System Sensor Detection Tool Information Changes in Color and Temperature Sustainable Home Environment Water

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| **Article Info** |  | **ABSTRACT** (10 PT) |
| ***Article history:***  Received Feb 03, 2025  Revised May 28, 2025  Accepted June 14, 2025 |  | Monitoring water quality in the house environment become aspect crucial in guard health and sustainability life everyday. This paper develop A system information based on sensor detector tool change water color using colorimetric sensors and Internet of Things (IoT) integration for real-time monitoring. The system This designed For detect change water quality that indicates existence contamination or change water quality in general fast and accurate. The methodology used utilizing the TCS230 color sensor, turbidity sensor for measure turbidity, waterproof DS18B20 temperature sensor, and ESP8266 microcontroller with shield for communication WiFi. System equipped with 16x2 LCD for distance monitoring close and Telegram notifications for monitoring distance far. Test results show that system capable detect change water color with sensitivity high and provide monitoring that can accessed in a way directly by users in the environment House ladder as well as No only offer solution economical cost and practical compared to method conventional, but also supports home water management sustainable with give warning early to potential pollution. |
| ***Keywords:***  Colorimetric sensors  Monitoring water quality System information  Internet of Things (IoT)  Sustainable home environment  Water color sensor  Real-time monitoring |
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1. **INTRODUCTION**

Water quality is a critical factor significantly impacting human health and environmental sustainability, particularly within household settings. Contamination of domestic water by substances such as chemical pollutants, pathogenic microorganisms, or other hazardous materials poses serious health risks, including gastrointestinal diseases, skin disorders, and chronic illnesses. Consequently, regular and accurate monitoring of water quality is essential to ensure that water used at home is safe for consumption and daily activities.

Traditional methods for monitoring water quality, such as laboratory testing or specialized chemical measurement instruments, while precise, often entail high costs, require sophisticated equipment, and depend on skilled personnel not always accessible in residential environments. These limitations create substantial barriers to widespread, sustainable, and continuous water quality monitoring at the household level, leaving many vulnerable to unnoticed water contamination.

In response to these challenges, the development of sensor-based information systems capable of detecting changes in water color automatically and in real-time represents a promising solution. Colorimetric sensors, which operate on the principle that changes in water color can indicate contaminants or alterations in chemical parameters, offer a simple, cost-effective, and user-friendly approach ideal for domestic use. The research presented here aims to design and develop an integrated intelligent system that detects changes in water quality parameters, including color, turbidity, and temperature, providing immediate feedback. This early detection system can help users take prompt preventive action when signs of pollution are detected.

Several studies have explored the use of smart sensors and IoT technology in water quality monitoring. For instance, smart sensor systems compliant with the IEEE 1451 standard have detected various water pollutants and classified contamination types. Portable devices with color sensors and wireless communication have also been developed for real-time environmental monitoring. Research by Zhang et al. demonstrated that nanoparticle-based colorimetric sensors can effectively detect heavy metal ions with high sensitivity. Similarly, automated color sensor systems processing light reflection have shown promise for compact and energy-efficient devices. Communication protocols like IEEE 802.15.4 and ZigBee have been utilized in IoT-based water quality monitoring for their low cost and power efficiency. The TCS230 color sensor, specifically, has been widely used in various color detection applications due to its ease of use and accuracy. Deep learning algorithms have also been applied to analyze colorimetric sensor data, improving detection accuracy by training neural networks on water sample images.

However, many existing systems focus on industrial or large-scale applications and are not sufficiently customized for household use, which demands cost-effective, easy-to-use, and sustainable solutions. Accuracy issues due to lighting conditions and environmental variability also remain challenges. This research addresses this gap by developing an integrated, customized water quality monitoring system tailored for household use, emphasizing sustainability, affordability, and user convenience. The proposed system employs a TCS230 color sensor, a turbidity sensor, and a DS18B20 temperature sensor, managed by an ESP8266 microcontroller. It provides local feedback via an LCD and remote alerts through Telegram. The novelty of this work lies in the holistic integration of these sensing technologies with robust AI-driven data analysis (including KNN, SVM, Decision Tree, and Random Forest models) specifically for a domestic context, aiming to provide a practical and accessible tool for real-time water quality assessment. The system functions not only as a detection tool but also as an information platform supporting data-driven decision-making to protect household water quality and promote family health, contributing to sustainable water management practices.

