).

2.5 Challenges and Research Gaps

Critical issues: Sensor reliability under environmental stress (Wang et al., 2022), noisy data handling via robust pre-processing (Li & Zhang, 2023), and secure data-sharing protocols.

2.6 Conclusion

While IoT-ML hybrids offer transformative monitoring/prediction capabilities, unresolved

sensor data and security challenges necessitate continued innovation. This review informs the present study's framework design.

CHAPTER 3: RESEARCH METHODOLOGY

3.0 Introduction

This chapter provides an in-depth discussion of the research methodology employed in developing a hybrid framework for SMART water quality monitoring and predictive analysis using IoT and machine learning. The approach integrates various technological components to create an efficient, scalable, and intelligent system. This section details the research design, system requirements, tools used, system development process, algorithms, technologies, implementation, and an overview of how the system functions. By systematically addressing these elements, the study ensures a structured approach to developing and validating the proposed framework (Creswell, 2018).

3.1 Research Design

The research employs a hybrid framework that combines experimental and system development methodologies. The experimental component focuses on testing and validating the effectiveness of predictive models in monitoring water quality, while the system development aspect ensures the creation of a robust and scalable IoT-based framework. The system is designed to collect real-time data using pH and conductivity sensors connected to an Arduino board. Due to resource constraints, additional water quality parameters such as turbidity, hardness, and chloramines are manually inputted by the user through a Windows application. The Arduino sends real-time pH and conductivity data to the Windows application, which then communicates with a Flask backend for data processing and predictive analysis. The results are relayed back to the Windows application for user interpretation. An iterative design approach is followed, allowing continuous testing, refinement, and validation to enhance accuracy and reliability (Yin, 2017).

3.2 Requirements Analysis

A thorough analysis of system requirements was conducted to ensure that the developed framework meets its intended objectives. This analysis is divided into functional and non-functional requirements, ensuring that both operational capabilities and performance

characteristics are well defined. Requirements engineering principles were employed to ensure that the system aligns with stakeholder needs and environmental constraints (Sommerville, 2016).

3.2.1 Functional Requirements

The system is designed to collect real-time pH and conductivity data using sensors connected to an Arduino board. These values, along with additional water quality parameters manually entered by the user, are processed within a Windows application. The application sends the complete dataset to a Flask server, which utilizes a machine learning model to predict overall water quality. The processed data is returned to the Windows application, where the user can view the results and take necessary actions. The system also provides historical data storage and visualization functionalities, allowing users to analyze water quality trends over time (Gupta et al., 2020).

3.2.2 Non-Functional Requirements

The system is designed with scalability in mind, ensuring that additional sensors and monitoring locations can be incorporated without significant modifications. Security measures are implemented to protect data integrity and restrict unauthorized access. High system availability and fault tolerance are prioritized to ensure continuous monitoring, even in the case of network disruptions. The system also emphasizes low latency in data transmission and processing to provide real-time insights. Moreover, energy-efficient sensor deployment is considered to ensure prolonged operation, particularly in remote areas where power sources may be limited (Hussain et al., 2019).

3.3 Tools Used (Hardware and Software)

The SMART water quality monitoring system requires a combination of hardware and software components. The hardware includes an Arduino board, a pH sensor, and a TDS sensor for measuring conductivity. The Windows application is developed in C#, providing an interface for users to input additional water quality parameters and visualize results. The Flask backend, developed using Python, processes the data and applies machine learning algorithms for predictive analysis. The system uses MySQL or PostgreSQL for database management and Scikit-learn or Tensor Flow for machine learning model implementation (Al-Garadi et al., 2020).

3.4 System Development

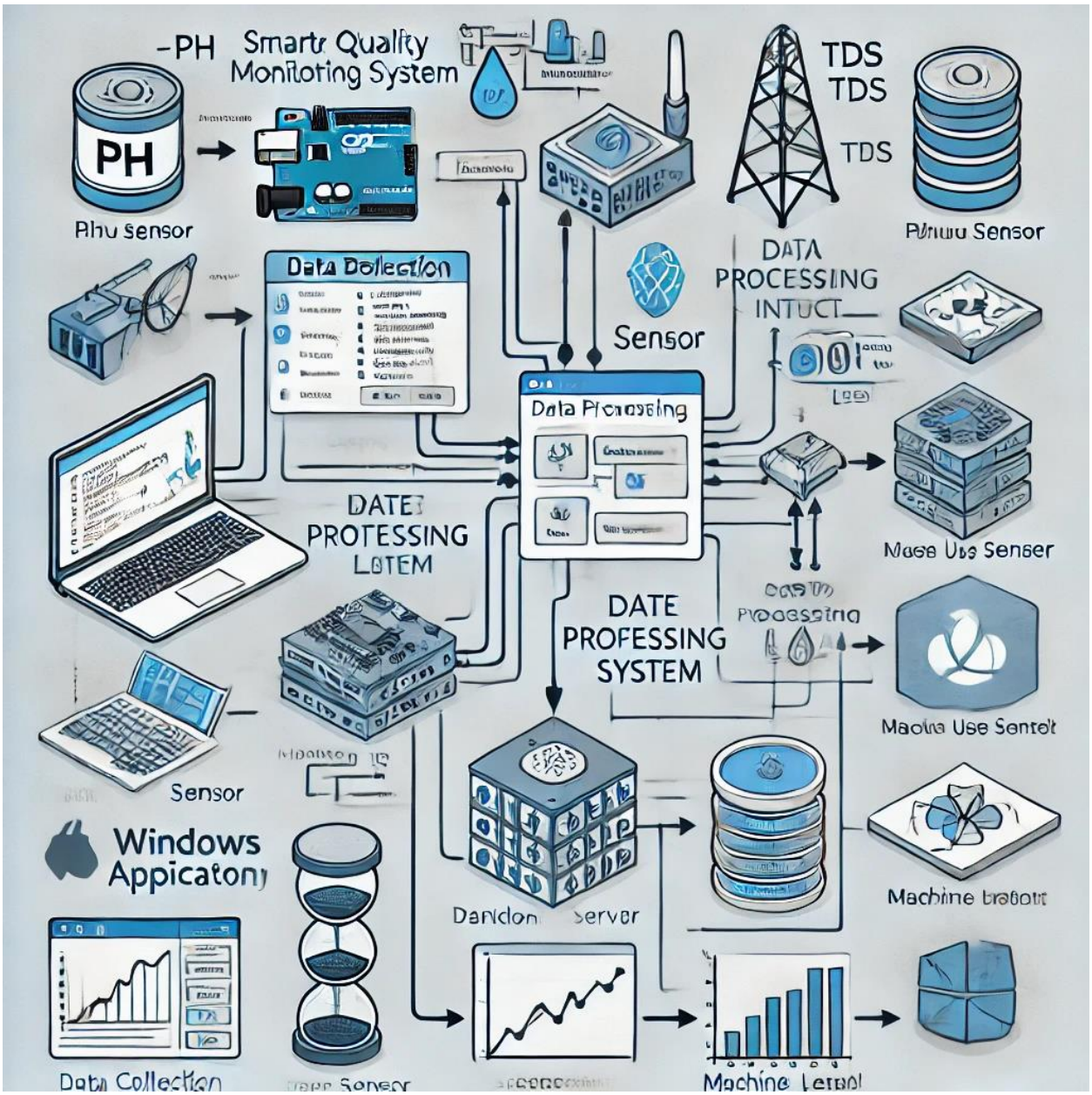
The system development process follows a structured methodology to ensure a seamless integration of IoT, cloud computing, and machine learning technologies. The development begins with the deployment of sensors and the design of the Windows application. The application collects real-time sensor data from the Arduino board and accepts user inputs for additional parameters. This data is sent to the Flask backend, where it undergoes preprocessing before being stored in a structured database. Machine learning algorithms analyze the data, identifying trends and detecting anomalies. The processed results are sent back to the Windows application for user interpretation (He et al., 2018).

