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Research Article

Development of a Portable Water Quality Monitoring System Integrating pH, TDS Sensors, and CNN-Based Visual Analysis

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ABSTRACT

Access to safe, clean drinking water is still a global challenge. Currently, over 2.2 billion people are using water sources that are not safe for consumption. Traditional water quality testing is labor intensive and time-consuming, limiting access. This study focuses on the design and development of a smart, portable prototype to assess tap water quality in real-time and to recommend filters/filtration methods. Using pH and TDS sensors along with a Convolutional Neural Network (CNN) on a Raspberry Pi (RP), the prototype classifies water samples into clean, colored, oily, saline, and turbid categories. The water sample's sensor readings and images are used to make suggestions about the suitable methods for filtration through an intuitive user interface. The classification accuracy of the CNN model is 75.53% on the test dataset and the sensors proved to be highly reliable against commercial meters. The entire inference pipeline takes less than three seconds, including image capture, classification, and recommendation. The proposed solution is a viable and cost-effective solution for monitoring water quality in both domestic and industrial settings; providing real-time support for decision-making regarding filtration methods while improving public health outcomes. Future work could include increasing CNN dataset diversity, incorporating additional sensors, adaptive learning mechanisms from user feedback, and adding cloud capabilities in the proposed system.

Keywords*:* Water Quality Monitoring, pH and TDS Sensor, Deep Learning, Convolutional Neural Network (CNN), Smart Water Filter Recommendation, Real-time Water Analysis, Embedded System, On-site Water Testing, IoT-based Water Quality Testing, Water Sample Classification, Portable Water Analysis Prototype.

I. INTRODUCTION

In the year 2022, roughly 6 billion individuals, corresponding to the majority of the global population, used safely managed drinking-water services, which are assured to be free from contamination. Meanwhile, an estimated 2.2 billion individuals, or one in three, used drinking water from a source that was not safely managed. In addition, about 296 million relied on water from unprotected wells and springs; approximately 115 million obtained water from untreated surface water sources like lakes, ponds, rivers, and streams. The public health implications of such disparities in access to drinking water are significant and this shows the need for continual improvement and monitoring of water quality. **[1]** Typical water quality monitoring techniques rely on costly and labor-intensive laboratory analysis to assess water quality which is slow to result in timely intervention and decision making. Furthermore, the current options are not fast and/or dependable methods to provide on-site evaluation which is important for consumers and water management authorities alike. This research focuses on the development of a portable prototype capable of evaluating tap water quality by conducting measurements of important parameters and providing an evaluation of visual characteristics simultaneously. The proposed system includes integrated sensors to measure pH values and Total Dissolved Solids (TDS), and also capture an image of the tap water sample. The image is then analyzed through a deep learning model built using convolutional neural network (CNN) to classify water quality and provide an immediate, appropriate water filter recommendation. This prototype not only detects anomalous water quality but also direct users to effective filtration techniques they can use. The solution is derived from utilizing various technologies. Specifically, it employs a Raspberry Pi device for running the deep learning model to enable accurate water quality analysis. It also integrates the pH and TDS sensors with the ESP32 M5Stamp S3 microcontroller to monitor water quality parameters. By analyzing sensor data with a sophisticated water sample image analysis, adding new rigor to water quality assessments. This investigation contributes to the existing body of work by integrating traditional sensor-based approaches with modern deep learning approaches. This method not only improves the accuracy of the water quality assessment process but may also function as a tangible link between meaningful assessments of water quality and a solution that could be used in a domestic and industrial setting. This research contributes value on multiple levels. Communities can rely upon quicker, onsite diagnostic capabilities of the proposed solution that will limit exposure to potential contaminants. Water treatment and filtration industries can utilize data from the prototype to improve product recommendations and develop better purification systems, grounded in data comparisons. Ultimately, this research provides an essential link between technology and practice about water quality, contributing to better water quality management practice.

