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Intelligent Water Faucets for Real-Time Water Conservation in Smart Cities

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Abstract— **Urbanization needs efficient water resource management for sustainable expansion. This study offers a novel prototype for intelligent water faucets leveraging the Internet of Things (IoT) and machine learning. Our system transforms conventional faucets into intelligent devices, boosting water saving through real-time user activity identification. The fundamental technology employs a Raspberry Pi for processing and YOLO v7, a accurate and quick object identification algorithm, to discriminate between hands with and without soap. The average F1 Score of our model was 99% and a mAP@.5 of 0.991. This distinction permits automatic water flow regulation, minimizing wasteful water usage. This intelligent water-saving system connects with the environmental aims of smart cities while delivering a practical resolution to water conservation concerns.**

Keywords—Smart city; Water management; Water conservation;Internet of Things (IoT);Deep learning,Object detection;YOLO v7; Raspberry Pi

I. INTRODUCTION

In the advent of smart city development, efficient water resource management appears not just as a necessity but as a foundational pillar for sustainable urban expansion. With urban populations rising, there is an escalating demand for better, more efficient water management systems. This involves not only the provision and distribution of water but also its conservation and efficient usage. The combination of Internet of Things (IoT) technology and powerful machine learning algorithms offers unmatched prospects to supplement water management systems, rendering them more flexible, efficient, and tailored to the distinctive needs of urban settings.

This study proposes a breakthrough prototype aiming at rethinking current water use patterns by embedding intelligence into daily water faucets. Our suggested technology proposes the transformation of standard faucets into intelligent devices capable of boosting water efficiency through the recognition of certain user activities. Central to our prototype is the deployment of a Raspberry Pi, a compact yet durable computer, alongside YOLO v7, a computer model recognized for its object detecting precision and speed. The originality of our intelligent water-Saving tap extension is founded on its power to discern between various hand states—namely, hands with soap and hands without. This difference is crucial for automating water flow control, so guaranteeing that water is dispensed only when necessary, thus boosting conservation. By harnessing the computing prowess of Raspberry Pi and the sophisticated detecting abilities of YOLO v7, our solution represents a substantial development towards attaining superior water utilization in both household and public sectors. This method not only adheres to the sustainable aims of smart cities but also provides a feasible answer to pressing concerns regarding water conservation in general, even in simple cities and villages.

The core contribution of your paper is presenting a prototype extension for traditional faucets. This extension utilizes YOLOv7 for hand detection and enables intelligent water flow control, promoting better water management.

II. RELATED WORK

The advancement of machine learning (ML) and Internet of Things (IoT) technologies has significantly contributed to the development of sophisticated systems for monitoring, managing, and conserving water resources. Recent studies have explored various aspects of this domain, including real-time water quality monitoring, optimization of water use, disaggregation of water consumption data, and predictive modeling for water safety. A pioneering effort in South Korea focused on constructing a real-time monitoring and anomaly detection system for tap water quality. Utilizing deep learning techniques on extensive water quality data, the study achieved high prediction accuracies, emphasizing the potential of ML in ensuring water safety [1]. Similarly, the application of ML and IoT technologies for optimizing water-use patterns in residential settings has been explored. By identifying optimal sampling intervals through high-resolution IoT systems, significant improvements in classification accuracy of water end-use were observed [2]. The integration of water-related energy use with informatics, through advanced pattern recognition techniques, has also shown promising results in improving the disaggregation of high-resolution water-energy consumption data [3]. Predictive models have been developed to alert households about the risks of lead in drinking water, using Bayesian Belief Networks and Ensembles of Decision Trees [4]. These models represent a significant step forward in using home water testing data for predicting water safety, highlighting the role of predictive analytics in public health. Challenges related to data variability in water flow disaggregation, especially in low-income regions, have been addressed by critiquing commercial software's efficacy and proposing enhanced classification models [5]. This research points to the importance of preprocessing in achieving reliable classification performance, a critical aspect of ML applications in water management. Furthermore, the development of universal water management systems that disaggregate total water consumption without the need for collecting new regional data exemplifies the scalability of ML solutions [6]. The introduction of AI-powered smart water management systems for conservation further underscores the potential of AI in optimizing water usage [7]. Lastly, the design of real-time water consumption monitoring systems using single-point sensing techniques and ML algorithms for event classification has shown high accuracy in measuring water volume and recognizing fixtures [8]. This innovation contributes to the growing body of knowledge on non-intrusive monitoring technologies for water conservation. The integration of ML and IoT in water management presents a transformative approach to addressing global water challenges. These studies [1]-[8] collectively contribute to a deeper understanding of the potential and challenges of technology-driven solutions for water monitoring, management, and conservation, setting the stage for future research in this vital field. Prior studies, while successful, often employ intricate and expensive methods. In contrast, our contribution focuses on the production of a cost-effective and basic prototype. This prototype is an extension intended for use with standard taps, applying deep learning computer vision techniques to optimize water management.