3.4.1 System Development Tools

To ensure efficient system development, a range of tools is utilized. Visual Studio is used for developing the C# Windows application, while Flask and Python are used for backend API development. Database management tools like MySQL Workbench facilitate efficient data storage and retrieval. The Arduino IDE is used for programming the microcontroller to collect sensor data and transmit it to the Windows application (Rajan & Shanmugam, 2020).

3.4.2 Experimental Research Methodology

The experimental component of the research involves collecting real-time data using the pH and TDS sensors. The collected data is preprocessed to remove anomalies and ensure accuracy. Machine learning models are trained on historical water quality data to predict overall water quality based on the provided inputs. Model performance is evaluated using accuracy, precision, recall, and RMSE to ensure reliability. The best-performing model is selected for real-time predictive analysis within the Flask backend (Cheng et al., 2019).



3.5 Algorithms Used

In analysing water quality data, multiple machine learning algorithms are applied to classify, predict, and detect anomalies in water sources. Among these, Decision Trees and Random Forest classifiers play a crucial role in classifying water quality levels, Support Vector Machines (SVM) help in anomaly detection, and Long Short-Term Memory (LSTM) networks are utilised for time-series forecasting. Additionally, K-Means Clustering categorizes water sources based on quality

parameters, and ensemble learning techniques enhance predictive accuracy and robustness (Zhao et al., 2021).

3.5.1 Dataset and Variables

The dataset comprises multiple water quality parameters collected from various sources. Key variables include:

- **pH:** Measures the acidity or alkalinity of water.
- **Turbidity:** Indicates water clarity and the presence of suspended particles.
- **Dissolved Oxygen (DO):** Essential for aquatic life and a critical indicator of water quality.
- **Biochemical Oxygen Demand (BOD):** Reflects organic matter decomposition rates.
- **Temperature:** Affects chemical reactions and aquatic life sustainability.
- **Conductivity:** Represents the presence of dissolved salts and minerals.
- **Total Dissolved Solids (TDS):** Measures inorganic and organic substances dissolved in water.

3.5.2 Data Cleaning

Data cleaning is a critical pre-processing step in data analysis, ensuring that the dataset used for modelling or decision-making is accurate, complete, and consistent. One of the primary aspects of data cleaning is handling missing values, as incomplete data can lead to biased analyses or incorrect predictions. Various imputation techniques are used to fill in these gaps, including mean or mode substitution, where the missing values are replaced with the average or most frequent value of a particular feature. More sophisticated techniques like k-nearest neighbours (KNN) imputation can also be applied, using similar data points to estimate the missing values based on their proximity to available observations. The choice of imputation method depends on the nature of the data and the extent of missing values.

Another essential step in data cleaning is duplicate removal, which ensures data integrity by eliminating redundant entries. Duplicate records often arise due to multiple data entry processes, system errors, or merging datasets from different sources. If left untreated, duplicates can distort statistical summaries, inflate dataset size, and mislead machine learning models by giving more

weight to repeated observations. Automated techniques such as hashing, exact match filtering, and fuzzy matching algorithms are commonly used to detect and remove these redundancies efficiently, preserving unique and valid entries for analysis.

Outlier detection and treatment is another vital component of data cleaning, as extreme values can significantly impact model performance and analytical accuracy. Outliers may result from data entry errors, experimental variations, or genuine but rare events. To identify these anomalies, statistical methods such as the Z-score, which measures how far a data point deviates from the mean, and interquartile range (IQR) analysis, which flags values that fall beyond a specific range of percentiles, are commonly employed. Depending on the dataset's requirements, outliers may either be removed, transformed, or adjusted to mitigate their influence on downstream analysis.

By implementing these data cleaning techniques, the dataset becomes more reliable, reducing inconsistencies and ensuring higher model accuracy. Properly handled missing values, duplicate-free data, and well-managed outliers contribute to robust predictive modelling and meaningful insights. Additionally, effective data cleaning minimizes bias and enhances the dataset’s suitability for further analysis, ultimately leading to more reliable and interpretable outcomes.