II.LITERATURE REVIEW

The research on intelligent water purifiers, conducted by **Liang Tianchun et al. [1]**, sought to address the urgent need to provide safe drinking water with optimized levels of TDS (Total Dissolved Solids) and pH (Potential of Hydrogen). The experiment made use of a multi-stage filtration system comprising three stages, which were the first, second, and third-level filtering groups along with ultrafiltration and nanofiltration membrane units. This setup facilitated the segregation of water into two streams, one of which went into the water tap and the other into an RO (Reverse Osmosis) unit. The test outcome showed that the purification process maintained the TDS value of less than 50 mg/L and adjusted the pH value within the range of 7.35 to 8.5. Thus, all WHO (World Health Organization) criteria for healthy drinking water were met. However, the study was limited by the scalability of the technology and possible maintenance issues of the multiple filtration units. Also, although the system reduced TDS and optimized pH, its long-term performance and effects on water quality need to be tested under different conditions. The study conducted by **A. N. Laghari et al. [2]** focused on determining the efficiency of different filter units in reducing turbidity, pH, total dissolved solids (TDS), and electrical conductivity (EC) in canal water. This resulted in the construction of three different water purifying systems: the slow sand, rapid sand, and dual media. The team also conducted a comparative analysis on the water quality parameters before and after being filtered, which included pH, turbidity, TDS, and EC by WHO standards. It was observed that the dual media system gave the highest reduction in pH, but, as far as turbidity removal is concerned, slow sand filtration has been noted to be the most effective. An increase in both TDS and EC was noted in the filtrate samples due to mineral elution from within the grains of the sand into the water. However, despite this increase in the mentioned element, in terms of the WHO limits, it was still within the required limits. Study constraints for such an experiment might spring from cases of disparities in the filtration performance because of the local water condition, or may necessitate longer testing to understand its performance for long-term operation. **Lina Rose et al. [3]** conducted a study concerning the need for estimation and documentation of Total Dissolved Solids (TDS), salinity, pH, and turbidity about the intensifying concerns regarding water safety. A photo sensor was used to transmit the light in the water samples that vary in salt content and to understand the optical properties of different salts, using a machine learning model. These findings have shown some expectations concerning the quality of water and underlining the threats with respect to water scarcity and contamination. However, limitations are concerned with sensor calibration and the potential for causing the salt content to vary across different water samples and thus influence the accuracy. Further validation of machine learning is still required, as the promising aspect would have to be verified against a wider pool of samples to make the machine learning model more reliable. A TDS detection system was embedded in a water purifier to investigate water quality monitoring by **Jianghong Zhu et al. [4]**. The concept was based on equipping an electrical conductivity sensor at the water outlet pipeline, converting conductivity into electricity. The electricity generation was followed by voltage signal conditioning, which was then changed into a digital signal by the AD converter module, and finally, processed by the controller to calculate the TDS level. As a result, the system was found to efficiently monitor TDS in water, investigating their performance as a tool for timely monitoring of filters and auto-detection of the failed filter core, ensuring the goal was to maintain consistency in water quality. As such, the study had not only feedback on the object of perceived limitation of the two associated variables but also on how conductivity could be subject to further interference from other dissolved substances. However, an inquiry for continuing improvement regarding its sensitivity and reliability, especially under varied conditions from the tap in a residence to groundwater, is needed.

The research by **Julio Garcia et al. [5]** focused on the quality of groundwater in six regions in West Texas with a solid interest in the effect of environmental changes on TDS (Total Dissolved Solids). To understand the dynamics of TDS from the 1990s to the 2010s, the researchers utilized advanced machine learning algorithms. Finally, with the assistance of the Texas Water Development Board (TWDB) and the Groundwater Database (GWDB), data on groundwater quality was obtained. There were remarkable patterns observed in TDS concentrations. The works of the scientists are backed up with heavy rigor in testing, which shows the effectiveness of machine learning in environmental studies. Limitations include the biases observed in reliance on data collection, the methodology used in the research, and the challenge of practically recording the environmental variables that affect groundwater quality. Gaps in groundwater management and policy were identified that needed further research, thereby hinting at the direction to proceed as far as other water quality parameters and their interactions are concerned. The study conducted by **Ummi Athiyah et al. [6]** concentrated on the groundwater quality assessment in rural areas. The Modified K- K-Nearest Neighbor (KNN) algorithm was used in the study. This was feasible for matching images, as well as for the sensor data from the pH, TDS, and temperature sensors. Model performance was measured with K-Fold Cross Validation and also in a Multiclass Confusion Matrix. The results received for the K-Fold values were 2, 9, and 10. The highest accuracy was 78%, where precision was still at 0.32, recall 0.37, and F1-score 0.33, resulting in its most accurate value having an optimal K of 5. The results showed that most of the waters considered for the case study are good for usage. However, the limitation includes a substantially low precision and recall value, suggesting that once there is a change in the nature of water in the area considered for testing, the challenge in accurate classification of water quality increases. Eventually, the algorithm needs fine-tuning to get the correct prediction. The study by **Hui Huang et al. [7]** focused on creating a Total Dissolved Solids (TDS) detection device for water purifiers, intending to monitor the water quality continuously. Conductivity sensors were installed in the water outlet pipeline to measure the electrical conductivity and convert it to a corresponding signal. By conditioning the signal, the signal was converted into a voltage range, from which the Analog-to-Digital (AD) conversion module was employed to convert it into a digital format. The TDS was then calculated by the controller from that digital output, which meant that filtered-down water quality could be immediately assessed. The results showed that the device could effectively detect the TDS status, making it possible to assess in real-time the performance of the filter, as well as timely decision-making about whether or not it requires maintenance, so that it could produce high-quality water. The disadvantage of the device included the problem concerning the deviation that would occur sometimes in conductivity reading, depending on the different water solutions, and this would require calibration of the sensors within a specific period for an accurate measurement. Besides, the integration of the device into the continued development of monitoring capability suggests that it will be necessary for future research to ascertain endurance over time and effectiveness among different types of water samples.

