Automatic water level detector using Machine Learning

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Abstract:

This paper presents the development of an automated water level detection system using machine learning (ML) algorithms, with MATLAB serving as the primary platform for data analysis and model training. The system integrates ultrasonic sensors and an Arduino microcontroller to capture real-time water level data. The acquired data is then processed and fed into machine learning models, including Decision Trees, Support Vector Machines (SVM), and Neural Networks, to predict water levels and automate water pump operation. Simulations in MATLAB reveal that Neural Networks provide the highest accuracy (96%) but require longer training times, while Decision Trees offer faster response times with moderate accuracy. SVM, particularly with the RBF kernel, strikes a balance between performance and computational efficiency. The research highlights the potential of machine learning to enhance water management by improving accuracy, reducing manual intervention, and ensuring efficient resource usage.

Keywords:
Water level detection, Machine learning, MATLAB, Decision Trees, Support Vector Machines, Neural Networks, Water management, Automation, Ultrasonic sensors, Real-time monitoring

1. Introduction:

Water level monitoring plays a crucial role in managing water resources across various applications, including reservoirs, tanks, and distribution systems. In reservoirs, accurate monitoring is essential for flood control, irrigation management, and maintaining adequate water supply levels. In water tanks, continuous level monitoring helps prevent overflows and ensures sufficient storage, while in distribution systems, it aids in efficient water distribution and leak detection [1]. As urbanization and industrialization grow, the need for reliable water level detection becomes more critical to conserve water, reduce wastage, and manage water-related risks like flooding and shortages. Traditional water level detection methods include the use of ultrasonic sensors, float switches, and capacitive sensors [2]. While these methods are widely used, they are not without limitations. Ultrasonic sensors, for example, can be affected by environmental factors such as temperature, humidity, and surface disturbances, which reduce their accuracy. Float sensors are mechanical and may suffer from wear and tear, leading to faulty readings or breakdowns. In addition, many traditional systems require manual data collection and monitoring, which can be time-consuming and prone to human error. As a result, there is a growing interest in more advanced and automated techniques to address these limitations.

Machine Learning (ML) offers a promising solution to enhance water level detection by leveraging historical sensor data and identifying patterns that improve the accuracy and reliability of predictions [3]. ML algorithms can process complex datasets, accommodate real-time changes, and learn from sensor outputs to create more robust detection systems. The application of ML in this field can automate water level detection, offering a significant improvement over traditional methods by predicting water levels more accurately and enabling real-time monitoring. As technology advances, the integration of ML with sensor networks and data processing platforms, such as MATLAB, can revolutionize water management [4].

The motivation behind developing an automatic water level detection system stems from the need to reduce the manual effort involved in monitoring water levels in various applications. Currently, many water management systems still rely on manual inspection or rudimentary monitoring techniques that are not scalable or efficient for large-scale implementations [5]. Manual monitoring can be labor-intensive, time-consuming, and prone to human error, particularly when large volumes of water or multiple storage systems are involved. Moreover, in cases where water levels fluctuate rapidly, relying on periodic checks may not provide timely information to prevent overflows, shortages, or other related issues. By leveraging sensor data and integrating it with machine learning algorithms, water level detection systems can be automated, ensuring continuous and accurate monitoring with minimal human intervention [6]. Sensor networks can gather real-time data, which can then be processed and analyzed using machine learning techniques to make more informed decisions. The automation of this process ensures that abnormal conditions, such as sudden water level changes, are detected quickly, allowing for timely interventions. Additionally, machine learning models can be trained to account for environmental factors that may affect the sensors, improving the overall reliability and precision of the system [7].