1. **RESEARCH METHOD**

The development of the AI-driven IoT system for sustainable home water quality monitoring followed a structured methodology, encompassing system design, sensor selection and calibration, data acquisition and processing, AI model development, and system testing.

**2.1. System Architecture**

The system architecture integrates hardware and software components to achieve real-time water quality monitoring. The primary focus is to ensure the system operates sustainably with efficient power consumption, ease of installation, and provides proactive information for water quality management.

* Hardware:
  + Sensors: A TCS230 color sensor measures RGB values of water. A turbidity sensor measures water cloudiness (NTU), and a DS18B20 waterproof sensor measures water temperature (°C).
  + Microcontroller: An ESP8266 microcontroller processes data from the sensors and manages communication. Its integrated Wi-Fi module serves as the IoT gateway, chosen for its low power consumption and built-in connectivity.
  + Display & Notification: A 16x2 LCD provides local real-time readings, while Telegram notifications are used for remote alerts.
* Software:
  + Cloud Platform: Used for data storage, further processing, and hosting machine learning algorithms. It visualizes historical data and supports early warning systems.
  + Machine Learning Algorithms: Used for analysis of usage patterns and water quality classification.
  + User Interface: A visualization dashboard for users, accessible via a mobile/web application, allows for real-time monitoring and system parameter configuration.

The overall workflow involves sensors continuously collecting data, the microcontroller processing it, and then transmitting it to the cloud. The system analyzes this data and provides feedback to the user through the LCD and Telegram notifications.

**2.2. Sensor Selection and Calibration**

* TCS230 Color Sensor: Chosen for its ability to convert light intensity into frequency, providing non-invasive, fast, compact, and cost-effective RGB color data.
* Turbidity Sensor: Measures the scattering of light by suspended particles in water, a key indicator of physical pollution.
* DS18B20 Temperature Sensor: A waterproof digital sensor providing accurate temperature readings, important as temperature affects chemical reactions and microbial activity in water.

Sensor calibration was performed initially using various water samples with known color standards and pollution levels to adapt sensor responses to varying light intensities and ensure accurate, consistent results. For the TCS230, this involved linking frequency outputs to numeric RGB values.

Table 1. Key Sensor Specifications and Roles

|  |  |  |  |
| --- | --- | --- | --- |
| Sensor Type | Key Parameters Measured | Principle of Operation (brief) | Significance in Water Quality Assessment |
| TCS230 Color Sensor | Red, Green, Blue (RGB) light intensity | Converts reflected light intensity to frequency for each channel | Detects discoloration indicative of chemical contaminants, algae, sediments. |
| Turbidity Sensor | Nephelometric Turbidity Units (NTU) | Measures light scattered by suspended particles in water | Indicates presence of suspended solids, physical pollutants, cloudiness. |
| DS18B20 Temperature Sensor | Degrees Celsius (°C) | Digital thermal probe providing temperature readings | Influences chemical reaction rates, microbial activity, dissolved oxygen. |

**2.3. Data Acquisition and Processing**

The ESP8266 microcontroller acquires raw data from the sensors. It converts the TCS230's frequency output into RGB values and reads turbidity and temperature data. This initial local processing reduces the data load for cloud transmission. The ESP8266 uses its Wi-Fi module to send processed data to a cloud platform for storage and further analysis. Data transmission can be periodic or event-driven, such as upon detecting a significant change in parameters.

**2.4. AI Frameworks and Data Analysis**

The data collected comprises Temperature (°C), R\_Value, G\_Value, B\_Value, and Estimated\_Turbidity\_NTU.