The research by **Karel Horak et al. [8]** focused on the assessment of the water quality using image processing and two ecologically important organisms, Daphnia magna and Lemna minor, which were used as biological detectors for determining water toxicity. These organisms help in the quantification of toxicity. The researchers have focused on high sensitivity to water-based toxins. The research targeted the most valuable factor/measurement of water quality at minimum cost. The research involved 24/7 imaging of these organisms, using cameras, separated in different vessels, and autonomously processing the images. This processing technique included color-space transformation and motion analysis. These results from Schuler, Stadnicka, and other findings showed that such a system effectively computes a relative indicator, given the obtained features drawn from the images, and has potential for use in evaluating water quality effectively. Limitations include the accuracy of image processing methods in varying light conditions and the extensive calibration needed to guarantee consistency in the results. It is worth noting that although this work may reveal much more about water toxicity, it does not address completely what other types of contaminants enter the water bodies. The study conducted by **Ashraful Islam et al. [9]** primarily focused on optimizing pH, Total Dissolved Solids (TDS), and color from textile effluent, highlighting the environmental challenge of the massive alkalinization and dissolved solids in textile-processing waste waters. One approach for dealing with this is using certain natural means of adsorbing agents, specifically water hyacinth, water lily, and plantain (their bark), to show that proper adsorption of contaminants could be achieved. This method led to a significant elimination of both pH and TDS, reducing the values of pH from 7.3 to 6.5 and those of TDS from 2700 to 2600mg/L when using plantain bark. Additionally, different combinations of the coagulants have been tested for color removal. The most effective one is a combination of FeSO4 and CaO for sludge separation. Certain restrictions were encountered while transferring the experiment to a larger scale. Using certain natural adsorbents in a treatment process would mean that the process should be easily adaptable in an industrial setting. Still, the process might be affected by the environmental circumstances under which it is implemented. The findings show that the materials are suitable for the treatment of textile mill effluent, although the optimization for wider application and the long-term impact evaluation related to the quality of water can be explored. The study by **Preeti Meghwani et al. [10]** focused on developing an automatic method to monitor water quality for the water collection process that helps decrease environmental pollution at various water sources, such as pools and ponds. They are labor-intensive, so training is not possible. However, the matter is time-consuming and needs a long time to take and analyze the sample. The mechanism proposed incorporated a Programmable Logic Controller (PLC) coupled with Arduino and Bluetooth technologies to allow data capture from multiple sensors. These sensors determine alkalinity, pH, and temperature. Results revealed that the prototype enables the monitoring of these parameters and hence can be utilized to ensure timely intervention to maintain the right standard of water quality. However, it was found that the limitations include drift in some of the sensors, affecting their accuracy. Regular maintenance of the prototype which is necessary for its proper functioning, is another disadvantage. Also, the study discussed swimming pool management applications, raising the need for further studies on how to use a system to manage wastewater. The study conducted by **Nitin Khatmode et al. [11]** focused on optimization of pH, Total Dissolved Solids (TDS), Total Suspended Solids (TSS), and color of textile effluent, thus addressing the significant environmental challenges of higher pollutant levels in textile industry wastewater. The methodology adopted included the use of sawdust as a natural adsorbent for effluent chunk adsorption, exploiting its property towards the removal of contaminants. Accordingly, from the experimental results, it was observed that the maximum removal efficiency of the monitored pollutants was reached, the pH dropped from 7.9 to 7.2 (45.50% removal efficiency). This proves the potential of sawdust as a cost-effective and ecologically friendly solution for textile wastewater treatment. Limitations have been attributed to the adsorbing capacity of sawdust, which may not always be the same in other setups of effluent and operating conditions.

