# Poster Abstract: A Beverage Intake Tracking System Based on Machine Learning Algorithms, and Ultrasonic and Color Sensors

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## ABSTRACT

We present a novel approach for monitoring beverage intake. Our system is composed of an ultrasonic sensor, an RGB color sensor, and machine learning algorithms. The system not only measures beverage volume but also detects beverage types. The sensor unit is lightweight that can be mounted on the lid of any drinking bottle. Our experimental results demonstrate that the proposed approach achieves more than 97% accuracy in beverage type classification. Furthermore, our regression-based volume measurement has a nominal error of 3%.

## CCS CONCEPTS

**•Computing methodologies →Machine learning; •Computer systems organization →Embedded hardware; Embedded software;** *Sensor networks; Sensors and actuators;*

## KEYWORDS

Hydration monitoring, nutrition monitoring, mobile health, machine learning

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## 1 INTRODUCTION

Consumption of water and other liquids reduces the incidence of bladder and colon cancer[4]. Many symptoms of fatigue, lightheadedness, xerostomia, bad taste in the mouth, and nausea can be due to dehydration; survivors are usually encouraged to try to remain adequately hydrated. Furthermore, drinking at least eight cups of liquid a day is recommended for the general public and is a reasonable recommendation for survivors as well, with the exception of those who have a specific medical reason for restricting fluid intake. The majority (i.e., 81%) of water intake is through beverages and drinking water and the remaining 19% is through food [3]. Prior research highlights that although most people are aware of importance of water consumption, up to 75% of the American population fall short of the recommended daily cups prescribed by the Institute of Medicine which, in medical terms, means that most people in the U.S are functioning in a chronic state of dehydration[2].

A major challenge is that dehydrated people are often unaware of their hydration status. Therefore, it is necessary to develop new solutions to improve hydration status of the individuals. We also note that people drink different type of beverages each of which can have a different nutrition value and contributes to hydration status differently. Therefore, developing technological solutions that detect beverage types in addition to tracking fluid volume is advantageous in health monitoring and interventions.

The new generation of bottles, such as HydrateMe, Smartlid and Trago, features Bluetooth wireless interfaces and custom smartphone and smartwatch applications, which allow for continuous water intake tracking. To the best of our knowledge, however, these technologies cannot detect the beverage type. In this paper, we present development of a new system based on ultrasonic sensors, color sensors, and machine learning algorithms to detect both volume and type of the liquid intake. The information provided by our beverage tracking system can be used to control and improve hydration status and thus prevent adverse clinical outcomes caused by dehydration.

## 2 SYSTEM OVERVIEW

### 2.1 Hardware Platform

We aim to develop an affordable and portable device to measure liquid intake volume and beverage type. We utilize three low-cost and light-weight sensors including accelerometer, ultrasonic and RGB color sensors. Each sensor is used for a unique purpose. All components of the sensing system together cost less than fifty dollars. We developed the prototype based on the Arduino mini controller and Sparkfun Bluetooth mate. The sensors can be mounted, from inside, to the lid of any cylinder shape bottle with different heights.

### 2.2 Computational Algorithms

Our system utilizes machine learning algorithms to calculate the volume and type of the liquid intake based on the sensor readings from ultrasonic sensor and RGB module. The system can store volume of the liquid intake and the type continuously and in real-time. When the system detects pouring liquid into the bottle it


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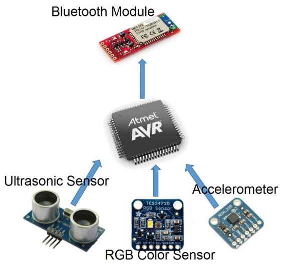
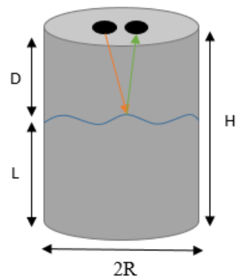



(a) Sensor components




(b) Ultrasonic sensor site

**Figure 1: Sensors and their placement on the bottle.**

starts measuring the liquid volume and detecting the liquid type. The system sends user notifications to help them reach their daily hydration goal (e.g., 1800 ml per day).