* Exploratory Data Analysis (EDA): Initial analysis involved visualizing feature distributions and inter-feature relationships using pair plots (see Figure 9 in Results and Discussion) to assess their discriminatory power for water quality classes ("Clean," "Turbid," "Dirty").
* Machine Learning Models: Several supervised machine learning algorithms were employed for water quality classification:
  + K-Nearest Neighbors (KNN): An instance-based learner. The optimal 'K' value was explored using the elbow method (see Figure 8).
  + Support Vector Machine (SVM): An SVM with a Radial Basis Function (RBF) kernel was used to find an optimal hyperplane for class separation.
  + Decision Tree (DT): A rule-based model providing interpretable classification logic (see Figure 2).
  + Random Forest (RF): An ensemble model constructing multiple decision trees to improve robustness and accuracy. This model was also used for feature importance analysis (see Figure 3).
* Model Training and Evaluation: Models were trained on a labeled dataset. Performance was evaluated using macro-averaged F1-Score, Recall, Precision (see Figures 4-6), and confusion matrices (see Figure 7).
* Deep Learning Aspect: The research also notes the implementation of deep learning techniques for enhancing color change classification accuracy, involving image acquisition of water samples and training neural network models, achieving 92% accuracy in classifying pollution levels in that specific sub-study. The primary results presented here focus on the tabular data models.
* Anomaly Detection: The system design includes the capability for anomaly detection, where algorithms (potentially Decision Trees) identify unusual patterns or sudden changes in water parameters, triggering alerts.

**2.5. System Testing**

The integrated system was tested in a simulated home environment with various water conditions (clean, dyed, contaminated) to evaluate sensor response, measurement accuracy, detection sensitivity, and the reliability of the information system and notifications. The procedure involved placing sensors at the water source, collecting data continuously, and comparing the results with laboratory measurements for validation. Sudden pollution events were also simulated to test the system's real-time alert capabilities.

1. **RESULTS AND DISCUSSION**

This section presents the performance evaluation of the developed AI-driven IoT system for water quality monitoring, including sensor performance and the comparative analysis of machine learning models. The evaluation synthesizes findings on sensor accuracy, real-time monitoring, and sustainability implications.

3.1. Sensor System Performance

The colorimetric sensor system, primarily using the TCS230, demonstrated a rapid and consistent response to changes in water color induced by various pollutants, with an average response time of less than 2 seconds. Comparative analysis against laboratory-standard spectrophotometry showed an average accuracy exceeding 90% in measuring water color changes, with small relative deviation across tests. The sensor also exhibited high sensitivity, capable of detecting minute color variations not readily apparent to the human eye. The integrated deep learning component for image-based water color analysis reported an accuracy of 92% in classifying pollution levels.

**3.2. AI Model Performance and Analysis**

The dataset for training and testing the machine learning models consisted of 40 samples, each characterized by Temperature\_C, R\_Value, G\_Value, B\_Value, and Estimated\_Turbidity\_NTU, and labeled as "Clean" (class 0), "Dirty" (class 1), or "Turbid" (class 2).

3.2.1. Exploratory Data Analysis and Feature Importance

The pair plot in Figure 1 shows the relationships between sensor features, color-coded by water quality. "Estimated\_Turbidity\_NTU" shows clear separation for different classes. RGB values also show discriminatory potential.