III.METHODOLOGY

A. *System Overview*

The prototype system that has been built in this study is effective in qualitative analysis of tap water and suggests effective filtration methods. The system utilizes the real-time data from the pH and Total Dissolved Solids (TDS) sensors and combines it with a CNN-based image classification model to classify the images of water samples into different categories. Based on the water quality parameters and water sample category, the system recommends a suitable type of water filter. The overall system consists of embedded hardware components like the ESP32 M5Stamp S3 microcontroller, Raspberry Pi 5 microcomputer, pH and TDS sensors, and a touchscreen display, all in a 3D printed case.

B. Hardware Components and Integration

i) pH and TDS Monitoring

To obtain water quality data in real time, analog pH and TDS sensors were used. The sensors were calibrated with standard buffer solutions and reference TDS samples. The sensors were connected to the ESP32 M5Stamp S3, which is the main analog sensor data acquisition unit. The ESP32 samples sensor readings at a defined interval and preprocesses the signals to reduce noisy and transitory signals.

ii) Microcontroller and Microcomputer Interface

The ESP32 microcontroller communicates with the Raspberry Pi 5 using serial communication (UART). The microcontroller transmitted both pH and TDS data in a formatted form to the Raspberry Pi, which was simultaneously conducting water sample image classification. The division of responsibility proved to be effective in utilizing parallel processing of data and water sample images without compromising computation. A 3.5-inch thin-film-transistor liquid-crystal display (TFT LCD) was interfaced with the Raspberry Pi (RPi) via the GPIO interface, which uses SPI communication. The sensor values, water category, and recommended filtration method were

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displayed on the graphical user interface (GUI) available on the TFT LCD. The GUI was created with Python's streamlit library.

iii) Enclosure Design and Fabrication

The entire setup was housed in a compact enclosure made from Polylactic Acid (PLA), a biodegradable thermoplastic, on a Fused Deposition Modeling (FDM) 3D printer, which is shown in Fig. 1 and Fig. 2. The enclosure was designed on SolidWorks, which is a computer-aided design software. The design of the prototype's enclosure with Raspberry Pi, pH sensor and TDS sensor modules has been shown in Fig. 3 and Fig. 4. Access to the RPi and ESP32 ports and the touchscreen display was made easily available for the user. The front view and the side view of the 3D printed enclosure with the Raspberry Pi, Camera, and the other components are shown in Fig. 5 and Fig. 6 respectively. The complete prototype with the camera, TFT screen, Raspberry Pi, TDS and pH sensor and all other components is shown in Fig. 7.

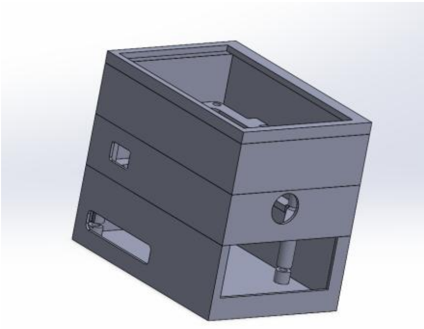

Fig 1. Prototype Enclosure's Design (Side View)

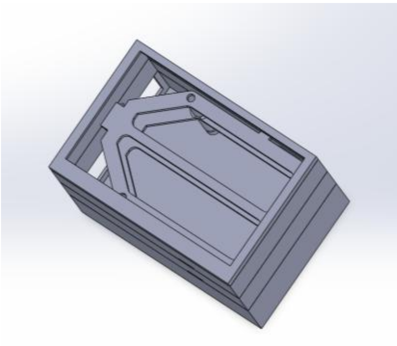

Fig 2. Prototype Enclosure's Design (Bottom View)

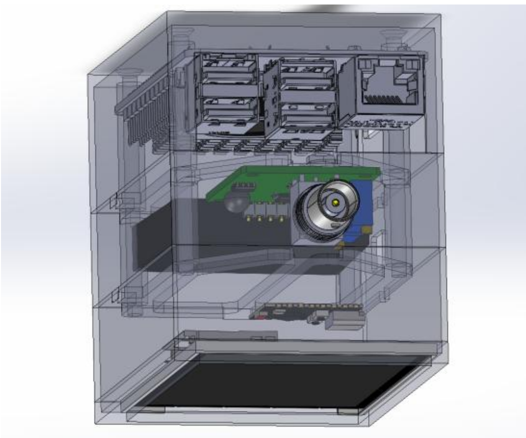

Fig 3. Prototype Enclosure's Design with Components

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(Front View)

