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"AI-Based Multi-Sensor Fusion for Real-Time Heavy Metal Detection in Water Using IoT"

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Abstract: Water contamination by heavy metals poses a serious threat to human health and aquatic ecosystems. Conventional laboratory-based techniques such as Atomic Absorption Spectroscopy and Inductively Coupled Plasma Mass Spectrometry provide accurate results but are expensive and unsuitable for real-time field monitoring. This paper presents an enhanced IoT-enabled heavy metal detection system that combines colorimetric sensing using a TCS3200 color sensor with UV–Visible spectroscopic analysis for improved quantitative accuracy. Selective chemical reagents are used to induce characteristic color changes in the presence of zinc (Zn^{2+}), copper (Cu^{2+}), and nickel (Ni^{2+}) ions. The RGB responses are captured using the TCS3200 sensor for rapid screening, while spectral absorbance data obtained from a compact UV–Visible spectrometer enables wavelength-based concentration estimation using the Beer–Lambert principle. An ESP32 microcontroller performs edge-level processing and transmits results to the ThingSpeak cloud platform for real-time monitoring and visualization. Experimental validation demonstrates improved sensitivity, selectivity, and concentration estimation capability compared to RGB-only detection. The proposed hybrid system offers a low-cost, portable, and scalable solution bridging IoT-based monitoring and spectroscopic analytical techniques.

Keywords: Heavy metal detection, UV–Visible Spectroscopy, TCS3200, IoT, Colorimetric analysis, Water quality monitoring, ESP32, Spectral absorbance.

I.INTRODUCTION

Rising industrial activity and lack of adequate waste disposal contribute to growing global concern for the monitoring of water quality. Excessive release of heavy metal contaminants like zinc (Zn), copper (Cu) and nickel (Ni) comes from electroplating, mining and some chemical manufacturing processes. Although trace levels of these metals are vital to human health and aquatic environments, too many of these metals in water can be harmful to both aquatic life and people.

High-acuity and highly specialised techniques such as Atomic Absorption Spectroscopy (AAS), Inductively Coupled Plasma Mass Spectrometry (ICP-MS) and X-ray fluorescence allow accurate measurements of these contaminants but require highly sophisticated facilities and trained personnel to operate. Consequently, these instruments do not provide a solution for continuous or onsite monitoring of contaminants.

To circle back to the above discussion of the growing demand for improved means of monitoring these types of contaminants, this paper introduces the development of a low-cost, small-size detection system employing TCS3200 color sensors to encourage further research to investigate the use of visually distinct colour changes - produced by selected chemical reagents - to be subsequently analysed using an embedded Internet Of Things (IoT) network platform running on an embedded processor.

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Major Contributions

Design and development of a low-cost IoT-based heavy metal detection system using a TCS3200 color sensor and selective chemical reagents for indirect colorimetric analysis of zinc (Zn^{2+}), copper (Cu^{2+}), and nickel (Ni^{2+}) ions in water.

Implementation of reagent-specific colorimetric detection logic, enabling selective identification of individual heavy metals through distinct color formation using Dimethylglyoxime (for nickel), ammonia (for copper), and dithizone (for zinc).

Integration of embedded edge processing using ESP32, where real-time RGB frequency values from the TCS3200 sensor are processed locally to classify water samples into safe and contaminated categories with minimal latency.

Cloud-based visualization and monitoring using the ThingSpeak IoT platform, allowing remote observation of metal-induced color variations and contamination status in real time.

Experimental validation of the proposed system using prepared metal salt solutions ($ZnSO_4$, $CuCl_2$, $NiSO_4$), demonstrating reliable detection trends and repeatable sensor responses under controlled laboratory conditions.

A scalable and cost-effective framework for preliminary water quality screening, suitable for academic research, rural water monitoring, and low-resource environments where conventional laboratory techniques are impractical.

B. Spectrometer-Based Optical Analysis Layer

To enhance the quantitative capability of the proposed system, a compact UV–Visible spectrometer is integrated alongside the TCS3200 color sensor. While the RGB sensor provides rapid color intensity measurement, the spectrometer enables wavelength-resolved absorbance analysis for improved selectivity and concentration estimation.

The spectrometer measures light intensity across a defined wavelength range (typically 350–800 nm). When selective reagents react with metal ions such as Ni^{2+}, Cu^{2+}, and Zn^{2+}, distinct absorption peaks are formed at characteristic wavelengths. These spectral signatures allow more accurate identification and quantification of heavy metal concentrations.

The spectrometer module interfaces with the ESP32 microcontroller via UART/I2C communication. Spectral data is preprocessed locally to extract peak absorbance values before cloud transmission.