*2.2.1 Volume Calculation.* In the developed prototyped, we installed an ultrasonic sensor on the lid of a bottle to detect the liquid level. Hence, we can determine the volume of the liquid intake accordingly. As it can be seen in Figure 1(b), the ultrasonic sensor measures the distance between the sensor and the liquid surface. This value is denoted as 'D' in the following equation and in Figure 1. Furthermore, the height of the bottle, denoted as 'H' in Figure 1 is known *a priori*. We capture 'D' when the bottle is empty, which will give us the bottle height (i.e., 'H'). The fluid volume is then computed by

$$L = H - D$$
$$V = \pi R^2 L$$

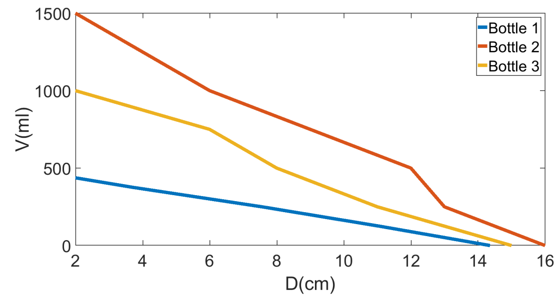
*2.2.2 Liquid Type Classification.* The RGB module shown in Figure 1(a) is mounted on the bottle lid. We then read the values of Red light ('R'), Green light ('G'), and Blue light ('B') captured by the sensor. For simplicity and power efficiency we convert the RGB readings to gray scale. Therefore, we only use one feature to detect the right class label in our machine learning algorithm. We use the following standard National Television System Committee conversion equation [1] to convert RGB readings to a single number:

$$Intensity = 0.2989 \times R + 0.5870 \times G + 0.1140 \times B$$

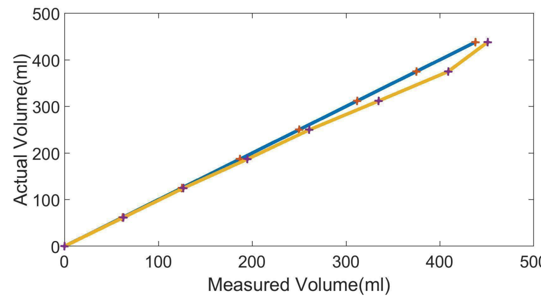
## 3 RESULTS

For validation of the system, we governed an experiment with different scenarios. We evaluated each sensing module individually. Figure 2(a) shows the sensor readings for three different bottles and the regression model we devised to compute the volume numbers. We used eight different beverages such as water, soft drinks, coffee, etc. For all liquid types, the system achieved similar results in measuring the beverage volume. Therefore, we conclude that the fluid type does not affect the ultrasonic sensor readings.

In a separate experiment, we gathered data for eight different liquids including water, lemon juice, orange juice, milk, chocolate milk, black tea, coffee, and Coke®. We used several machine learning algorithms on the collected data. The accuracy of the classifier was 97.9% for Random Forest classifier as shown in Table 1.




**(a) Ultrasonic sensor readings for three bottles of varying diameters**




**(b) Regression Model**

**Figure 2: Volume measurement results**

**Table 1: Classifier accuracy (beverage type detection)**

| | Random Forest | Naive Bayes | Simple Logistic |
|---|---|---|---|
| Accuracy(%) | 97.9 | 72.1 | 64.1 |
| Precision(%) | 97.9 | 68.1 | 57.2 |
| Recall(%) | 97.9 | 72.1 | 64.1 |

## 4 CONCLUSION AND FUTURE WORK

In this paper, we presented a smart bottle prototype for monitoring beverage intake using lightweight wireless sensors and machine learning algorithms. Our system detects beverage type with more than 97% accuracy in addition to measuring the beverage volume. Our future plans include (1) conducting user studies to assess the feasibility of our prototype for use in end-user settings; (2) refining our system to include additional information such as temperature; and (3) developing a hierarchical sensing architecture for power-efficient sensing and data processing.

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