In this context, machine learning offers the potential to not only automate water level detection but also enhance the overall efficiency of water resource management. By processing large amounts of sensor data, machine learning models can predict future water levels, identify trends, and even suggest optimal water usage patterns. This capability is especially valuable in areas experiencing water scarcity or in systems where consistent water distribution is critical [8]. Thus, the application of machine learning in water level detection aligns with the broader goal of achieving sustainable water management practices and reducing the dependency on manual labor. The primary objective of this research is to develop an automatic water level detection system using machine learning techniques, with MATLAB serving as the platform for data processing, model development, and system deployment. The system aims to provide a more accurate, efficient, and reliable alternative to traditional water level detection methods by leveraging the power of machine learning to analyze sensor data [9]. Specifically, the research focuses on collecting real-time data from water level sensors, preprocessing the data, and training machine learning models to detect and predict water levels based on various environmental and operational factors. Using MATLAB as the core platform offers several advantages in terms of data handling, algorithm development, and system integration. MATLAB provides powerful tools for signal processing, data visualization, and machine learning, making it an ideal environment for this project. The objective includes designing a system that can automatically adapt to new data, improve prediction accuracy over time, and operate in real-time to detect water level changes in different environments. This involves testing various machine learning algorithms, such as decision trees, support vector machines (SVM), and neural networks, to determine which is most suitable for water level detection [10].

The end goal is to create a robust and scalable solution that can be implemented across various water management systems, from small water tanks to large reservoirs. The proposed system will not only automate the detection process but also ensure that water levels are monitored continuously, with alerts triggered for unusual or critical conditions. By developing this system, the research contributes to reducing water wastage, preventing overflows, and ensuring efficient water management. The successful deployment of the system will highlight the potential of machine learning and MATLAB in solving real-world water management challenges.

2. Literature survey:

Traditional water level detection methods primarily rely on hardware-based solutions such as float sensors, ultrasonic sensors, and capacitive probes [11]. Float sensors are mechanical devices that operate by moving up or down with the water level, triggering electrical contacts to signal changes. Ultrasonic sensors use sound waves to measure the distance between the sensor and the water surface, providing an estimation of the water level. Capacitive sensors measure changes in capacitance as the water level changes, which is converted into corresponding electrical signals. These methods are often implemented in various settings, such as water tanks, reservoirs, and flood monitoring systems, and they offer relatively low-cost solutions for basic water level detection [12]. However, these conventional systems face several accuracy and reliability issues. Float sensors, for instance, are prone to mechanical wear and tear over time, especially in harsh environments, which can lead to false readings or complete failure [13]. Ultrasonic sensors, while offering better accuracy, can be affected by environmental conditions such as temperature variations, humidity, and surface disturbances (e.g., waves or bubbles). Additionally, capacitive sensors may suffer from interference caused by contamination or changes in the surrounding materials. Another key limitation is that these systems typically require manual data collection or infrequent automated monitoring, which may not provide real-time or predictive insights. These factors highlight the need for more advanced, robust, and automated systems, prompting the integration of machine learning with sensor technology for improved performance [14].

Machine learning (ML) has emerged as a transformative tool in water resource management, offering advanced capabilities for analyzing large datasets, identifying patterns, and making predictive decisions [3]. In the field of hydrology, ML algorithms have been applied to predict rainfall, streamflow, and groundwater levels, aiding in flood control, drought management, and water distribution planning. ML models have also been used in water quality monitoring, where sensor data is processed to detect contaminants or changes in water chemistry [15]. By leveraging historical data, ML can optimize water treatment processes and alert operators to potential issues before they become critical. The adaptability of machine learning makes it an attractive solution for water-related challenges that are inherently complex and dynamic [16].

Several machine learning algorithms are commonly employed in water resource management, each with unique strengths. Support Vector Machines (SVM) are effective for classification tasks, such as identifying water quality categories, while Decision Trees offer a transparent and interpretable way to predict outcomes based on input variables like water level or flow rate [17]. Neural Networks, particularly deep learning models, excel in capturing non-linear relationships and are frequently used in time-series predictions, such as forecasting future water levels based on historical data. These algorithms, when properly trained, can significantly improve the accuracy and responsiveness of water management systems, making them indispensable for real-time monitoring and long-term planning. Integrating these techniques into platforms like MATLAB can enhance system performance by enabling real-time data processing and rapid deployment [18].