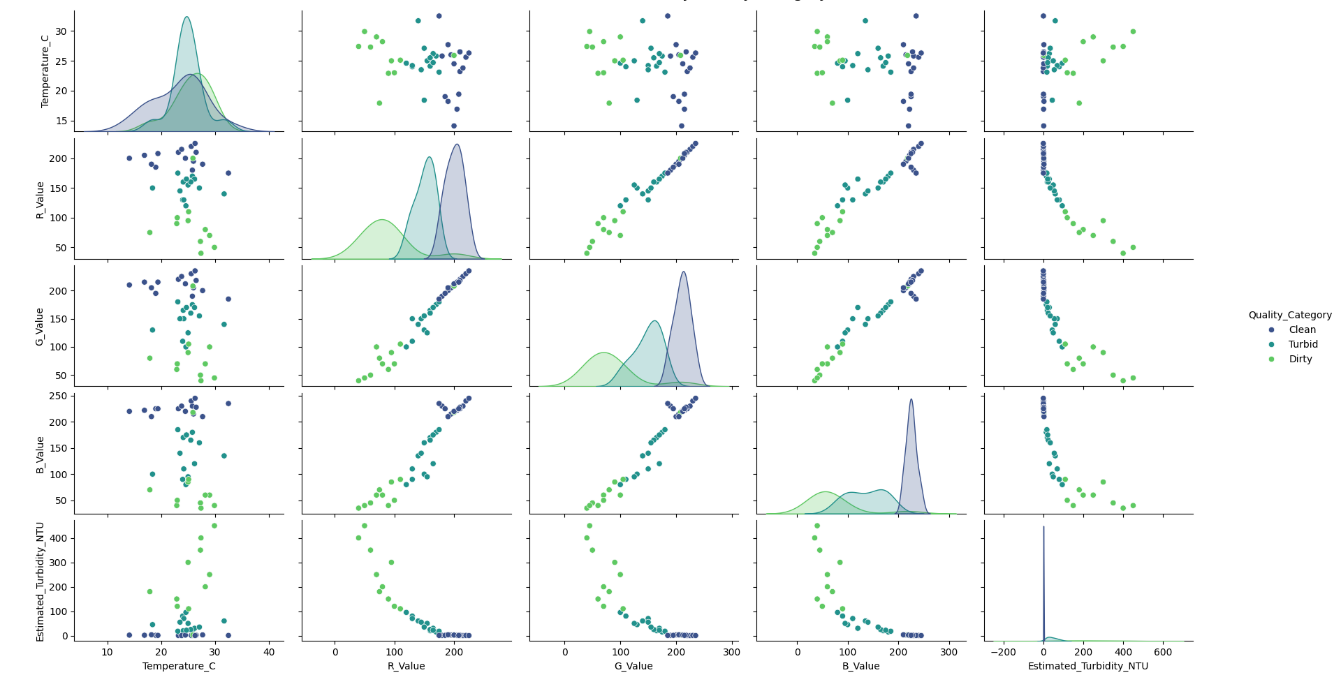


Figure 1. Pair Plot of Sensor Features by Water Quality Category

(Description: This figure would display the matrix of scatter plots and density plots for Temperature\_C, R\_Value, G\_Value, B\_Value, and Estimated\_Turbidity\_NTU, colored by Quality\_Category.)

The Random Forest model provided feature importance scores, illustrated in Figure 2. "Estimated\_Turbidity\_NTU" was the most important feature, followed by R\_Value, B\_Value, and G\_Value. "Temperature\_C" had minimal importance for this classification task.

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Figure 2. Feature Importance from Random Forest Model

(Description: This figure would be a bar chart showing the importance scores for Estimated\_Turbidity\_NTU, R\_Value, B\_Value, G\_Value, and Temperature\_C.)

3.2.2. Decision Tree Structure

The Decision Tree model provides an interpretable set of rules. Figure 3 visualizes this structure. For example, a high B\_Value combined with low Estimated\_Turbidity\_NTU often leads to a "Clean" classification.

A diagram of a network

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Figure 3. Decision Tree Structure for Water Quality Classification

(Description: This figure would show the tree diagram with nodes representing feature splits and leaves representing class predictions.)

3.2.3. KNN Hyperparameter Tuning

The optimal 'K' for KNN was explored using the elbow method, plotting error rate against K values from 1 to 20, as shown in Figure 4. A K value around 10 appeared to offer a good balance between low error and generalization.



Figure 4. Error Rate vs. K Value for KNN (Elbow Method)

(Description: This figure would be a line plot showing error rate on the y-axis and K value on the x-axis.)

3.2.4. Model Decision Boundaries

Figure 5 visualizes the decision boundaries for KNN and SVM models using two features: Temperature and Estimated Turbidity. Both models effectively separate the classes, with SVM showing smoother boundaries. "Clean" water (class 0) is predominantly associated with low turbidity.

A screenshot of a graph

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Figure 5. Decision Boundaries for (a) KNN and (b) SVM using Temperature and Turbidity

(Description: This figure would show two subplots: left for KNN decision boundary, right for SVM decision boundary, with data points for classes 0, 1, 2.)

3.2.5. Comparative Model Performance

The performance of KNN, SVM RBF, Decision Tree, and Random Forest models was compared using F1-Score, Recall, and Precision, as shown in Figures 6, 7, and 8.