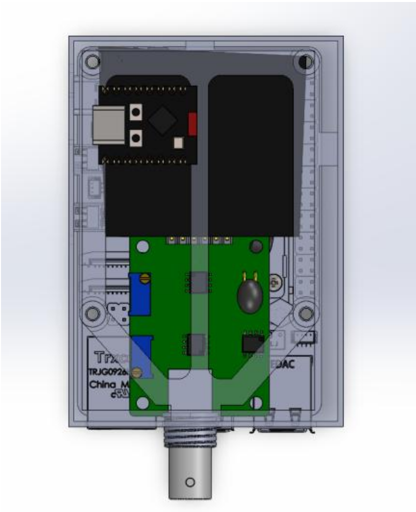

Fig 4. Prototype Enclosure's Design with pH and TDS Sensor Modules (Top View)

Fig 5. 3D-Printed Prototype Enclosure with Camera, TFT Screen, and Other Components (Front View)

Fig 6. 3D-Printed Prototype Enclosure with Camera, TFT Screen, and Other Components (Side View)

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Fig 7. 3D-Printed Prototype Enclosure with Camera, TFT Screen, pH Sensor, and TDS Sensor

C. CNN-Based Water Sample Classification

i) Dataset Preparation

To train a CNN-based deep learning model for visual water quality classification, an image dataset of 353 images was compiled. Each sample of water was placed in a clean, textureless bowl to remove background noise, and each sample was photographed in consistent lighting and controlled conditions, so that consistency across images could be maintained. Pictures were taken at a fixed angle. The captured images were sorted into different folders according to the type of water. These labeled folders were used for supervised learning. Each sample of water was classified into five folders based on visible characteristics: clean water, water with oil, water with salt, water with soil, and water of a different color (16 images). Fig. 8 shows the class distribution of the created dataset. This custom dataset provided a diverse set of samples useful for training a robust convolutional neural network (CNN) to classify water quality from an image.

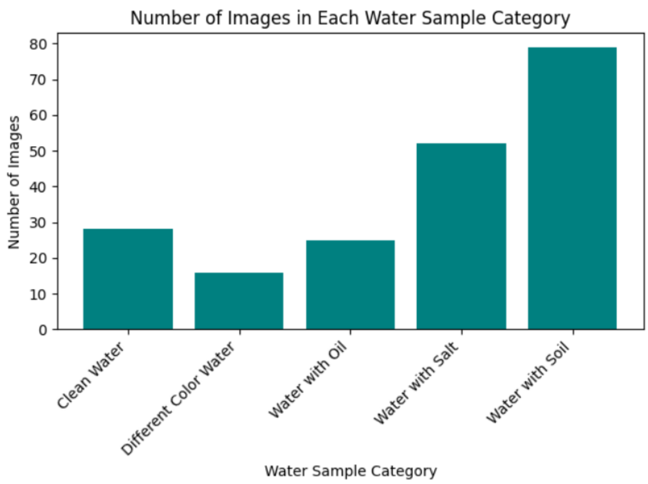

Fig 8. Class Distribution of the Water Samples Dataset

ii) Data Splitting

The collected image samples were randomly shuffled and divided into training, validation, and testing subsets using a stratified folder-based split method. Each subset was divided based on a standard 70:15:15 split ratio, ensuring that all classes consisting of clean_water, different_color_water, water_with_oil, water_with_salt, and water_with_soil were completely represented in all three subsets. Directories were created for each split within a root directory. For each class, the images corresponding to that class were randomly shuffled to ensure randomness and eliminate

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sampling bias, after which the images for that class were copied into their corresponding subdirectories within the train, val, and test folders. This uniform structure provided an efficient approach for loading the images and mapping their labels for model training and inference evaluation.

iii) Data Preprocessing

Prior to using the images as input into the CNN, the dataset was prepared using the ImageDataGenerator from TensorFlow. All images were resized to 224×224 pixels with normalization scaling of 0-1 for pixel intensity. We only performed data augmentation using the range of random rotation (rotation, width and height shifts (10%), shear (10%), zoom (20%), and horizontal flipping) for the training set for the need of generalization and to restrict overfitting, with any newly gained pixels being set as unmodified using the 'nearest' strategy. The validation and test sets were also rescaled; there was no data augmentation for comparable testing. The datasets were loaded in batches of 32 images with categorical classifications/labels. Each dataset split was directly used from the dataset directory when building the model, with the class/labels used by referencing the folder structure.