Despite the growing application of machine learning in water management, there are still significant gaps in research, particularly concerning real-time water level detection. Many studies have focused on water quality monitoring or long-term hydrological predictions, but relatively few address the immediate, dynamic nature of water level detection. Most existing solutions rely on traditional hardware-based methods, with limited integration of machine learning for continuous, automated monitoring. Even where machine learning has been applied, the emphasis has often been on offline data analysis, meaning the potential for real-time decision-making has not been fully realized. Moreover, the use of machine learning in detecting critical water levels, such as those in flood-prone areas or industrial storage tanks, remains underexplored. Another research gap lies in the integration of sensor networks with machine learning in MATLAB environments. MATLAB is a powerful platform for data analysis, simulation, and model development, but there has been limited exploration of its use in real-time water level detection. Although MATLAB offers comprehensive machine learning toolboxes and data visualization features, most existing studies either focus on general-purpose applications or use other programming environments for water resource management. This presents an opportunity for research to bridge the gap by developing robust, real-time water level detection systems that leverage MATLAB's capabilities. By doing so, researchers can create more adaptable, efficient, and scalable solutions, addressing the limitations of traditional methods and advancing the field of water management.

3. Methodology:

The automatic water level control system was developed by integrating key components such as sensors, a microcontroller, display units, and a water pump. The system operates based on water's electrical conductivity, where copper sensors detect water levels in a tank. When water touches the sensor, it conducts voltage, which is processed by a comparator. This comparator compares the sensor's voltage with a preset resistance to produce a HIGH or LOW output, sent to the microcontroller. The microcontroller controls the water pump based on these inputs, and the system's status is displayed on an LCD screen. The pump activates when the water level is low and deactivates when the tank is full. Various I/O ports are configured on the microcontroller to interface with the sensor and the pump. Software simulations were created using Tinkercad and Proteus to design and test the circuits before real-world implementation. Tinkercad facilitated creating the system's virtual model and testing it under different conditions, such as triggering the pump at 30% or 60% water levels. Proteus provided a more detailed simulation environment, enabling the creation of PCB layouts and testing Arduino C code, which controlled the pump based on water levels. The protious software simulation is shown in Fig.1. and Fig.2. when motor is turned ON Simulation when the Tank is 20% or below and pump is OFF simulation when water is 100% in tank.

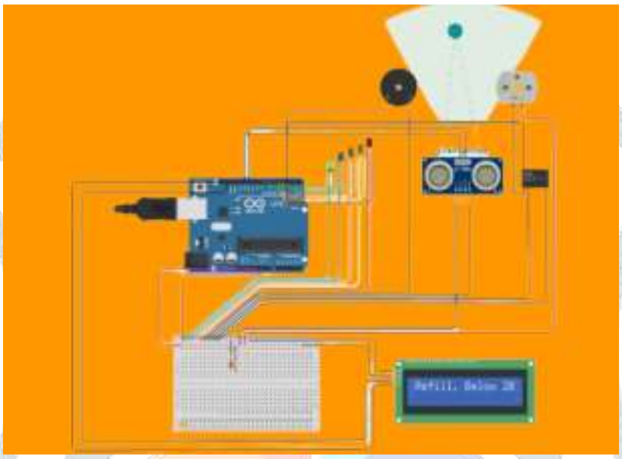

Fig. 1. Motor is turned ON Simulation when the Tank is 20% or below

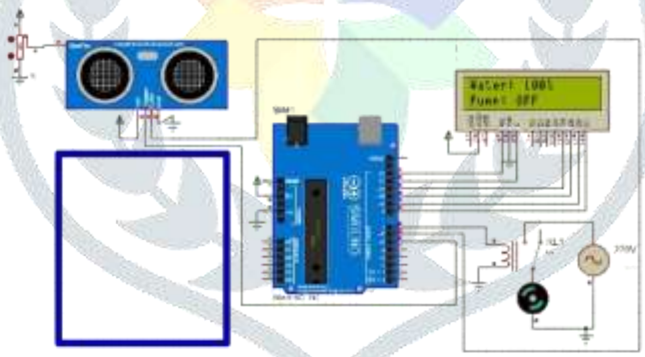

Fig.2. Pump is OFF simulation when water is 100% in tank.