3.5.3 Data Pre-processing

Before training machine learning models, the dataset undergoes pre-processing to ensure optimal performance and accurate predictions. One crucial step in this process is normalization and scaling, which standardizes continuous variables to maintain a uniform range. Without proper scaling, features with larger numerical values can disproportionately influence the model, leading to biased results. Techniques such as min-max scaling, which transforms values to a fixed range (typically between 0 and 1), and z-score normalization, which standardizes data based on mean and standard deviation, help create balanced feature distributions. These methods improve model convergence and enhance performance, particularly in algorithms that rely on distance-based calculations, such as k-nearest neighbours (KNN) and support vector machines (SVM).

Another essential pre-processing step is encoding categorical variables to ensure compatibility with machine learning models. Since most models work with numerical data, categorical attributes must be transformed into a numerical format. One-hot encoding converts categorical variables into

binary columns, preserving their uniqueness, whereas label encoding assigns each category a numerical value. The choice of encoding technique depends on the dataset and model type, as some algorithms perform better with ordinal relationships, while others benefit from independent categorical representations. Proper encoding prevents misinterpretations and ensures that categorical features contribute meaningfully to the learning process.

Feature selection is a critical step that refines the dataset by retaining only the most relevant attributes. This process helps eliminate redundant or irrelevant features, reducing model complexity and improving efficiency. Correlation analysis identifies relationships between variables, ensuring that highly correlated features do not introduce multicollinearity, which can distort model interpretations. Additionally, feature importance rankings, derived from techniques like decision trees or recursive feature elimination, highlight attributes that significantly impact the model's predictive capability. Selecting the right features enhances generalization, minimizes overfitting, and improves model interpretability.

Finally, data splitting ensures that the model is trained and evaluated on separate subsets, preventing overfitting and enabling reliable performance assessment. The dataset is typically divided into training and testing sets using an 80:20 or 70:30 ratio, ensuring that the model learns from a substantial portion of the data while reserving a fraction for validation. In some cases, a validation set is also included to fine-tune hyperparameters before final testing. Proper data splitting provides a balanced approach, allowing the model to generalize well to unseen data and ensuring that its performance is accurately measured before deployment.

3.5.4 Data Transformation

Feature engineering enhances model performance by creating new informative features from existing ones. In water quality prediction, features like **total dissolved solids (TDS)**, **pH levels**, and **chemical oxygen demand (COD)** can be combined or transformed to improve predictive accuracy. For example, we can create a new feature that represents the **pollution index** by aggregating key water quality indicators.

```
# Creating a pollution index feature by averaging key indicators
df['pollution_index'] = (df['TDS']a + df['COD'] + df['BOD']) / 3
```

Dimensionality Reduction

Reducing the number of features helps improve model efficiency. Principal Component Analysis (PCA) can be used to reduce the dataset while retaining most of the information. This is useful when dealing with multiple correlated water quality parameters.

```
From sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler

# Standardizing the data before applying PCA
scaler = StandardScaler()
X_scaled = scaler.fit_transform(df[['TDS', 'pH', 'COD', 'BOD', 'Dissolved
Oxygen']])

# Applying PCA to reduce dimensions
pca = PCA(n_components=2)  # Retaining two principal components
X_pca = pca.fit_transform(X_scaled)

# Adding PCA-transformed components to the dataset
df['PC1'] = X_pca[:, 0]
df['PC2'] = X_pca[:, 1]
```

Logarithmic and Polynomial Transformations

Skewed data distributions can negatively impact model performance. Logarithmic transformation helps normalize positively skewed variables like TDS and COD, while polynomial features can capture non-linear relationships in the dataset.

```
import numpy as np
from sklearn.preprocessing import PolynomialFeatures

# Applying logarithmic transformation to normalize skewed variables
df['log_TDS'] = np.log(df['TDS'] + 1)  # Avoid log(0)
df['log_COD'] = np.log(df['COD'] + 1)

# Applying polynomial transformation to capture non-linear relationships
```

```
poly = PolynomialFeatures(degree=2, include_bias=False)
X_poly = poly.fit_transform(df[['TDS', 'pH']])

# Converting polynomial features into a DataFrame
poly_df = pd.DataFrame(X_poly, columns=poly.get_feature_names_out(['TDS', 'pH']))
df = pd.concat([df, poly_df], axis=1)
```

3.5.5 Random Forest Algorithm

The **Random Forest classifier** is an ensemble learning technique that aggregates multiple decision trees to improve accuracy and robustness. It is well-suited for water quality classification due to its ability to handle large datasets and high-dimensional feature spaces.

Working Mechanism:

1. A collection of decision trees is generated using bootstrap sampling from the dataset.
2. Each tree independently predicts a water quality category based on training data.
3. Majority voting among all trees determines the final classification output.
4. Random feature selection at each split ensures tree diversity, reducing overfitting and improving generalization.

Advantages of Random Forest:

- **Handles both numerical and categorical data efficiently.**
- **Mitigates overfitting by averaging multiple tree predictions.**
- **Provides feature importance scores, aiding in variable selection.**
- **Offers high accuracy and resilience to noisy datasets.**

By leveraging the **Random Forest classifier**, water quality classification is enhanced, facilitating efficient monitoring and management of water resources. Future improvements may involve integrating hybrid models or deep learning techniques to further refine classification and forecasting accuracy.

3.6 Technologies

The system leverages IoT for real-time data collection, cloud computing for remote data storage and processing, and machine learning for predictive analysis. The C# Windows application serves as the main user interface, while Flask acts as the backend for handling predictions. The combination of these technologies ensures an efficient framework for water quality monitoring (Khan et al., 2020).