iv) CNN Model Architecture

The CNN model developed for water quality classification using visual assessment was a sequential model created with TensorFlow and Keras. The model had four convolutional blocks with the same approach for each block using a 2D convolution, 3×3 kernel and a `same'padding; followed by batch normalization, a ReLU activator, max pooling, and then a dropout layer. The number of filters started with 16 in the input layer and incremented to a maximum of 128 in the last convolutional block for extraction of deeper features at increasignly higher levels of abstraction. Global average pooling was applied in order to decrease the dimensionality of the data. After the global pooling was a dense layer with 256 neurons fitted with a ReLU activator and then a softmax layer that had the same number of output neurons as the number of classes to classify within the dataset. The recommended architecture reasonably balanced complexity and effectiveness for use on embedded platforms with severe resource restrictions.

v) CNN Model Training

The model was trained for 100 epochs with the augmented training data set, with the validation data set being used to monitor performance overfitting during training. The training was able to train using the image generators to generate and batch load the data. As the model learns the patterns to distinguish the water samples in different categories. The epochs training history with the trends for accuracy and loss for the training and validation sets were also saved for retrospective analysis to investigate both convergence and generalisation ability.

vi) Model Evaluation

After training, the model was comprehensively assessed by utilizing the unseen test dataset, to assess generalization. The test loss and accuracy were determined. In addition to this, the training and validation loss and accuracy were plotted for all epochs in order to understand the model's behaviour, as well as the convergence trends and general indications of overfitting. The classification performance of the model was appraised via the confusion matrix and corresponding classification report, for the test set. The test set predictions were made using batches of data fed to the trained model and predicting the class label where the softmax probability was largest. The confusion matrix represented the true versus predicted labels across all 5 classes (i.e. clean water, water different color, water with oil, water with salt, water with soil), and reflected areas where the prediction class was correct, as well as areas of predicting classes which may not have been fully disclosing of the true label. The classification report illustrated the precision, recall and F1-score metrics for each class, providing overall knowledge with respect to the models predictive capability across all classes.

D. Filter Recommendation

The camera used to capture images of the water sample via the Raspberry Pi–ESP32–based prototype is associated with a CNN model that classifies each water sample image into five classifications - clean, colored, oily, saline, and turbid. Concurrently, the prototype's ESP32 is measuring the pH and Total Dissolved Solids (TDS) of the water sample they are submerged in using pH and TDS sensors connected to the ESP32. Once the CNN model classifies the water sample images, the predicted class is displayed on the prototype's GUI along with the measured pH and TDS

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value, together with recommendations about which filtering technique would be appropriate for that water sample, and which filtration method is suitable for filtering that type of water. For clean water purification, the prototype recommends a filter with a ultraviolet treatment chamber because it inactivates residual living microorganisms while not affecting the chemical nature of the water, and can be used with in conjunction with an activated-carbon stage for taste and odor enhancement, if desired. For colored water, activated-carbon adsorption is recommended. The activated carbon will adsorb organic discolorants, and it can be followed by reverse osmosis (RO), which removes any dissolved discolorants and inorganic constituents. If water is contaminated with oily impurities, water filters with an oil-adsorbing filter cartridge or filters capable of distillation could be effective. The recommended filter for a saline water sample is RO, or ion-exchange deionization, as both these methods reject dissolved salt. The suspended solids from turbid water samples can be removed with filters containing mechanical sediment filters (standard, ceramic, or biosand filters).

E. User Interface for Prototype

Using Python's Gradio library, a user interface (UI) was developed for the prototype. The user can take a picture of the tap water sample using the prototype's camera from the UI. The image taken is sent to the trained CNN model, which will then classify the image into its appropriate category by doing a visual analysis of the water sample. The pH and total dissolved solids (TDS) sensors attached to the prototype and submerged in the same water sample provide the pH and TDS value of the water, simultaneously. Finally, the UI shows the predicted water category, along with the pH and TDS of the water sample, in real-time. The user is also presented with a recommendation of the water filter type that could be used for purifying the water sample that was tested. The UI also gives the user a short description of that filter, with reasoning explaining why that filter is suitable for that water type.