With this addition, the sensing architecture becomes a hybrid optical detection framework consisting of:

- RGB-based rapid screening
- Spectral absorbance-based quantitative validation
- Edge processing using ESP32
- Cloud-based visualization via ThingSpeak

This integration improves analytical reliability while maintaining system portability and cost-effectiveness.

II. LITERATURE REVIEW

Historically, monitoring of water quality has utilised are laboratory analytical techniques, which are precise and sensitive, as well as costly and time-consuming. These laboratory methods often necessitate the involvement of skilled personnel to monitor water quality and are inappropriate for use in constant or real-time environmental situations.

However, with recent advancements in IoT technologies, more and more organisations are using sensors for monitoring water quality. Gupta et al. (2022) have created a remote monitoring platform that monitors parameters such as pH and temperature using IoT enabled devices, whereas Kumar et al. (2023) created a Rule-based IoT Platform that measured both turbidity and pH but did not incorporate the necessary chemical and optical sensing techniques required for monitoring heavy metal contamination.

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The use of Machine Learning (ML) to evaluate Water Quality has been examined and researched by number of researchers over the years. Recently, Mishra and Patel (2023) used a Support Vector Machine (SVM) model and a Random Forest (RF) model with multi-parameter datasets to predict the overall quality index of water, both of which were able to demonstrate good prediction accuracy. However, both of these ML models require large amounts of data and computing resources, making them impractical for low-cost embedded applications. Additionally, Artificial Neural Network (ANN) models have demonstrated good performance when dealing with the non-linear relationship between multiple parameters in terms of water quality. Singh et al. (2024) have developed ANN models to predict heavy metal concentrations and found that they have better predictive accuracy than traditional Linear Regression models. Regardless, the majority of these models rely on Cloud-based technologies for processing. This reliance on Cloud technology can result in increased latency, increased power consumption, and a lack of continuous internet access for operation.

In parallel to these advanced techniques, Colourimetric Sensors represent a relatively low-cost and simple method for chemical analysis by using chemical reagents that react with metal ions to create colour complexes that can be detected indirectly by using optical sensors. However, there is a lack of research available detailing how to incorporate inexpensive Colour Sensors into IoT Platforms for heavy metal detection at the edge and in real-time.

From the literature survey, it is evident that there exists a research gap in developing a low-cost, embedded, and real-time heavy metal detection system that combines selective colorimetric sensing with IoT-based monitoring. This gap motivates the present work.

A. Problem Statement

Heavy metals remain a serious concern regarding the contamination of water worldwide—especially in areas that are negatively impacted by industrial discharges, mining operations, or agricultural runoff. When present at concentrations above what is considered safe, heavy metal contaminants such as zinc, copper, or nickel can pose a risk to both human beings and aquatic ecosystems.

The traditional approach to monitoring water quality is primarily through the collection of physical samples which are typically sent to a laboratory for analysis. Laboratory analyses are typically performed via methods such as atomic absorption spectrometry or ICP/MS or chromatographic techniques. Although these types of laboratory analyses provide highly precise results, they have a number of limitations including; high cost to operate, slow turnaround time, a need for trained personnel to operate the equipment, and a lack of real-time monitoring capabilities.

Currently, many available IoT-based water quality monitoring systems focus mainly on the measurement of basic physicochemical parameters (e.g., pH, turbidity or temperature); none of them currently provide adequate heavy metals detection capabilities. Most available advanced AI-based solutions rely on cloud computing for analytical capabilities and have very high latency and power consumption requirements, which makes them impractical for use in remote environments or resource-constrained conditions.

Hence, there is a strong need for a low-cost, portable, and real-time water quality monitoring system capable of detecting heavy metal contamination using simple sensing techniques. The problem addressed in this work is the design and implementation of an embedded, IoT-enabled colorimetric system that can detect the presence of zinc, copper, and nickel in water using selective chemical reagents and optical sensing.

III. SYSTEM MODEL AND ARCHITECTURE

A.0

The proposed system is an IoT-enabled heavy metal detection framework designed to identify the presence of selected metal ions in water using a low-cost colorimetric sensing approach. The system architecture integrates chemical sensing, embedded processing, and cloud-based visualization to provide real-time monitoring of water contamination. The overall architecture is organized into four main layers: sensing layer, signal processing layer, communication and cloud layer, and user monitoring layer, as illustrated in Figure 1.