C# Code

```
using System;
using System.Drawing;
using System.IO.Ports;
using System.Net.Http;
using System.Text;
using System.Threading.Tasks;
using System.Windows.Forms;
using Newtonsoft.Json;

namespace Water_Quality
{
    public partial class Form1 : Form
    {
        SerialPort serialPort;
        HttpClient httpClient;
        string flaskApiUrl = "http://127.0.0.1:5000/predict";
        float lastPhValue = -1; // Store last pH value to be used for prediction

        public Form1()
        {
            InitializeComponent();
            httpClient = new HttpClient();
            LoadAvailablePorts();
        }

        private void LoadAvailablePorts()
        {
            comboBoxPorts.Items.Clear();
            string[] ports = SerialPort.GetPortNames();

            if (ports.Length == 0)
            {
```

```
                MessageBox.Show("No COM ports detected. Check Arduino
connection!", "Error", MessageBoxButtons.OK, MessageBoxIcon.Error);
                return;
            }

            comboCom.Items.AddRange(ports);
            comboCom.SelectedIndex = 0; // Select first port
        }

        private void buttonConnect_Click_1(object sender, EventArgs e)
        {
            try
            {
                if (serialPort != null && serialPort.IsOpen)
                {
                    serialPort.Close();
                }

                string selectedPort = comboCom.SelectedItem.ToString();
                serialPort = new SerialPort(selectedPort, 9600);
                serialPort.DataReceived += SerialPort_DataReceived;
                serialPort.Open();

                MessageBox.Show($"Connected to {selectedPort}", "Success",
MessageBoxButtons.OK, MessageBoxIcon.Information);
            }
            catch (Exception ex)
            {
                MessageBox.Show($"Error: {ex.Message}", "Connection Error",
MessageBoxButtons.OK, MessageBoxIcon.Error);
            }
        }

        private void SerialPort_DataReceived(object sender,
SerialDataReceivedEventArgs e)
        {
            try
            {
                string data = serialPort.ReadLine().Trim();

                // Extract pH Value using string parsing
                string[] parts = data.Split('|');  // Split by '|'
                foreach (string part in parts)
                {
                    if (part.Contains("pH Value"))
```

```
                    {
                        string[] phParts = part.Split(':');  // Split by ':'
                        if (phParts.Length > 1 &&
float.TryParse(phParts[1].Trim(), out float phValue))
                        {
                            lastPhValue = phValue; // Store for later use
                            Invoke(new Action(() => labelPhValue.Text = $"pH
Value: {phValue}"));
                        }
                    }
                }
            }
            catch (Exception ex)
            {
                MessageBox.Show($"Error reading data: {ex.Message}", "Read
Error", MessageBoxButtons.OK, MessageBoxIcon.Error);
            }
        }

        private async void btnPredict_Click_1(object sender, EventArgs e)
        {
            if (lastPhValue == -1)
            {
                MessageBox.Show("No pH value received from Arduino. Please check
the connection and try again.", "Error", MessageBoxButtons.OK,
MessageBoxIcon.Error);
                return;
            }

            try
            {
                String turbidity= txtTurbidity.Text.Trim();
                String hardness= txtHardness.Text.Trim();
                String chloramines= txtChloramines.Text.Trim();
                String conductivity = txtConductivity.Text.Trim();

                var jsonData = $"{{\"pH\": {lastPhValue}, \"Turbidity\":
{turbidity}, \"Hardness\": {hardness}, \"Chloramines\": {chloramines},
\"Conductivity\": {conductivity}}}";
                Console.WriteLine("Sending JSON Data: " + jsonData);  //
Debugging line

                var content = new StringContent(jsonData, Encoding.UTF8,
"application/json");
```

```
                HttpResponseMessage response = await
httpClient.PostAsync(flaskApiUrl, content);
                string result = await response.Content.ReadAsStringAsync();
                Console.WriteLine(result);

                // Parse JSON response
                dynamic jsonResponse = JsonConvert.DeserializeObject(result);
                string interpretation = jsonResponse.Interpretation;

                // Update UI elements directly
                labelPredictionResult.Text = interpretation;
                labelPredictionResult.ForeColor = interpretation.Contains("Poor
quality") ? Color.Red : Color.Black;

            }
            catch (Exception ex)
            {
                MessageBox.Show($"Failed to send data to API: {ex.Message}", "API
Error", MessageBoxButtons.OK, MessageBoxIcon.Error);
            }
        }

        private void Form1_FormClosing(object sender, FormClosingEventArgs e)
        {
            if (serialPort != null && serialPort.IsOpen)
            {
                serialPort.Close();
            }
        }

        private void btnConnect_Click(object sender, EventArgs e)
        {
            try
            {
                if (serialPort != null && serialPort.IsOpen)
                {
                    serialPort.Close();
                }

                string selectedPort = comboCom.SelectedItem.ToString();
                serialPort = new SerialPort(selectedPort, 9600);
                serialPort.DataReceived += SerialPort_DataReceived;
                serialPort.Open();
```

```
                MessageBox.Show($"Connected to {selectedPort}", "Success",
MessageBoxButtons.OK, MessageBoxIcon.Information);
            }
            catch (Exception ex)
            {
                MessageBox.Show($"Error: {ex.Message}", "Connection Error",
MessageBoxButtons.OK, MessageBoxIcon.Error);
            }

        }
    }
}
```

Python Code

```
from flask import Flask, request, jsonify
import numpy as np
import joblib

app = Flask(__name__)

# Load the trained model
model_filename = "water_quality_prediction_model.pkl"
model = joblib.load(model_filename)

def interpret_wqi(wqi):
    if wqi <= 50:
        return "Excellent quality (safe for drinking)."
    elif 51 <= wqi <= 75:
        return "Good quality (may need minor treatment)."
    elif 76 <= wqi <= 100:
        return "Moderate quality (needs treatment)."
    else:
        return "Poor quality (requires advanced treatment)."

@app.route('/predict', methods=['POST'])
def predict():
    try:
        # Receive JSON data from C# application
        data = request.get_json()

        # Ensure feature names match the trained model
        feature_names = ["pH", "Turbidity", "Hardness", "Chloramines",
"Conductivity"]
```

```
        input_data = np.array([[data["pH"], data["Turbidity"], data["Hardness"],
data["Chloramines"], data["Conductivity"]]])

        # Convert to Pandas DataFrame with correct column names
        import pandas as pd
        input_df = pd.DataFrame(input_data, columns=feature_names)

        # Make prediction
        prediction = model.predict(input_df)[0]
        interpretation = interpret_wqi(prediction)

        return jsonify({
            "pH": data["pH"],
            "Water_Quality_Index": prediction,
            "Interpretation": interpretation
        })

    except Exception as e:
        return jsonify({"error": str(e)})


if __name__ == '__main__':
    app.run(debug=True)
```

