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ULTRASONIC BASED MEASUREMENT SYSTEM FOR LIQUID LEVEL AND TYPE MONITORING

P. SURYANARAYANA Assistant Professor, Department of ECE, Eluru College of Engineering and Technology, Eluru, A.P
M.G. DEEPAK SAI KUMAR, A.VAMSI KRISHNA, B.B.S.KRISHNA VAMSI UG Student, Department of ECE, Eluru College of Engineering and Technology, Eluru, A.P

ABSTRACT

Low-cost ultrasonic sensors are widely used for non-contact distance measurement problems. Speed of ultrasonic waves is greatly affected by environmental conditions such as temperature and relative humidity among a few other parameters. Presence of acoustic and electronic noise also influence ultrasonic sensor-based distance measurement system. Existing standard techniques assume that the temperature and relative humidity level remains constant throughout the measurement medium. In our proposed system, we measure water level in storage containers, which exhibits a gradient of temperature and relative humidity across the measurement medium. Hence, the standard Ultrasonic Measurement System (UMS) is not able to estimate distance accurately. Fluid intake tracking is crucial in providing interventions that assist individuals to stay hydrated by maintaining an adequate amount of fluid. It also helps to manage calorie intake by accounting for the amount of calorie consumed from beverages. While staying hydrated and controlling calorie intake is critical in both physical wellness and cognitive health, existing technologies do not provide a solution for monitoring both fluid type and fluid volume. To address this limitation, we present the design, implementation, and validation of Liquid Intake Detection System for real-time tracking of fluid intake type and volume. The system devises a sensing module that is composed of ultrasonic, RGB color, temperature, and accelerometer sensors as well as a computational framework for fluid intake type classification, volume estimation, and bottle-state-recognition. And the system uploads data to a web page where we can monitor the data up-to a long duration of time. We conduct extensive experiments to collect data in a variety of bottles and environmental settings.

Keywords – *Bottle, Smart sensors, liquid intake, ultrasonic sensor, ultrasonic measurement system (UMS), distance measurement, temperature, relative humidity, color.*

1. INTRODUCTION

Maintaining an adequate amount of fluid intake is critical in both physical and cognitive wellness and health. Prior research emphasizes the serious physical and cognitive consequences of dehydration, as well as the preventive care benefits of taking a sufficient amount of fluid. For example, while dehydration could result in complications in the cardiovascular system,

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thermoregulation, metabolism, and central nervous functions, sufficient fluid intake helps reduce the incidence of bladder and colon cancer. Dehydration can also result in negative cognitive performance, such as poor concentration, increased reaction time, degraded visual attentiveness, short-term memory problems, moodiness, and anxiety. Recent research suggests that even a mild degree of dehydration (e.g., a body water loss of 1%–2%), which may occasionally occur throughout daily routines, can impair cognitive abilities.

Most of the fluid intake (i.e., approximately 81%) should be achieved through fluids rather than solid foods. A major challenge in maintaining a sufficient fluid level and preventing dehydration is that people are often unaware of their hydration status. A recent survey reported that, although most people understand that sufficient water consumption is important, approximately 75% of the American population falls short of the recommended daily fluid intake (i.e., 2.7 L for women and 3.7 L for men). In addition to gender, healthcare providers recommend different amounts of daily fluid intake based on age, health condition, and one's activity level. For example, it is recommended that young children consume fluid regularly to improve memory recall, and patients with cancer consume fluid frequently to improve their health condition because they often do not feel thirsty even when dehydrated.

Many mobile systems (e.g., smart bottles) have been introduced to 1) serve as a reminder for the users to adhere to maintaining an adequate hydration level and 2) track the volume of fluid intake using various types of sensors and analytic methods. There exist many commercially available products, such as HydraCoach R, Hidrate Spark R, and H2OPal R, which can track fluid intake. These smart bottles estimate the amount of fluid intake using sensors such as resistive sensor and flow meter. Users can track their fluid intake via mobile applications that these products provide and they can also use these systems to set daily hydration goals. More recently, researchers presented alternative technologies for measuring fluid intake and estimating body hydration. FluidMeter, AutoHydrate and are examples of such studies that use wearable systems to estimate fluid intake. In addition, studies such as

and use a bottle-attachable Inertial Measurement Unit (IMU) sensor for volume estimation purposes. However, the above-mentioned technologies mainly focus on tracking the volume of fluid intake and therefore fall short in identifying the type of consumed fluids.

Objective

To develop a viable solution for ubiquitous monitoring of fluid intake, it is essential to monitor the type of consumed fluid, because different fluids have different hydrating capabilities depending on their electrolyte and glucose contents. In other words, the suggested amount of fluid intake may vary depending on the beverage type. Furthermore, identification of the fluid type could be effective in monitoring the user's cheating behaviors on the prescribed/recommended regimen (e.g., drinking sugar-sweetened high-calorie beverages) or tracking one's calorie intake from fluid consumption. For instance, prior research reported that individuals consume, on average, 10%–15% of their total daily calories from sugar sweetened beverages. Hence, the development of a personalized tracking solution for fluid intake—in terms of both the volume and the type is in great need to assist users to achieve their hydration goals in everyday living situations.