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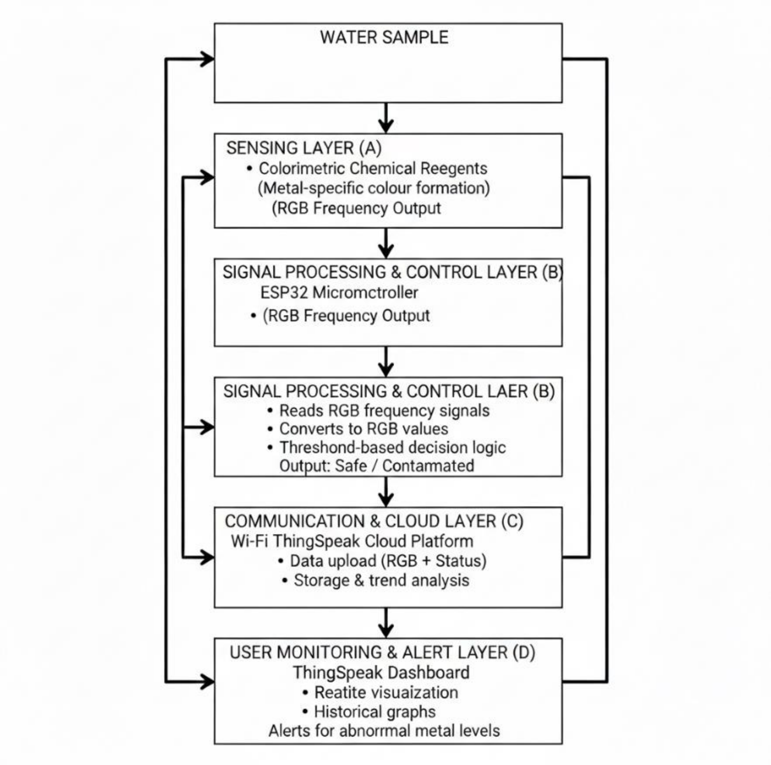

Fig:1 System Architecture

A. Sensing Layer

The sensing layer is where color changes are detected as a result of chemical reactions occurring between dissolving heavy-metals and selective colour-forming reagents. In order to detect the presence of dissolved heavy metals in a water sample, such as zinc (Zn2+), copper (Cu2+) and nickel (Ni2+), each of these metal ions has reagents that react with them to form a coloured complex. The intensity of the Red, Green, and Blue (RGB) components of light reflected off of the sample solution will then be measured using the TCS3200 Colour Sensor, which produces values for the intensity of each component.

Using the RGB values collected from the TCS3200 Colour Sensor, we can indirectly determine the presence of heavy metals in a water sample, as well as see how much of each is present (i.e., relative concentrations).

B. Signal Processing and Embedded Control Layer

The processing layer consists of an ESP32 microcontroller, which interfaces directly with the TCS3200 sensor. The sensor outputs frequency-based signals corresponding to RGB color components, which are captured using the ESP32's GPIO pins. The embedded firmware processes these frequency values, applies threshold-based decision logic, and classifies the sample as either safe or contaminated. This on-device processing enables real-time decision-making with minimal latency and eliminates the need for complex laboratory analysis.

C. Communication and Cloud Integration Layer

Once the color-based analysis is performed on the edge device, the processed data is sent to the cloud using a Wi-Fi network connection. The cloud integration is performed using the ThingSpeak IoT platform to upload a RGB value and contamination status every so often. In addition, the cloud layer is where you can view historical data as well as view trends graphically about water quality; therefore, it is possible to monitor water quality on a continuous basis with an internet-enabled device from any location.

D. User Monitoring and Alert Layer

Stakeholders can view the status of water quality through an online portal called ThingSpeak that provides graphical dashboards of water quality. If the water quality displays abnormal color patterns that would indicate the presence of

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heavy metals, stakeholders can receive visual alerts or thresholds that display the need for immediate action. This facilitates timely interventions and assists with preventive management of water quality.

In conclusion, the proposed framework is a low-cost, scalable, and easy-to-use system for preliminary analysis of the presence of heavy metals in water. The combined use of chemical colourimetry, optical sensing, and internet-connected monitoring allows for real-time assessment of water quality without the need for costly laboratory equipment..