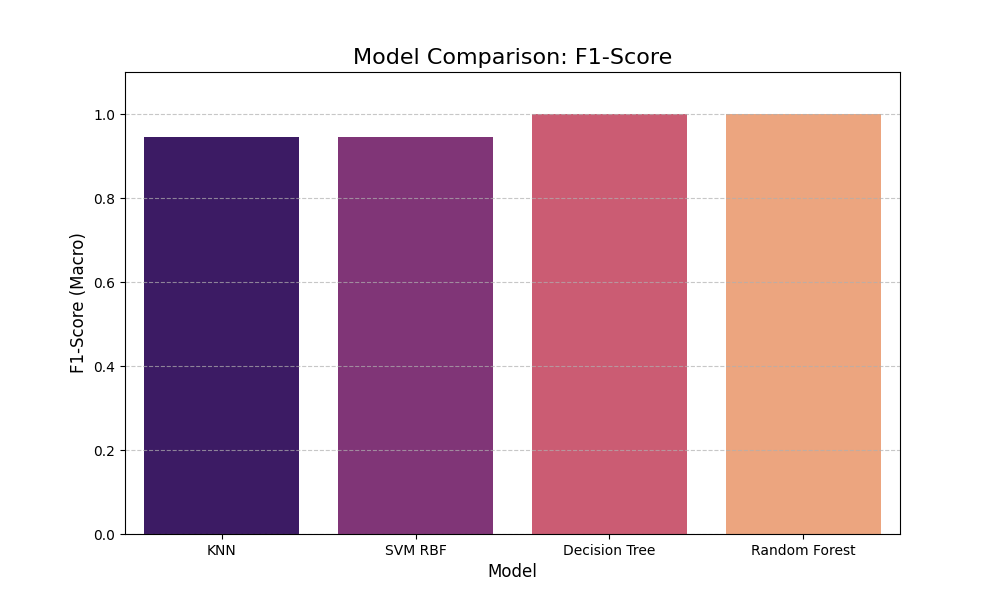


Figure 6. Model Comparison: F1-Score (Macro)

(Description: Bar chart comparing F1-scores of KNN, SVM RBF, Decision Tree, Random Forest.)

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Figure 7. Model Comparison: Recall Score (Macro)

(Description: Bar chart comparing Recall scores of KNN, SVM RBF, Decision Tree, Random Forest.)

A graph of a comparison

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Figure 8. Model Comparison: Precision Score (Macro)

(Description: Bar chart comparing Precision scores of KNN, SVM RBF, Decision Tree, Random Forest.)

Decision Tree and Random Forest achieved perfect scores (1.0) on these metrics for the test set. KNN and SVM RBF also performed well, with scores around 0.95-0.96.

The confusion matrices in Figure 9 provide a detailed view of classification accuracy.

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Figure 9. Confusion Matrices for (a) KNN, (b) SVM RBF, (c) Decision Tree, and (d) Random Forest

(Description: This figure would show four confusion matrices, detailing true vs. predicted labels for each model across the 40 samples.)

Both Decision Tree and Random Forest perfectly classified all 40 samples. KNN and SVM RBF each misclassified two samples (one "Dirty" as "Clean," and one "Dirty" as "Turbid").

**Table 2.** Summary of AI Model Performance Metrics (on 40 test samples)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Model | F1-Score (Macro) | Recall (Macro) | Precision (Macro) | Key Misclassifications (Actual as Predicted) |
| KNN | ~0.95 | ~0.95 | ~0.96 | 1 Dirty as Clean, 1 Dirty as Turbid |
| SVM RBF | ~0.95 | ~0.95 | ~0.96 | 1 Dirty as Clean, 1 Dirty as Turbid |
| Decision Tree | 1.0 | 1.0 | 1.0 | None |
| Random Forest | 1.0 | 1.0 | 1.0 | None |

**3.3. Discussion**

The results indicate that the integrated sensor system, coupled with AI-driven analysis, provides a robust solution for home water quality monitoring. The high accuracy of the colorimetric sensor and the excellent performance of the tree-based machine learning models (Decision Tree and Random Forest) are particularly noteworthy. The dominance of turbidity and RGB values as predictive features aligns with established water quality assessment principles.