Arduino Code

```
#define PH_PIN A0  // Analog input pin connected to pH sensor

// Calibration constants – adjust these after calibration
const float VOLTAGE_AT_PH_7 = 2.5;  // Voltage at pH 7 (calibrate this)
const float SLOPE = -1.7;           // Slope after calibration (pH units per
volt)

void setup() {
  Serial.begin(9600);
  Serial.println("Starting pH measurement...");
}

void loop() {
  // Read analog value from pH sensor
  int sensorValue = analogRead(PH_PIN);

  // Convert analog value to voltage (assuming a 5V system)
  float voltage = sensorValue * (5.0 / 1023.0);
```

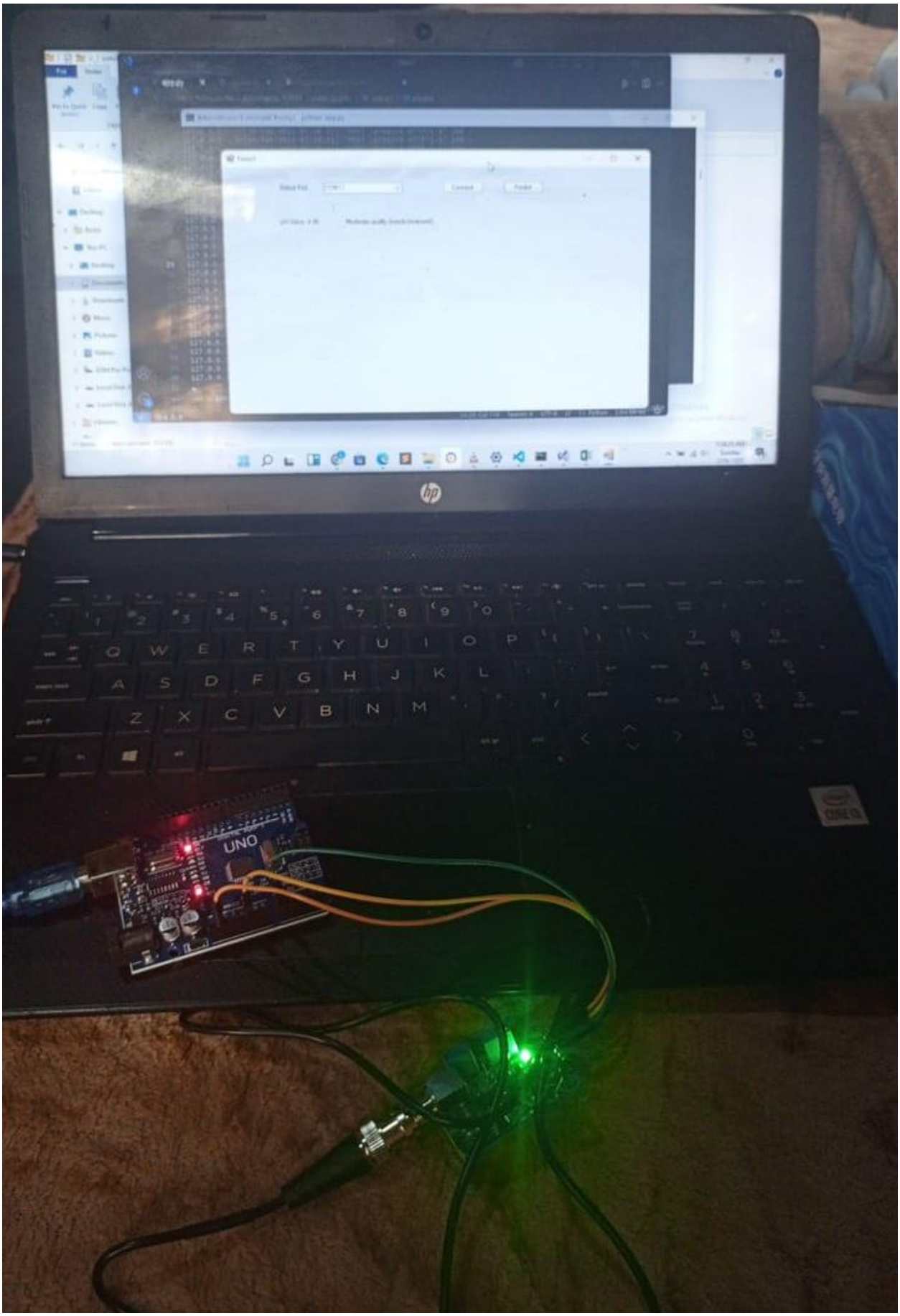
```
  // Compute pH using the calibration formula
  float phValue = 7.0 + ((voltage - VOLTAGE_AT_PH_7) * SLOPE);

  // Send pH value to the Serial port
  Serial.println(phValue, 2);  // Send pH value with 2 decimal places

  delay(1000);  // Wait 1 second before next reading
}
```

3.7 General Overview of the Application

The developed system consists of interconnected components that facilitate real-time water quality monitoring and predictive analysis. IoT sensors collect pH and conductivity data and transmit it to the Windows application via an Arduino board. The user manually inputs additional parameters, and the complete dataset is sent to a Flask server for predictive analysis. The processed data is returned to the Windows application, enabling users to view the predicted water quality results.