IV. RESULTS

The prototype developed for water quality assessment was thoroughly assessed for its ability to collect multi-modal data (visual and chemical) to deliver accurate, real-time water quality information and filter recommendations. The pH and Total Dissolved Solids (TDS) sensors were calibrated with reference samples. On average, the pH sensor was accurate to approximately ±0.2 units, and the TDS sensor at ±25 parts per million (ppm) when compared to commercial-grade meters. The integrated ESP32 M5Stamp S3 captured and pre-processed raw data from sensors, while the Raspberry Pi 5 captured and processed the water sample image in real-time. The custom-trained Convolutional Neural Network (CNN) model achieved an accuracy of 75.53 % on the testing dataset for classifying clean water, water of another color, water with oil, water with salt, and water with soil. The improvement in the CNN model's accuracy and decrease in loss during training and validation have been shown have been shown in Fig. 9 and Fig. 10 respectively. The confusion matrix evaluation and classification report confirmed that the model was able to generalize across unseen water sample images. The confusion matrix of the CNN model on the test dataset is shown in Fig. 11. The entire pipeline - from water sample image capture and CNN-based classification to retrieving sensor data and providing filtration recommendations - occurred in under few seconds, allowing for responsive and real-time interactivity. The final water quality assessment prototype is shown in Fig. 12. The prototype's Gradio-based user interface (UI) was evaluated for usability and efficacy. Users were able to easily take a water sample image with the device camera, view pH and TDS readings from the immersed sensors in real-time, and receive appropriate recommendations for a water filter type with a contextual rationale for the recommendation as shown in Fig. 13, Fig. 14 and Fig. 15. For example, oily water samples result in recommendations of filters that have oil-adsorbing cartridges or can distill water, while saline water samples would cause the system to recommend reverse osmosis (RO) or ion-exchange filters. The GUI displayed all outputs on a touchscreen LCD located in a 3D-printed housing unit. Altogether, the system performed well on all fundamental performance metrics: real-time acquisition of data, classification based on image analysis, an intelligent recommendation system, and an interactive user interface, confirming its potential as a smart and portable device for evaluating and recommending treatments for household water quality.

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Fig 9. Training and Validation Accuracy across epochs of the CNN Model

Fig 10. Training and Validation Loss across epochs of the CNN Model

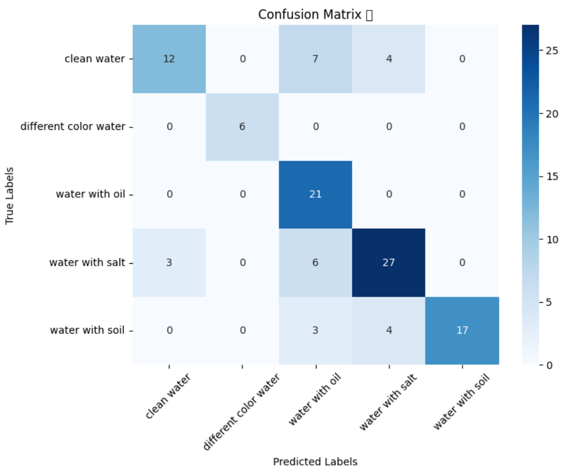

Fig 11. Confusion Matrix showing the performance of the CNN Model across all classes

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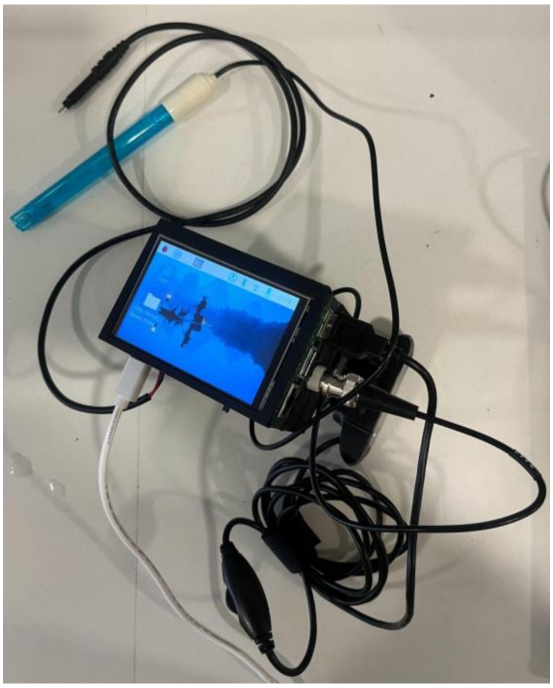

Fig 12. Portable Water Quality Monitoring System

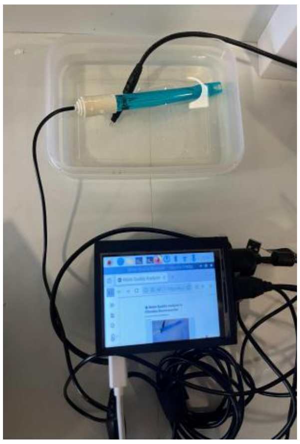

Fig 13. Portable Water Quality Monitoring System with its TDS and pH Sensors Dipped in Water with Little Oil