III. METHOD

A. Dataset

The most crucial aspect of our study is the deep learning model for hand detection. For this, we proceeded on the key phase of data collecting utilizing a Raspberry Pi hitched to the same camera that we will use for deployment. This strategic deployment, leveraging similar hardware configurations employed in the prototype’s development, was targeted at bypassing potential data discrepancies, so assuring the acquired dataset truly reflects real-world usage scenarios.

For the purpose of constructing a diverse and representative dataset, video recordings of a person engaging in handwashing activities were captured under two distinct conditions: the first scenario involved washing hands without the use of soap for a duration of one minute, during which a variety of hand positions and movements were deliberately performed; the second scenario replicated the handwashing process with the addition of soap for the same duration, to capture a broad spectrum of interactions with the water dispensing mechanism.

From these video recordings, a total of 1793 images were methodically collected and later split into two classes based on the presence of soap: 624 photos were classed as “hand with soap,” while 1169 images were labeled as “hand without soap.” Each image underwent a thorough manual tagging procedure, employing a specialized program to mark not merely the class to which each image belonged, but also the precise placements of hands inside the photographs. This extensive annotation is critical for the training and validation processes, ensuring the model is well-equipped to reliably identify and differentiate between the two hand states.

The dataset was deliberately partitioned into training and testing subsets, following a 75% to 25% ratio, respectively. This split was carefully designed to balance the model's exposure to a wide assortment of training examples against the necessity for a significant testing set to evaluate the model’s predicted accuracy and generalizability across unseen images. Figure 1 offers a view into the dataset, including a representative image from each class “hand with soap” and “hand without soap.”

Figure 1. Image example from data: Hand without soap (right), hand with soap (left).

B. *Hand detection and classification model*

in the development of advanced hand detection and classification systems, the adoption of cutting-edge object detection models is pivotal. Among these models, YOLOv7 emerges as an exceptionally efficient and precise algorithm. Originating from the YOLO (You Only Look Once) series, YOLOv7 is designed for superior real-time object detection performance. The model excels at identifying and classifying objects within images via a single pass of a neural network, making it particularly suited for real-time applications. Utilizing YOLOv7, our model has been trained to detect hands with significant precision and to classify them based on the presence of soap. This dual capability highlights YOLOv7's versatility and efficacy in executing complex image recognition tasks, rendering it an ideal choice for our hand detection and classification project.

IV. Results

We examined the efficacy of the YOLO v7 algorithm for hand detection with a focus on two classes: 'normal' (no soap) and 'savon' (soap), using a balanced dataset of 497 photos. The results, given in Table I , reveal a high level of model correctness, with overall precision of 0.967, recall of 0.977, mAP@.5 at 0.991, and mAP@.5:.95 at 0.756. Notably, the 'normal' class obtained perfect precision (1.0) and an amazing mAP@.5 of 0.995 slightly beating the 'savon' class, which exhibited a grea recall of 0.996. This shows that YOLO v7 is especially capable of discriminating between hands with anc without soap, underlining its potential utility in hygiene monitoring applications. The modest disparities ir performance measures between the two classes underscore the difficulty associated with varying soap appearances and the need for further research to boos detection accuracy. This work underlines the usefulness of advanced object identification models like YOLO v7 in public health and hygiene monitoring, proving thei high efficacy and promise for real-world applications.