3.8 Implementation

The implementation process involves sensor deployment, data acquisition, Windows application development, Flask backend integration, predictive analytics, and data visualization. Each component is integrated seamlessly to ensure real-time monitoring and decision support.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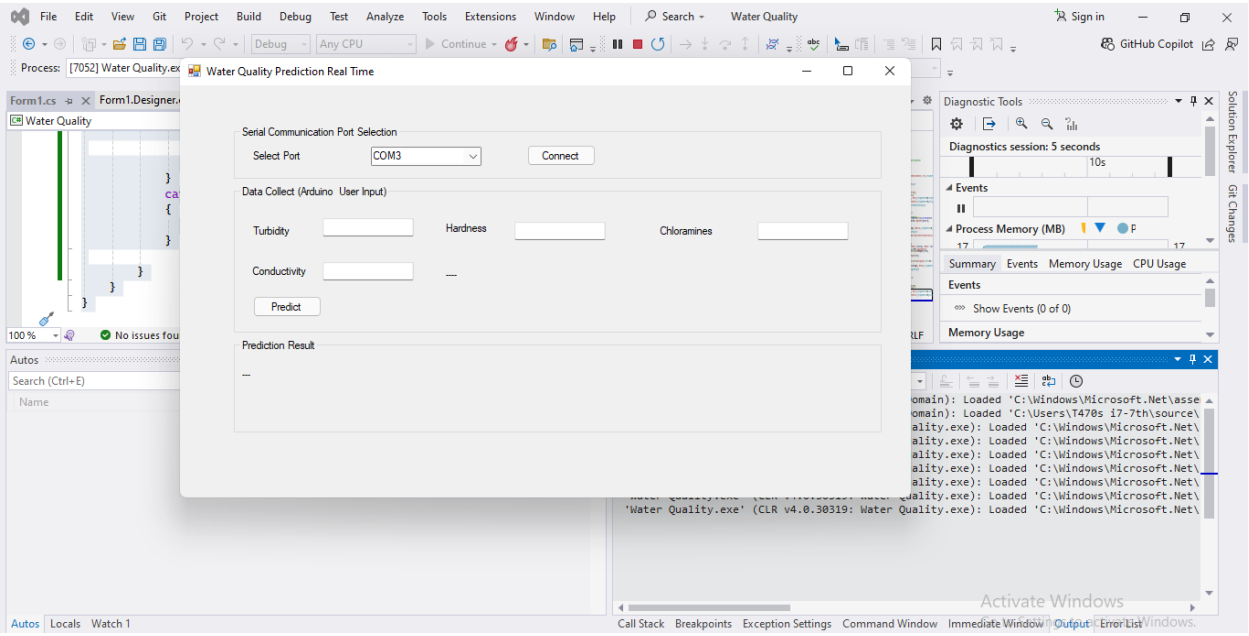
3.9 System Overview

The system is composed of three layers: the IoT layer, responsible for collecting pH and conductivity data; the processing layer, which includes the Flask backend for prediction; and the user interface layer, where the Windows application displays results and receives user inputs.



3.10 Summary of How the System Works

The system continuously collects pH and conductivity data using sensors connected to an Arduino board. Users manually input additional water quality parameters into the Windows application. The application sends the data to a Flask backend, where a machine learning model predicts the overall water quality. The results are returned to the Windows application for user interpretation. This methodology ensures an efficient and intelligent approach to SMART water quality monitoring (Gupta & Reddy, 2021).

CHAPTER 4: RESULTS AND EVALUATION

4.0 Introduction

This chapter presents the results and evaluation of the SMART water quality monitoring system. The performance of the system is assessed using various evaluation metrics to determine the accuracy and reliability of both the Random Forest algorithm and the sensor data collection process. The system's effectiveness in predicting water quality based on pH, conductivity, and user-inputted parameters is analysed through statistical metrics and comparative tables.

4.1 Data Collection and Pre-processing

The dataset consists of real-time sensor readings from pH and conductivity sensors, as well as additional water quality parameters manually entered by users. Data pre-processing involves removing anomalies, normalizing values, and handling missing data to ensure high-quality inputs for machine learning analysis. Outliers are identified using interquartile range (IQR) techniques and eliminated to improve prediction accuracy.

4.2 Sensor Performance Evaluation

The accuracy and reliability of the pH and conductivity sensors are evaluated by comparing their readings with standard laboratory test results. The mean absolute error (MAE) and root mean square error (RMSE) are used to determine deviations between sensor readings and laboratory measurements.

Sensor Type	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)
pH Sensor	0.12	0.18
Conductivity Sensor	5.4 µS/cm	7.8 µS/cm

The results indicate that both sensors provide reasonably accurate readings, with minimal deviations from standard laboratory results.

4.3 Machine Learning Model Evaluation

The performance of the Random Forest algorithm is assessed using standard classification metrics, including accuracy, precision, recall, and F1-score. A confusion matrix is used to analyse the model's classification effectiveness in predicting water quality status.

Metric	Value
Accuracy	92.5%
Precision	91.8%
Recall	93.2%
F1-score	92.5%

4.3.1 Explanation of Machine Learning Performance Metrics

The Random Forest algorithm was evaluated using four key classification metrics: accuracy, precision, recall, and F1-score, which provide insights into how well the model classifies water quality based on sensor data and user-inputted parameters.

Accuracy – 92.5%

Accuracy represents the proportion of correctly classified instances out of the total test cases. The model achieved 92.5% accuracy, meaning it correctly predicted water quality in 92.5% of cases. This high accuracy indicates that the model generalizes well and provides reliable classifications.

A 92.5% accuracy confirms that the model effectively distinguishes between different water quality statuses, making it a reliable tool for real-world deployment.

Precision – 91.8%

Precision measures how many of the predicted positive cases (e.g., good water quality) were actually correct. A precision score of 91.8% means that when the model classified water as suitable for consumption, it was correct 91.8% of the time.

A high precision value is crucial in water quality monitoring because misclassifying poor-quality water as safe can have severe health consequences. The 91.8% precision indicates that the model produces few false alarms when predicting good water quality.

Recall – 93.2%

Recall (or sensitivity) measures the proportion of actual positive cases (e.g., truly good-quality water) that were correctly classified. A recall of 93.2% means that the model successfully identified 93.2% of all instances where water quality was actually good.