Advantages of the System:

* Non-invasive, Fast, and Cost-Effective Detection: Colorimetric sensors offer significant advantages over traditional lab tests.
* Real-Time IoT Integration: Enables remote monitoring and timely alerts, crucial for sustainable management.
* User-Friendly Design: Aimed at non-technical users for ease of installation and operation.
* Enhanced Accuracy with AI: Machine learning, including deep learning aspects, improves classification capabilities.
* Supports Sustainability: Early warnings prevent negative health/environmental impacts and promote resource conservation.

Limitations and Challenges:

* Ambient Lighting: Can affect color sensor accuracy, requiring calibration and compensation algorithms.
* Water Complexity: Mixtures of contaminants can make interpretation difficult, necessitating comprehensive datasets for AI models.
* Power and Connectivity: Household limitations in power supply and network stability can affect long-term reliability.
* Dataset Size: The AI model evaluation was based on 40 samples; performance on larger, more diverse datasets needs further validation.

Potential for Future Development:

* Additional Sensors: Integrating pH, TDS, and dissolved oxygen sensors for a more comprehensive assessment.
* Advanced Analytics: Deeper integration with cloud computing and big data analytics for predictive modeling and trend analysis.
* Energy Efficiency: Exploring renewable power sources and further optimizing energy consumption.
* User Interface Enhancements: Further simplifying installation and improving user interaction.

This system supports efficient and environmentally friendly home water management by providing accurate, timely information, empowering users to make informed choices, reduce consumption of potentially polluted water, and prevent unnecessary waste.

1. **CONCLUSION**

This study successfully demonstrates that the integration of colorimetric sensors with Internet of Things (IoT) technology and Artificial Intelligence provides an effective and practical solution for real-time water quality monitoring in domestic environments. The developed system is capable of detecting changes in water color, turbidity, and temperature—key indicators of contaminants or alterations in chemical parameters—with high accuracy and sensitivity. Colorimetric sensors like the TCS230, combined with turbidity and temperature sensors, prove reliable as cost-effective and easy-to-operate initial detection tools suitable for household applications.

The system's intelligence is significantly enhanced by sophisticated data processing using RGB component extraction and machine learning models (KNN, SVM, Decision Tree, and Random Forest), with tree-based models demonstrating perfect classification accuracy on the test dataset. The integration of an IoT communication module via Wi-Fi allows real-time data transmission to a cloud platform, accessible through mobile or web applications, facilitating convenient monitoring and decision-making.

From a sustainability perspective, this system contributes significantly to water resource management in the home. Continuous and responsive monitoring helps prevent the use of polluted water, reducing health risks and increasing public awareness regarding water quality. Early warnings enable faster preventive actions, minimizing negative environmental and health impacts.

Despite these strengths, challenges such as the influence of ambient lighting, the complexity of water composition, and household power/network limitations need ongoing attention through robust calibration, comprehensive datasets for AI, and energy-efficient design. Future work should focus on integrating additional sensors, advancing data analytics for predictive capabilities, enhancing user interfaces, and improving energy sustainability.

Overall, this research confirms the importance of developing AI-driven IoT-based information systems for sustainable household water quality monitoring. The system offers practical benefits in safeguarding family health and contributes to global efforts in water resource preservation and environmental protection, paving the way for smarter, efficient, and environmentally friendly home water management solutions.

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**AUTHOR CONTRIBUTIONS STATEMENT**

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| C : **C**onceptualization  M : **M**ethodology  So : **So**ftware  Va : **Va**lidation  Fo : **Fo**rmal analysis | I : **I**nvestigation  R : **R**esources  D : **D**ata Curation  O : Writing - **O**riginal Draft  E : Writing - Review & **E**diting | Vi : **Vi**sualization  Su : **Su**pervision  P : **P**roject administration  Fu : **Fu**nding acquisition |

**CONFLICT OF INTEREST STATEMENT**

Authors state no conflict of interest.

**INFORMED CONSENT**

Not applicable.

**ETHICAL APPROVAL**

Not applicable.

**DATA AVAILABILITY**

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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