In this, we introduce a Liquid Intake Detection System a mobile sensor system attached to the lid of a reusable water bottle (e.g., a tumbler) from inside, capable of automatically monitoring fluid intake volume, type, and temperature. The proposed system also detects important activities related to fluid intake, such as drinking from the bottle and opening the lid, which enables the opportunistic but continuous monitoring of the target fluid volume and type, further optimizing the power consumption of the embedded system. LIDS consists of several sensor modalities including an ultrasonic sensor, an RGB (Red, Green, and Blue) colour sensor, a temperature sensor, and an accelerometer. These sensors are coupled with an ultra-low power micro-controller and a wireless module for real-time sensor data sampling, processing, and transmission.

The system leverages machine learning algorithms to estimate and recognize the volume and the type of the fluid content in the bottle. We perform a series of comprehensive analyses on the data collected in different experimental settings to assess accuracy, robustness, and generalizability of our system for its use in real-world environments. Moreover, we propose a novel feature embedding to tackle a significant challenge of deploying our system in the real world which is predicting fluids in new bottles that have not been in the training data. Our results demonstrate an accuracy of 97.6% for detecting fluid type when training data contain data of the bottle that is being tested and root relative squared error of 1.1% for estimating volume by leveraging our proposed feature embedding classification method and Random Forest regression algorithm, respectively.

The feature embedding methods achieved an average accuracy of 84.8% while evaluating with unseen bottles.

2. LITERATURE SURVEY

This chapter reviews literature related to commonly used liquid level measurement techniques and highlights existing works related to ultrasonic level measurements.

There are various types of level measurement sensors are used to measure liquid level [2], [13]. These are mainly float type [14], [15], capacitive type [2], [16], [17], optical type [18], [19], radar type [2], [20] and ultrasonic type [2]–[5], [11], [12], [21], [22]. A float type level switch consists of a magnetic float which floats on the liquid surface. As the fluid level rises, the float moves vertically and this motion is used to measure the level. Float level devices are contact-type point level sensors, which have been used since early times due to their simple structure and reasonable cost. However, float level sensors suffer from low accuracy and frequent maintenance. Capacitive level sensors are made from two copper plates and the dielectric constant observed between two plates is proportional to the water level [16]. The dielectric constant of the liquid must be known for this type of measurement. The main advantages of these capacitive level measurement sensors include broad application range and good accuracy [17]. Performance of capacitive sensors gets affected by the change in the dielectric constant which varies with temperature of the liquid to be measured. These sensors are well-suited for both point and continuous level measurements.

In optical type level measurement, the reflective property of light is exploited for the measurement of liquid level. Optical level sensor consists of an infrared light-emitting diode (LED) and a light receiver. Light from the LED is directed to a prism and is reflected from the prism to the receiver when there is no liquid. When the sensor is immersed in liquid, the light is refracted out into the liquid, leaving little or no light to reach the receiver. The amount of received light by the receiver transistor indicates the liquid level. It is also a contact-type and point level detection sensor. The optical type requires frequent maintenance and it is adversely affected by the change in the reflective property of the medium [19]. Unlike ultrasonic sensors which use sound waves, radar level sensors use radio waves [2]. Main advantages of radar level sensors are high accuracy, non-contact type, and continuous level measurement. However, radar level sensors are of high cost and the cost increases exponentially with an increase in desired accuracy. Ultrasonic sensors are low-cost, long-range, non-contact and continuous level measurement devices. These sensors are widely used in many applications because of their simplicity of use, high level of safety and measurement resolution, ease of installation and very little maintenance.

Carullo et al. [3] described an ultrasonic distance measurement technique for automotive applications to measure the height from the ground to a vehicle body. In their experiment the measured distance is in the range of 100−600 mm and the temperature is in the range of 0−40 ◦C. The standard distance measurement uncertainty reported in their experiment is 1 mm. In [17], authors presented an extensive review of the existing state-of- the-art techniques for liquid level monitoring along with a comparison between capacitive and ultrasonic water level measurement system. Terzic et al. [11] developed Support Vector Machine (SVM) based signal processing and classification approach coupled with a single ultrasonic sensor to accurately determine the fuel level in an automotive fuel tank under dynamic conditions. Bucci and Landi [22] presented a novel algorithm for the measurement of signal transit time and applied it to the ultrasonic sensor for water level measurement in a water tank. The results obtained from their experiment indicated a mean error of 0.5 mm for water level ranging from 100 to 1000 mm in ambient temperature conditions.