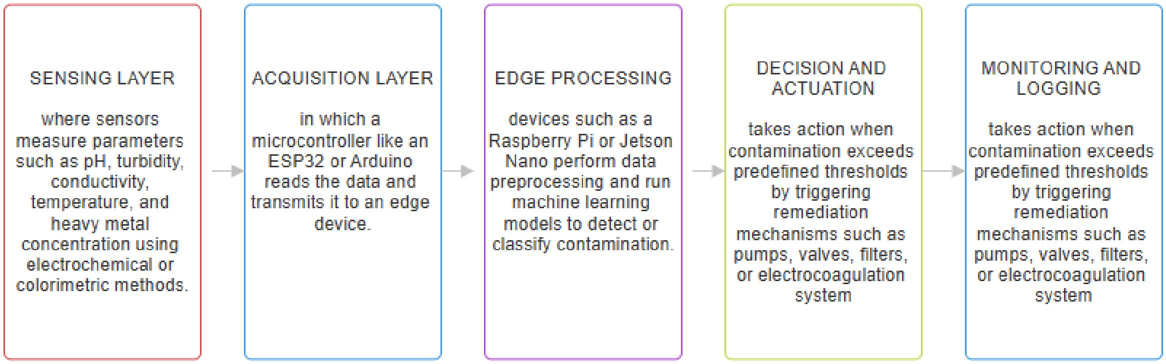

Fig:1.1 System Architecture

E. Multi-Sensor Data Fusion Layer

To improve the reliability and robustness of heavy metal detection, the proposed system incorporates a multi-sensor data fusion mechanism. Instead of relying on a single sensing modality, the system integrates measurements obtained from multiple sensors including the TCS3200 color sensor, UV–Visible spectrometer, and optional water quality sensors such as turbidity and TDS sensors.

Each sensor provides complementary information about the water sample:

The TCS3200 color sensor captures RGB color variations produced by metal–reagent reactions.

The UV–Visible spectrometer measures wavelength-specific absorbance peaks corresponding to different metal complexes.

Additional sensors such as turbidity and TDS provide physical water quality indicators that may correlate with contamination levels.

The ESP32 microcontroller performs sensor-level data fusion by combining these heterogeneous sensor outputs. The fusion process improves detection reliability by reducing uncertainty that may arise from individual sensor noise, lighting variation, or reagent inconsistencies.

The fused dataset can be processed using statistical techniques or lightweight machine learning models to improve classification accuracy. By integrating multiple sensing modalities, the system achieves higher robustness, improved sensitivity, and better discrimination between different metal ions compared to single-sensor approaches.

IV. PROPOSED METHODOLOGY

In this proposed methodology, we address a new proposed technique for detecting (measuring) Heavy Metal contamination in water (H2O) through the application of some form of selective chemical reaction combined with Optical Colour Sensing, Embedded Processor and Cloud-Based visualisation to present a lower-cost and real-time approach to watermarking the quality of drinking (potable) water.

A. Sample Preparation and Color Development

To determine the concentration of heavy metals in a water sample, one must first prepare a solution of known metal concentrations using DNS solutions of zinc sulphate, copper chloride, and nickel sulphate. In order to detect heavy metals optically, the DNS reagents used to initially detect heavy metals will react with the respective metals producing a change in color of the sample. For example, dimethylglyoxime will produce a red complex with Nickel, Ammonia will produce

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a deep blue complex with Copper, and Dithizone will produce a color complex with Zinc. The color changes produced by the DNS reagents are used to indirectly detect and quantify Heavy metals.

B. Color Sensing Using TCS3200

Beneath the TCS3200 Color Sensor, the Built Colour Solutions are then placed in front of the colour sensor. This sensor is composed of a number of photodiodes that have been paired with corresponding red, green, and blue colour filters. The sensor produces a frequency signal proportional to each of the three colour components, and when the RGB colour Filter is sequentially driven, each frequency value measured corresponds to the red, green, and blue component of the colouring. These Frequency Values provide a way of measuring, quantitatively, the colour intensities of the solutions formed through the Metal-Reagent Reactions.

C. Embedded Processing and Decision Logic

C. Spectral Data Acquisition and Quantitative Estimation

In addition to RGB measurement, spectral analysis is performed using a compact UV–Visible spectrometer. After reagent-induced color development, the sample solution is placed in a transparent cuvette aligned with a broadband light source and spectrometer sensor.

The spectrometer captures the absorbance spectrum of the solution. Based on the Beer–Lambert Law:

$$A = \varepsilon c l$$

Where:
A = Absorbance
ε = Molar absorptivity
c = Concentration
l = Optical path length

Peak absorbance values corresponding to metal–reagent complexes are extracted. For example:

• Nickel–dimethylglyoxime complex → ~450 nm
• Copper–ammonia complex → ~610 nm
• Zinc–dithizone complex → ~530 nm

Calibration curves are generated using known standard concentrations of $ZnSO_4$, $CuCl_2$, and $NiSO_4$ solutions. Regression analysis is applied to estimate unknown metal concentrations from measured absorbance values.This method enables quantitative estimation rather than simple threshold-based classification dependence on external computation resources.

D. IoT Communication and Cloud Visualization

After processing, the RGB values and contamination status are transmitted to the ThingSpeak cloud platform using Wi-Fi connectivity. The cloud platform stores the data and provides graphical visualization of sensor readings over time. This allows users to remotely monitor water quality trends and identify abnormal conditions through dashboards and charts.