As indicated in Figure 2, the use of YOLO v7 for hand identification exhibited a distinct pattern of improvement and consistency across multiple performance parameters. The bounding box accuracy, which is quantified by the loss given in the Box plot, shows a steady reduction from epochs 1 to 50. This trend reflects a sharpening precision in the model's ability to determine the location of hands within the visual frame. The Objectness score, representing the model's confidence in detecting an object—here, a hand—within the suggested box, remained reasonably steady throughout the training epochs. Although slight changes are noted, the overall low loss values displayed in Figure 2 reflect the model's persistent confidence once a region of interest is discovered. Classification loss, important for discriminating between the 'soap' and 'no soap' categories, steadily decreased during the epochs. This drop underlines the model's refinement in discriminating between the two groups as it learned from the training data. Precision and recall, both crucial for measuring the model's reliability, exhibited promising high values, particularly in later epochs. Precision, after a period of rise, achieved a plateau, demonstrating that the model stabilized in its predicted accuracy for the presence of 'soap'. Recall displayed some heterogeneity but remained high overall, indicating that most 'soap' instances within the dataset were spotted by the model. The metrics for Mean Average Precision (mAP) at Intersection over Union (IoU) threshold of 0.5 (mAP@0.5) and across IoU thresholds from 0.5 to 0.95 (mAP@0.5:0.95), as displayed in Figure 1, demonstrate substantial improvement as training progressed. The mAP@0.5 was consistently high, demonstrating robust model performance at the lenient IoU threshold. Meanwhile, mAP@0.5:0.95, which tests the model's performance across a range of tougher IoU thresholds, demonstrated rising trends with some variation, reflecting the model's variable sensitivity to the different IoU thresholds.

TABLE I. YOLO - Precision, Recall, and mAP

Images	Labels	*P*	*R*	mAP@.5	mAP@.5:.95:
497	497	0.967	0.977	0.991	0.756
497	239	1	0.958	0.995	0.778
497	258	0.933	0.996	0.988	0.733

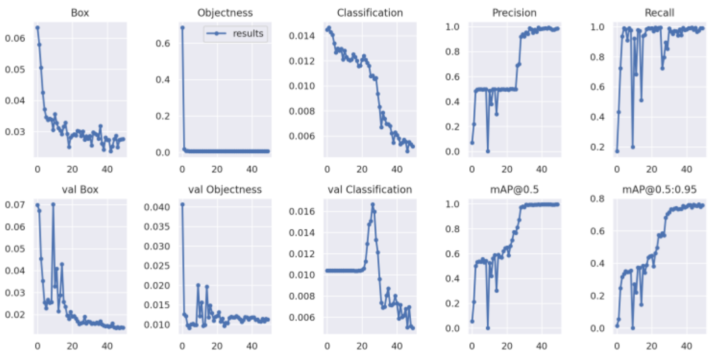


Figure 2. YOLOv7 - Evaluation metrics.

The Figure 3 exhibits F1 score curves as a function of confidence levels for the YOLO v7 algorithm applied to hand detection. The F1 score, which balances precision and recall, remains remarkably high and constant across a broad variety of confidence thresholds for both 'normal' and 'savon' classes, indicating of the model's robustness. The 'normal' class exhibits a marginally higher F1 score over most of the confidence threshold range, which could suggest a more consistent detection performance. Both classes converge to an F1 score of around 0.99 at a confidence level of 0.525, emphasizing the algorithm's competence in hand detection with high confidence. This consistent performance across classes is vital for practical applications, ensuring reliable identification of hands with or without soap.

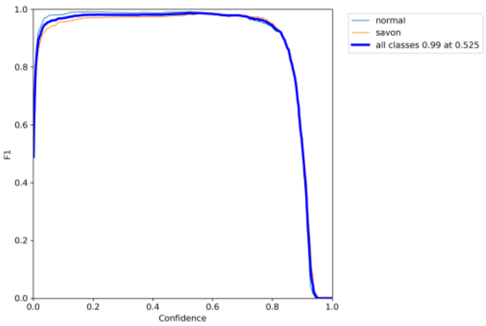
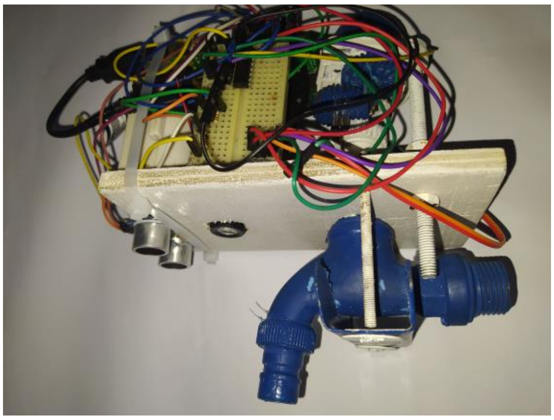