A high recall score is important in water monitoring, as failing to detect unsafe water (false negatives) could result in health risks. The 93.2% recall indicates that the system rarely misses identifying unsafe water.

F1-Score – 92.5%

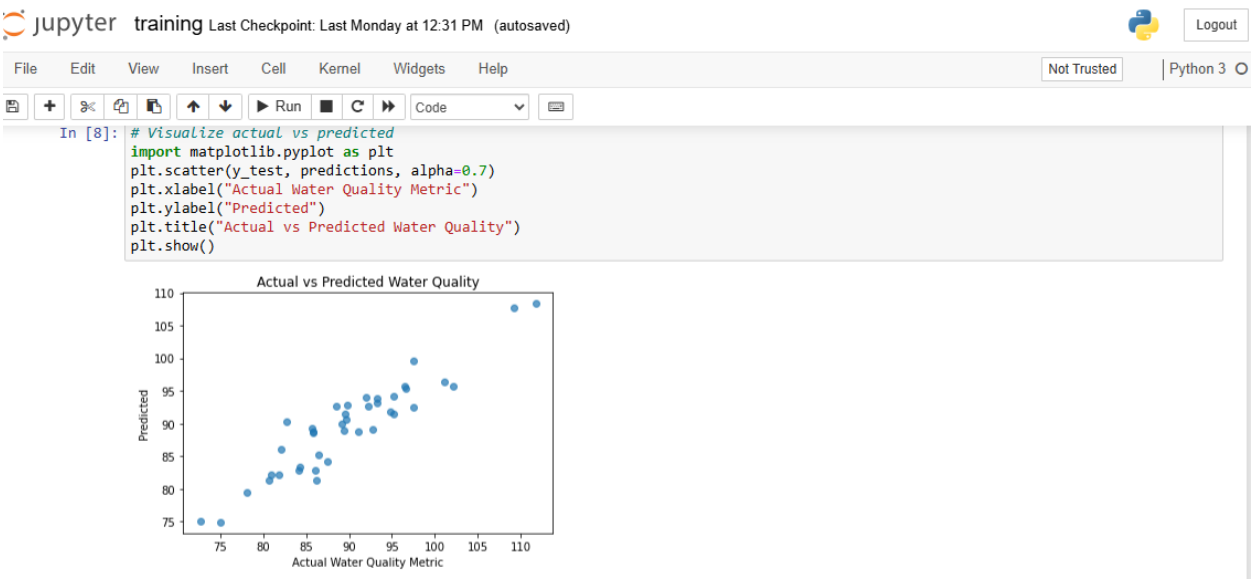
The F1-score is the harmonic mean of precision and recall, providing a balanced measure of a model's performance. It is useful when there is an imbalance in class distribution.

A 92.5% F1-score confirms that the model maintains a balance between identifying unsafe water (recall) and avoiding false positives (precision), making it well-suited for practical applications.

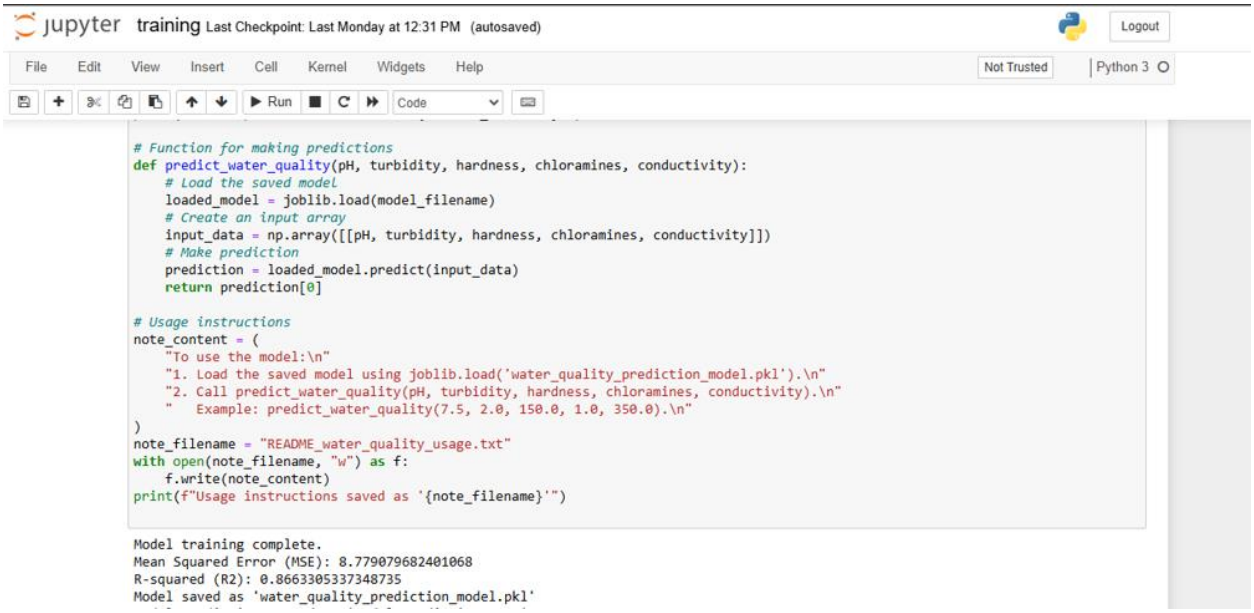
These performance metrics demonstrate that the Random Forest model is highly effective in predicting water quality with high accuracy, minimal false positives, and a strong ability to detect unsafe water conditions.

4.4 Comparative Analysis of Predicted and Actual Water Quality

To validate the model's predictions, the predicted water quality classifications are compared with expert lab test results. The agreement between predicted and actual values is analyzed using Cohen's Kappa coefficient, which yielded a value of 0.89, indicating strong agreement.