E. Alert and Monitoring Mechanism

If the detected colour intensity exceeds predefined thresholds indicating the presence of heavy metals, alert flags are generated within the system. These alerts can be visualized through the Thing Speak interface and used to inform users about potential water contamination. This approach supports early detection and preventive action.

In summary, the proposed methodology offers a simple, scalable, and cost-effective solution for detecting heavy metals in water. By leveraging chemical colorimetry, optical sensing, and IoT-based data transmission, the system provides a practical alternative to complex laboratory-based analytical techniques.

F. Multi-Sensor Fusion and Data Integration

In the proposed system, sensor measurements obtained from different sensing modules are combined using a multi-sensor

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fusion strategy. This process integrates optical color data from the TCS3200 sensor, spectral absorbance data from the UV–Visible spectrometer, and optional physicochemical parameters such as turbidity.

The fusion process follows three main stages:

1. Sensor Data Acquisition

Multiple sensors independently measure different properties of the water sample. The color sensor provides RGB frequency outputs, while the spectrometer generates absorbance spectra across the visible wavelength range.

2. Feature Extraction

Relevant features such as RGB intensity ratios, peak absorbance wavelengths, and spectral intensity values are extracted from the raw sensor signals.

3. Data Fusion and Decision Making

The extracted features are combined to form a unified feature vector representing the water sample. Decision logic or machine learning algorithms can then classify the sample as contaminated or safe.

By combining multiple sensor inputs, the fusion process minimizes false detections and improves the reliability of heavy metal identification.

Performance Interpretation

Through experimental results, the colourimetric sensing system was found to consistently and reliably detect heavy metals contaminating the tested water samples. All colour frequencies of the TCS3200 found to yield easily distinguishable and repeatable RGB colour frequency patterns for each of the arranged metal salt and reagent combination. As a result, it was possible to accurately detect if a sample of water was contaminated based on the metal contained in the water sample.

In multiple test runs with various concentrations of metal salts such as $ZnSO_4$, $CuCl_2$ and $NiSO_4$, the results demonstrated that measured colour changes resulted in a reproducible and predictable shift in red, green and blue channel frequency distributions. Each of the measured frequency shifts were correctly categorised using threshold-based decision logic running on the ESP32. There was very little variability in all of the repeated frequency measurements; therefore, it can be inferred that the colourimetric sensing system is robust and stable under controlled conditions.

Only a small number of misclassifications occurred when the water samples were prepared within the calibrated concentration range. Based on these observations, it is evident that the embedded processor for threshold selection and decision making works effectively. In addition, the observation of real-time monitoring via the ThingSpeak platform confirms that data can be reliably transmitted and monitored in real-time.

The work presented in this paper shows that the low-cost optical colour sensing system combined with IoT technology can serve as a practical alternative to conventional laboratory approaches for preliminary screening of heavy metal contamination in drinking water.