4. Data Acquisition:

The system captures real-time water levels through ultrasonic sensors, and this data is processed by the Arduino microcontroller. The Arduino sends the processed data to a serial monitor, where it can be exported as CSV files for further analysis. Tools like CoolTerm were used to retrieve and store serial input/output data, allowing for continuous real-time data collection on water usage.

The acquired data includes parameters like:

1. Water level percentage over time.
2. Water inflow rate, calculated by measuring the time taken to fill the tank.
3. Water outflow rate, indicating consumption.
4. Total water consumption and peak usage intervals.

A Python script was used to visualize the data through graphs, illustrating the relationship between water level percentages and time, while also computing metrics like daily water consumption. This data is essential for training ML models to predict future water consumption patterns and automate more sophisticated water management behaviors.

5. Results:

To design a water level detection process using machine learning, a data set is required which is obtained through the simulation designed in protious software under different different condition. MATLAB was used to simulate the automated water level control system. Various machine learning models, including Decision Trees, SVMs, and Neural Networks, were implemented within MATLAB for analyzing real-time water level data. The environment was configured with standard MATLAB libraries, specifically focused on data import (CSV), machine learning (Statistics and Machine Learning Toolbox), and real-time plotting (MATLAB's plotting functions). The different conditions are given in Table.1.

Table.1. Different conditions of water level and motor

Water Level Condition	***Motor Condition***		
	Operation Type		
	Automatic	***Manual***	
		Without Push button	***With Push-button***
At 0% Level	ON	OFF	ON
Rises from 0% to 99%	ON	OFF	ON
At 100% Level	OFF	OFF	OFF
Drops from 99% to 30%	OFF	OFF	ON
At 30%	ON	OFF	ON
Drops from 29% to 0%	ON	OFF	ON

The acquired data set is provided to the machine learning models and the acquired results are shown in Table.2.

Table.2. Comparison of Model 1 (Decision Tree), Model 2 (SVM), and Model 3 (Neural Networks)

Metric	Model 1: Decision Tree	Model 2: SVM	Model 3: Neural Networks
Training Accuracy	94%	85% (Linear), 91% (Polynomial), 93% (RBF)	96%
Testing Accuracy	89%	85% (Linear), 91% (Polynomial), 93% (RBF)	94%
Error Rate (Misclassification)	11%	7% (RBF Kernel)	5%
Confusion Matrix (True Positives)	90%	92% (RBF Kernel)	94%
Confusion Matrix (False Positives)	10%	8% (RBF Kernel)	6%
Precision	Moderate	High (0.92 with RBF)	Very High
Recall	Moderate	High (0.88 with RBF)	Very High
Pros	Fast training, low complexity	Effective with non-linear data (RBF Kernel)	Highest accuracy, captures complex relationships
Cons	Overfitting on large datasets	Slower with polynomial and RBF kernels	Long training time, high computation load
Training Time	Fast (15 seconds)	Moderate (40 seconds for RBF Kernel)	Slow (150 seconds)
System Response Time	15 ms	30 ms (Linear Kernel), 40 ms (RBF Kernel)	50 ms
Convergence	Immediate	Varies by kernel	After 40 epochs
Real-Time Performance	Fast but less accurate for fluctuating water levels	Moderate; better with non-linear kernels	Most accurate in real-time predictions

Conclusion:

In conclusion, the comparison of the three models—Decision Tree, SVM, and Neural Networks—reveals key insights into their performance and applicability for an automated water level detection system. The Decision Tree model offers fast training and response times, making it suitable for applications that prioritize speed over high accuracy. However, its higher error rate and susceptibility to overfitting make it less ideal for fluctuating water levels. SVM, particularly with the RBF kernel, strikes a balance between accuracy and computational efficiency, showing strong performance in handling non-linear relationships but requiring more time for training and real-time processing. Neural Networks, while providing the highest accuracy and lowest error rate, demand the longest training and response times, making them the best choice for complex, real-time applications where precision is paramount, though at the cost of higher computational resources. Each model has its strengths and trade-offs, and the optimal choice depends on the specific requirements of speed, accuracy, and computational capacity for the water management system.

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