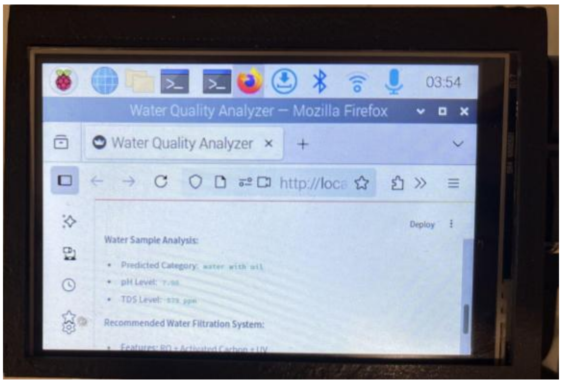

Fig 14. Water Category, pH and TDS Detections Made by Portable Water Quality Monitoring System for a Test Sample

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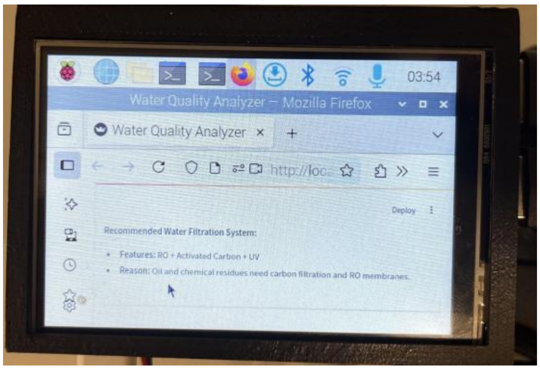

Fig 15. Water Filtration Technique Recommendation by Portable Water Quality Monitoring System for a Test Sample

V. LIMITATIONS

While the prototype system developed in this project exhibited strong performance in a standardized testing environment, several constraints need to be addressed to assess the feasibility of the system in real-life contexts. First, the model was trained on a small dataset of 353 images. While much effort was made to ensure external conditions were consistent in terms of lighting and angle during the preparation of the dataset, this type of dataset may not encompass the variety of tap water collected from various places at different times. As a result, after deployment, the generalizability of the model may be impaired by different lighting effects on the camera, camera position, and the diversity of the sample. Second, although the analog pH and TDS sensors demonstrated high accuracy during the testing phase, but are subject to long-term drift based on electrode degradation, and other variables like temperature and conductivity. Maintaining measurement integrity over longer periods would require the routine calibration of both sensors based on standard buffer and reference solutions. Third, the image classification module could be sensitive to ambient light. Although augmentation was applied during training, when input images contain shadow, light reflection, or low light, the accuracy of classifications could still be compromised. Furthermore, the underlying logic behind the filter recommendation operates under deterministic rules. There is currently no adaptive mechanism to improve the recommendations utilizing probabilistic inference. Hence, the system cannot learn from prediction patterns or user feedback, and cannot generate recommendations from borderline classification states. This strict reliance on specific categorical inferences may restrict decision-making flexibility in certain circumstances (e.g., dealing with mixed contamination scenarios).

VI. CONCLUSION

This research outlines the design and development of an embedded prototype for qualitative tap water assessment and filter recommendation using computer vision and real-time sensor data. The system effectively integrates a Convolutional Neural Network (CNN) model for image-based classification of water samples with pH and Total Dissolved Solids (TDS) values to provide users with useful information about the water quality and filtration solutions. The CNN model correctly predicted test image categories with an accuracy of 75.53 %, based on five distinct categories, and the analog pH and TDS sensors predicted in acceptable ranges when compared to commercial meters. The complete end-to-end inference pipeline, from image acquisition, and sensor reading to classification and filter recommendation, was completed in less than three seconds, allowing feedback to the user almost instantly. The user interface, created using Gradio, was intuitive and effectively communicated the water category predictions, sensor values, and filter recommendations with appropriate reasoning. This system can support informative decision-making by end-users for the practical consideration of at-home tap water purification needs.

VII. FUTURE SCOPE

Future work will address the current limitations and improve robustness. Expanding the image dataset with additional water samples that are more diverse in terms of various environmental conditions, lighting, and container types for improved model generalization. Additional sensors that may include measuring temperature and turbidity, among existing capabilities, would further enhance profiling water quality and improve recommendations. Future iterations of the system may also possibly overcome some of the limitations in rule-based logic as described, with the possible introduction of adaptive or reinforcement learning algorithms for providing users with context-based personalized filter recommendations. A fully wireless IoT-enabled system that includes cloud connectivity for remote monitoring of water quality, allows for historical trends, and better data collection can also be pursued. This can be valuable in rural or lower-resource populations. Exploring the functionality of providing a mobile app for the prototype could further increase user awareness while facilitating more real-time interaction through their smartphones.

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