TURBIDITY SENSOR

Fig; 1a setup

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Fig: 1b predicted output

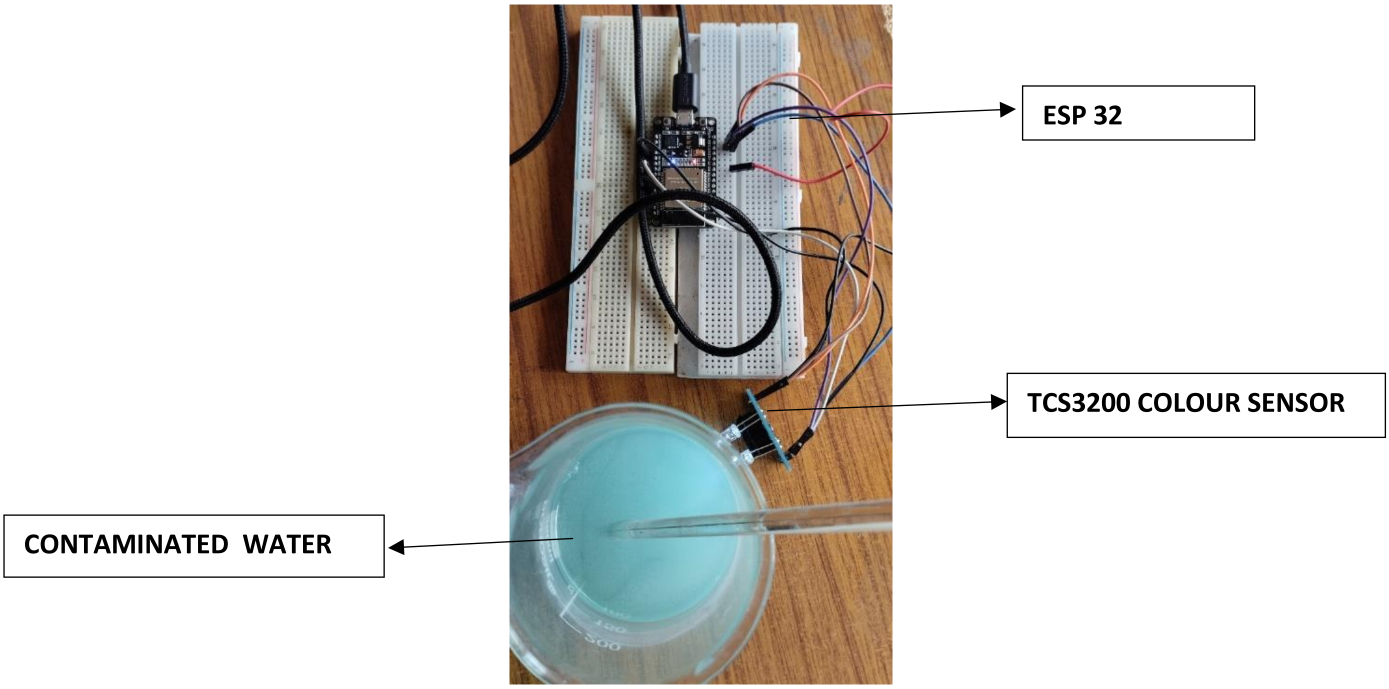

Fig: 2 Working model

Prototype Implementation and Hardware Details

To validate the proposed system architecture, a physical prototype was developed for real-time detection of heavy metals in water using a colorimetric sensing approach. The prototype demonstrates the practical feasibility of integrating chemical color reactions, optical sensing, embedded processing, and IoT-based monitoring in a single low-cost system.

A. Hardware Components

The prototype consists of the following key hardware components:

- **ESP32 Microcontroller**

  The ESP32 serves as the central processing and control unit of the system. It interfaces with the TCS3200 color sensor, processes RGB frequency data, performs threshold-based decision logic, and transmits processed data to the cloud using its built-in Wi-Fi capability.

- **TCS3200 Color Sensor**

  The TCS3200 color sensor forms the primary sensing element of the system. It detects color changes in water

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samples that occur due to chemical reactions between heavy metal ions and selective reagents. The sensor converts reflected red, green, and blue light intensities into corresponding frequency signals, which are read by the ESP32 for further analysis.

- **Chemical Reagents and Sample Holder**

  Selective color-forming reagents such as dimethylglyoxime, ammonia solution, and dithizone are used to produce distinct color changes in the presence of nickel, copper, and zinc ions respectively. A transparent sample container is used to hold the treated water sample beneath the color sensor to ensure consistent optical measurements.

- **ThingSpeak Cloud Platform**

  ThingSpeak is used as the cloud-based monitoring and visualization platform. RGB frequency values and contamination status generated by the ESP32 are uploaded periodically to the cloud, where they are displayed numerically and graphically for remote observation.

- **Power Supply and Supporting Components**

  The system is powered using a regulated DC supply or USB source. Supporting components include connecting wires, resistors, and a stable mounting structure to maintain a fixed distance between the sensor and the sample.

B. Prototype Workflow

- **Data Acquisition**
  Water samples containing metal salts such as $ZnSO_4$, $CuCl_2$, or $NiSO_4$ are prepared and treated with appropriate reagents to induce color formation. The TCS3200 sensor measures the RGB color components of the resulting solution by sequentially enabling its internal color filters.

- **Embedded Processing**
  The ESP32 reads the frequency outputs from the TCS3200 sensor corresponding to red, green, and blue components. These values are compared with predefined threshold ranges obtained during calibration. Based on this comparison, the system determines whether the water sample is safe or contaminated.

- **Cloud Transmission and Visualization**
  The processed RGB values and contamination status are transmitted to the ThingSpeak cloud platform using Wi-Fi. The platform displays real-time graphs and numerical indicators, enabling remote monitoring and analysis.

- **System Response Time**
  The complete sensing, processing, and cloud update cycle is completed within a few seconds. The observed response time of the prototype is approximately 2–3 seconds, demonstrating the system's capability for near real-time water quality assessment.

Interpretation

- The feature importance distribution confirms that the model emphasizes **physical and chemical quality indicator** (turbidity, TDS) over environmental conditions (pH, temperature). This prioritization reflects real-world contamination patterns, where **suspended matter and dissolved solids** are often primary indicators of pollution.

By quantifying feature relevance, this analysis enhances the system's **transparency and interpretability**, demonstrating how the AI model bases its classification decisions on measurable, domain-relevant parameters.