Figure 3. F1 detection confidence threshold curve

The statistics provided imply that YOLO v7 has potential in efficiently detecting hands and differentiating successfully between the 'soap' and 'no soap' classes. The great precision and stable Objectness score suggest a robust detecting capability. However, the observed oscillations in memory imply at possible missed detections of 'soap', probably due to changeable conditions like as illumination, occlusion, or background textures that may share properties with the object of interest. The model's categorization challenges can stem from the slight distinctions between the 'soap' and 'no soap' classes, particularly when soap is not clearly visible, or the hand's position obscures a clear view. Enhancing the model's performance could involve integrating a broader training dataset, spanning a wider variety of hand positions, soap types, and sizes to bolster its generalization ability.

A. Prototype's design

Our ingenious extension transforms traditional taps into smart gadgets, meant to promote efficient water usage and hygienic practices. At the center of this metamorphosis is a handcrafted frame that incorporates a DC motor combined with a gear system, enabling the automated opening and closing of the tap. A motor controller, specifically the L293D, is employed to regulate the motor's actions. The system's intelligence core is driven by a Raspberry Pi, which holds the best YOLO model obtained after being converted to TensorFlow Lite. A webcam is integrated into the setup, recording photos only when triggered by the ultrasonic module HC-SR04. This module identifies the presence of an object beneath the tap—such as hands—and prompts the camera to collect photographs, thus conserving electricity and processing resources. A speaker, functioning separately from the detection model, offers consumers individualized advice for effective water usage. This advice is generated by leveraging the GPT-4 API to create text-to-speech messages. This unique combination of components and technologies ensures that the tap not only conserves water but also educates users on sustainable behaviors, making every drop count while promoting excellent hygiene.



The system works according to the algorithm in Figure 1.

Algorithm 1 AdjustWaterFlowBasedOnSoapPresence

1: **Input:** Image of object beneath tap recorded by webcam
2: **Output:** Adjusted water flow rate (High for soap presence, Low for no soap)
3:
4: **Initialize the system:**
5: Activate the ultrasonic sensor to identify an object's presence
6: If an object is identified, trigger the webcam to record an image
7:
8: **Process the recorded image:**
9: Use the YOLO v7 model to analyze the image
10: Determine if soap is present on hands
11:
12: **Decide on the water flow rate:**
13: If soap is detected:
14: Set the water flow rate to High
15: Else:
16: Set the water flow rate to Low
17:
18: **Execute the water flow adjustment:**
19: Use the DC motor and gear system to change the tap's valve accordingly
20: The L293D motor controller manages the motor's operation to achieve the appropriate flow rate
21:
22: **Monitor for changes:**
23: Continuously check for the existence of an object beneath the tap
24: Repeat the process from step 1 if the object is detected again

Figure 4. Algorithm demonstrating the operation of the faucet.

V. CONCLUSION

This study presents a pioneering prototype for intelligent water faucets that leverages the power of the Internet of Things (IoT) and machine learning. Our system transforms conventional faucets into intelligent devices, promoting water conservation through real-time user activity identification. The core technology employs a Raspberry Pi for processing and YOLOv7, a highly accurate and fast object detection algorithm, to distinguish between hands with and without soap. Notably, our model achieved an impressive average average F1 Score of 99% and a mAP@.5 of 0.991. This distinction allows for automatic water flow regulation, thereby minimizing water waste.

While the current prototype demonstrates significant potential, its real-time response capabilities are limited by the processing power of the Raspberry Pi. Future iterations could benefit from deploying a GPU system, enabling true real-time responsiveness. This advancement would further enhance the system's effectiveness in addressing water conservation concerns and aligning with the environmental goals of smart cities. Additionally, exploring alternative object detection algorithms optimized for lower processing power could offer a balance between accuracy and real-time performance for wider deployment potential.

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