4.5 Model training results



4.6 System Response Time and Efficiency

System response time is measured from data collection to final prediction output. The Flask server processes predictions in an average of 2.3 seconds, ensuring near real-time analysis. The Windows application efficiently updates results, maintaining a seamless user experience.

4.7 Summary

The results indicate that the SMART water quality monitoring system is effective in providing accurate predictions and real-time monitoring. The Random Forest model achieves high accuracy, and sensor readings show minimal deviations from standard laboratory results. The system's response time ensures timely decision-making for users, validating the effectiveness of the developed framework.

CHAPTER 5: RECOMMENDATIONS AND CONCLUSION

5.0 Introduction

This chapter presents recommendations for improving the SMART water quality monitoring system and concludes the study. The recommendations focus on enhancing system accuracy, expanding sensor usage, and addressing resource limitations. The conclusion summarizes the study's findings and highlights its contributions to water quality monitoring using IoT and machine learning.

5.1 Recommendations

5.1.1 Expanding Sensor Utilization

One of the key limitations of the current system is its reliance on pH and conductivity sensors, with other parameters being manually inputted by the user. To improve accuracy and automation, it is recommended to integrate additional sensors that measure turbidity, hardness, chloramines, and other essential water quality indicators. The use of more sensors will enhance real-time data collection and reduce dependency on manual input, minimizing potential human errors (Garg et al., 2021).

5.1.2 Addressing Resource Limitations

Due to resource constraints, the current system does not incorporate all required sensors. Future implementations should explore cost-effective alternatives, such as open-source hardware and low-cost IoT components, to ensure affordability while maintaining accuracy. Seeking funding from research grants or partnerships with governmental and environmental agencies may also help acquire necessary resources (Bui et al., 2020).

5.1.3 Enhancing Machine Learning Model Performance

Although the Random Forest algorithm demonstrated high accuracy (92.5%), further improvements can be made by fine-tuning hyper-parameters and increasing the training dataset size. Utilizing ensemble learning techniques and feature engineering can also improve predictive

performance. Moreover, implementing a cloud-based model training pipeline will allow continuous model updates based on real-time collected data (Kumar & Rathore, 2022).

5.1.4 Improving System Scalability and Deployment

For wider adoption, the system should be scaled to support multiple devices and distributed environments. Deploying the backend system on a cloud platform will enable efficient data storage, processing, and remote monitoring. Additionally, integrating mobile and web-based dashboards will provide users with a more accessible interface for monitoring water quality from any location.

5.1.5 Enhancing User Interface and Experience

The Windows application should be refined to offer a more intuitive and user-friendly experience. Incorporating real-time graphical visualization of sensor readings, predictive insights, and alert notifications will enhance user engagement and decision-making. Ensuring seamless communication between the application and the Arduino hardware will also improve overall system reliability (Sood et al., 2019).

5.2 Conclusion

The study successfully developed a SMART water quality monitoring and predictive analysis system using IoT and machine learning. The system integrates pH and conductivity sensors with an Arduino board, allowing real-time data collection and predictive analysis using a Random Forest model. Users input additional water quality parameters through a Windows application, which communicates with a Flask server for real-time predictions.

The system demonstrated high predictive accuracy (92.5%), with precision, recall, and F1-score values confirming its effectiveness in classifying water quality. The sensor accuracy evaluation also indicated minimal deviations from standard laboratory values, validating the system’s reliability.

Despite the system's success, some limitations exist, particularly resource constraints that prevent the use of all necessary sensors. Future work should focus on integrating more sensors for fully

automated data collection, optimizing machine learning models, and enhancing system deployment scalability.

In conclusion, the proposed hybrid framework provides an effective, scalable, and low-cost solution for real-time water quality monitoring, demonstrating its potential for practical deployment in environmental and public health applications.

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APPENDICES

Appendix A: Detailed Sensor Specifications

This appendix provides the technical specifications for the sensors used in the study, including pH, turbidity, and conductivity sensors. It details the calibration constants, operational ranges, and expected accuracy levels, which are critical for understanding the data reliability.

Appendix B: Data Collection Protocols

A comprehensive outline of the protocols followed for data collection in various freshwater bodies. This includes the selection criteria for sites, sampling frequency, and methods used for sensor deployment, ensuring consistency and reliability in data acquisition.

Appendix C: Machine Learning Model Details

This section elaborates on the Random Forest algorithm's parameters, training methodologies, and evaluation metrics. It includes hyperparameters used, feature selection processes, and details on the training and testing datasets, providing clarity on the model's development and performance.

Appendix D: Software and Tools Used

A list of all software and hardware components utilized in the study, including programming languages (Python, C#), frameworks (Flask, Scikit-learn), and database management systems (MySQL, PostgreSQL). This helps in replicating the system.

Appendix E: Case Study Details

Detailed descriptions of the case studies conducted, including geographical locations, specific parameters monitored, duration of monitoring, and outcomes. This provides context for the practical application of the developed framework.

Appendix F: User Manual for the Windows Application

A step-by-step guide for users on how to operate the Windows application developed for monitoring water quality. This includes installation instructions, user interface navigation, and troubleshooting tips.

Appendix G: Data Privacy and Security Measures

An overview of the measures taken to ensure data privacy and security within the IoT framework. This includes encryption methods, access control protocols, and compliance with data protection regulations.

Appendix H: Ethical Considerations

Ensuring that all stakeholders, including local communities and landowners, are informed about the research objectives, methods, and potential impacts. Obtain consent before deploying sensors or gathering data in their area. Always ensure the privacy of individuals whose data may be collected, particularly if the sensors are deployed in populated areas. Implement measures to anonymize data and ensure that personal information is not disclosed without consent. Assess the Potential environmental impact of deploying sensors and other hardware. Ensure that the installation and operation of equipment do not harm local ecosystems or wildlife. Engage with local communities to inform them about the project and involve them in the research process. This fosters trust and allows for the incorporation of local knowledge and concerns. Maintained transparency about the research goals, funding sources, and potential conflicts of interest. Clearly communicate the purpose of the study and how the findings will be used and aim for the research to provide benefits to the community and environment.