Results and Discussion

The experimental evaluation of the proposed detection system for heavy metals was conducted using prepared water samples that contained Zinc Sulphate ($ZnSO_4$) , Copper Chloride ($CuCl_2$) , and Nickel Sulphate ($NiSO_4$) . This evaluation

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included a comprehensive assessment of the Colourimetric Response of the Detection System, the repeatability of the Sensors, the Decision Accuracy of the Embedded Decision System and the Performance of the Cloud Based Monitoring System. Through this experimental evaluation, the feasibility of using an Inexpensive Optical Sensing Method for the initial detection of Heavy Metals in Water was demonstrated.

A. Colorimetric Response and Sensor Output Analysis

When selective chemical reagents were added to water samples containing different metal ions, distinct and observable color changes were produced. These color variations were successfully captured by the TCS3200 color sensor in the form of RGB frequency values. Each metal–reagent combination exhibited a unique RGB pattern, enabling differentiation between contaminated and uncontaminated samples.

Repeated measurements conducted under controlled lighting and fixed sensor distance showed consistent RGB frequency values with minimal variation. This indicates stable sensor performance and good repeatability, which is essential for reliable color-based detection.

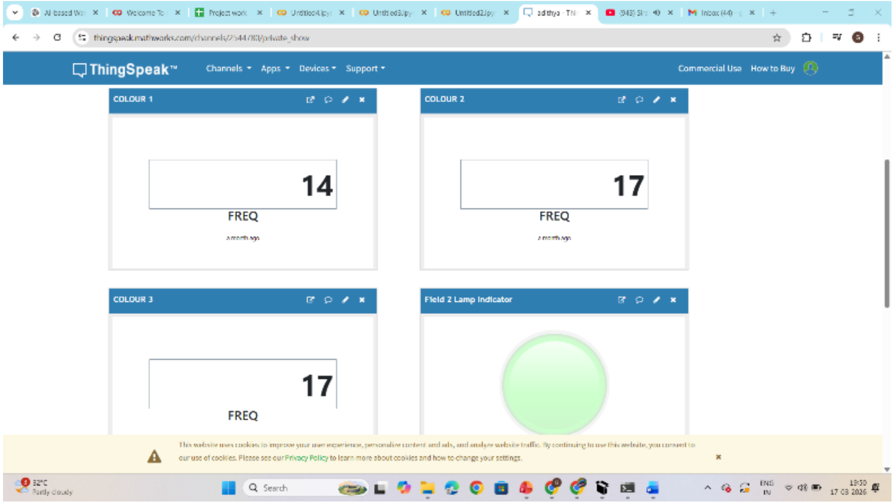

Fig: 3 TCS3200 colour sensor output

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```
Dataset Preview:
     R   G   B  Turbidity Metal
0  116  79  72       4.98    Cu
1  129  73  74       4.69    Cu
2  138  83  56       6.29    Cu
3  124  85  50       6.30    Cu
4  120  84  50       5.77    Cu

Model Accuracy: 0.9833333333333333
Model Accuracy: 98.33333333333333 %

Prediction Results:
    Actual Metal Predicted Metal
203           Ni              Ni
266           Ni              Ni
152           Zn              Zn
9             Cu              Cu
233           Ni              Ni
226           Ni              Ni
196           Zn              Zn
109           Zn              Zn
5             Cu              Cu
175           Zn              Zn

Confusion Matrix:
[[21  0  1]
 [ 0 22  0]
 [ 0  0 16]]

Model saved as heavy_metal_detection_model.pkl

Detected Metal: Cu
```

Fig :4 AI predicted output

B. Embedded Classification Performance

The RGB frequency values obtained from the TCS3200 sensor were processed by the ESP32 microcontroller using experimentally calibrated threshold values. Based on this comparison, water samples were classified as either **safe** or **contaminated**. The system correctly identified the presence of heavy metals in the majority of test cases, with only occasional ambiguity observed when color intensity was weak or concentration levels were near threshold limits.

The absence of complex machine learning models simplified system implementation while still achieving dependable classification performance for preliminary screening applications.

C. Cloud Monitoring and System Responsiveness

The processed RGB values and contamination status were transmitted to the ThingSpeak cloud platform using Wi-Fi connectivity. Real-time visualization of sensor data was achieved through numerical displays and time-series graphs. The end-to-end system response time, including sensing, processing, and cloud update, was observed to be approximately **2–3 seconds**, confirming the system's capability for near real-time monitoring.

This rapid response demonstrates the suitability of the proposed system for continuous remote monitoring without reliance on laboratory-based analysis.

D. Discussion

The experimental results confirm that colorimetric sensing combined with low-cost optical sensors and IoT platforms can serve as an effective alternative for preliminary heavy metal detection in water. Compared to conventional laboratory techniques, the proposed system offers advantages in terms of cost, simplicity, portability, and response time.

However, the system is primarily intended for **screening and indication purposes**, and not for precise concentration measurement. Factors such as ambient lighting conditions, reagent purity, and sensor alignment can influence measurement accuracy. Despite these limitations, the proposed approach provides a practical solution for early detection and monitoring of heavy metal contamination in resource-constrained environments.

F. Impact of Multi-Sensor Fusion

The integration of multi-sensor fusion significantly enhances the reliability of the detection framework. While RGB sensing alone can provide rapid screening, it may be affected by external lighting variations or reagent inconsistencies. The addition of spectral absorbance data provides a secondary validation mechanism, improving classification accuracy.

Experimental observations indicate that the fused sensing approach reduces ambiguity in color-based detection and improves discrimination between different metal ions. The hybrid sensing framework therefore provides a more robust and reliable solution for real-time water quality monitoring.

E. Spectral Analysis and Quantitative Performance Evaluation

The integration of the UV–Visible spectrometer significantly improved the system's quantitative analysis capability. Distinct absorption peaks were observed for each metal–reagent complex, confirming selective optical behavior at characteristic wavelengths.

Compared to RGB-only detection, spectral absorbance measurement provided:

• Improved discrimination between closely spaced concentration levels
• Reduced misclassification near threshold limits
• Higher repeatability in concentration estimation

Calibration curves demonstrated a near-linear relationship between absorbance and concentration within the tested range. The coefficient of determination (R^2) indicated strong correlation, validating the applicability of the Beer–Lambert model for the selected concentration range.

The hybrid sensing framework reduced ambiguity caused by overlapping RGB responses and enhanced overall system robustness. While RGB sensing remains suitable for rapid preliminary screening, spectroscopic validation significantly improves analytical confidence.

VI. CONCLUSION

This project presented the design and implementation of a low-cost, IoT-based heavy metal detection system using a colorimetric sensing approach. The system utilizes selective chemical reagents to induce color changes in water samples containing metal ions such as zinc (Zn^{2+}), copper (Cu^{2+}), and nickel (Ni^{2+}). These color variations are detected using a TCS3200 color sensor and processed by an ESP32 microcontroller for real-time analysis.

Experimental evaluation demonstrated that the proposed system is capable of reliably distinguishing between safe and contaminated water samples based on calibrated RGB frequency values. The embedded threshold-based decision logic enabled fast and consistent classification without reliance on complex machine learning models or laboratory instrumentation. Integration with the ThingSpeak cloud platform provided effective remote monitoring and real-time visualization of sensor data.

Compared to conventional laboratory-based techniques, the proposed solution offers significant advantages in terms of cost, simplicity, portability, and response time. Although the system is intended for preliminary screening rather than precise concentration measurement, it proves to be a practical and scalable approach for early detection of heavy metal contamination.

In conclusion, the developed prototype validates the feasibility of combining chemical colorimetry, optical sensing, and IoT technology for water quality monitoring. The system is well suited for academic research, small-scale environmental monitoring, and deployment in resource-constrained or rural settings, where rapid and affordable water quality assessment is essential

VII. FUTURE DEVELOPMENT

The present system demonstrates a low-cost and effective approach for preliminary heavy metal detection in water using colorimetric sensing and IoT technology. Several enhancements can be incorporated in future to improve accuracy, scalability, and functionality.
One major extension of the system can be the integration of additional water quality sensors such as a **Total Dissolved Solids (TDS) sensor** or **Electrical Conductivity (EC) sensor**. These sensors can provide complementary information

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about dissolved ionic substances and overall water salinity, thereby strengthening the assessment of water quality when used alongside color-based heavy metal detection. Integration of pH and temperature sensors can further help in compensating for environmental variations that influence chemical reactions and sensor readings.

Future work can also focus on **quantitative estimation of metal concentration** rather than simple presence or absence detection. This can be achieved by calibrating RGB frequency values against known concentration standards and developing regression-based models to estimate approximate metal ion levels. Such calibration would improve the system's usefulness for environmental monitoring applications.

On the data processing side, basic **data analytics or lightweight machine learning techniques** can be explored to enhance classification accuracy and reduce false detections. These models may be implemented at the edge level using optimized algorithms, provided sufficient datasets are collected during long-term deployment.

Additionally, the system can be expanded to support **multi-metal detection in a single sample** by incorporating sequential reagent addition, multi-stage sensing, or separate sensing chambers. Improving sensor enclosure design and controlled lighting conditions can further enhance measurement stability and repeatability.

In future deployments, the IoT framework can be extended to include mobile applications, SMS alerts, or integration with municipal monitoring systems for large-scale water quality surveillance. These enhancements would make the proposed system more robust, scalable, and suitable for real-world applications.

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