In [10], Canali et al. designed an ultrasonic measurement system that can operate in air medium with temperature range from −20 ◦C to +100 ◦C and measure distance up to 100 cm. They only considered the effect of temperature on the speed of ultrasonic waves. Matsuya et al. [23] proposed a new method for liquid-level measurement utilizing wedge waves (generated by the ultrasonic transducer) and then demonstrated through finite element method (FEM) simulation using both interface echo method and end echo method. The standard deviations and the uncertainties of their

measurement method observed to be 0.65 mm and
0.21 mm respectively for interface echo method, and 0.39 mm and 0.12 mm respectively for end echo method. Zhang et al. [24] proposed a novel method for ultrasonic sensor measurement based on balanced echo energy for level measurement. This method uses the balance of ultrasonic echo energy received by two sensors to determine the liquid level from outside the sealed container.

In [12], the authors developed a sensing device that can monitor flash flood and traffic congestion in urban cities. This device consists of an ultrasonic sensor and a passive infrared temperature sensor. Machine learning techniques such as ANN, fuzzy logic and nonlinear regression were used to predict the water level. In their experiment, raw distance measurement varies by 12 cm but with their proposed method the estimated distance error reduced to less than 2 cm. Carullo et al. described a performance improvement technique for ultrasonic distance sensors using two-level neural networks. Neural network is used to process the ultrasonic echo's to improve measurement accuracy. Their method could limit the
error to 0.5 mm over a distance range up to 500 mm. All ultrasonic liquid level sensing techniques discussed above have different application areas, different measurement ranges, and varied ranges of temperatures. None of the aforementioned methods explicitly considered the effect of relative humidity and gradient of temperature and humidity in the measurement medium. Therefore, in this work, we propose an ANN based adaptive UMS to measure the distance with higher accuracy wherein, the error is limited to millimeter range.

Wearable-based Fluid Monitoring System:
Several studies have introduced wearable-based systems to estimate fluid intake volume. Fluid Meter is a ubiquitous system that can track the amount of fluid intake by using sensors embedded in smartwatches. Fluid Meter estimates the overall amount of fluid intake in grams with an estimation error of 15% and recognizes drinking gestures with an accuracy of 80.8%. Mengistu et al. presented Auto Hydrate, a wearable hydration monitoring system consisted of a microphone attached to the neck to monitor acoustic signals related to drinking and a smartwatch for collecting body activities and gestures. Based on an experiment involving eight individuals, authors reported a drinking detection accuracy of 91.5% and a body activity classification accuracy of 89.1%. Wearable-based solutions are less-obtrusive and less-invasive. However, these systems often suffer from low estimation accuracy for the amount of consumed fluid due to an obvious reason that the estimation relies on the counts of drinking body gestures. Furthermore, these wearable-based solutions cannot effectively monitor fluid intake when the user takes gestures other than the conventional drinking gestures (e.g., using a straw to drink from a bottle).

Sensor-instrumented Smart-Bottles:
One of the earliest sensor-equipped smart-bottles that could track and display daily fluid intake of the user includes HydraCoach R. The device uses an oral-suction-activated flow meter to measure the volume of the liquid moving from the bottle through a tube. Chiu et al.

proposed Playful Bottle that measures fluid intake volume using phone cameras. The average error rate obtained from 16 participants was 3.86%.

Hidrate Spark R is a commercial product that tracks the hydration level using accelerometer and touch sensors. The smartphone application associated with the device stores the hydration-related data along with the location information where drinking events occur. Borofsky et al. validated the fluid intake measurement of Hidrate Spark R and showed an error rate of 3% compared to the user-reported measurement. In addition to these popular reusable water-bottles that integrate embedded sensors, there exist other smart bottles such as Moikit R, Thermos R, and H2OPal R that have been used to measure fluid intake and temperature. Moikit R monitors water volume and the amount of fluid consumption by measuring air pressure in the bottle, which yields an accuracy of 5%. Thermos R has a sensor tube that measures the liquid volume with a resistive sensor. Jovanov et al. presents intelligent water bottle that can measure the amount of liquid in a bottle, monitor activity using inertial sensors, and physiological parameters using a touch and photoplethysmographic sensor. Kreutzer et al. introduces a fluid monitoring method that consists of passive sensor cups including a resistive sensor, an RFID transponder, and an RFID reader. H2OPal R uses an accelerometer and a weight sensor to monitor the water level in the bottle. Dong et al. proposed a miniaturized embedded system equipped with just an accelerometer that can be attached to a regular bottle to monitor fluid intake. The system captures and detects acceleration signatures related to drinking events, such as pouring and drinking. Then it classifies the amount of consumed liquid based on drinking motion which is captured by accelerometer. The system transmits information regarding the detected events to a smartphone via Bluetooth. The authors show that the system can achieve 99% accuracy in detecting drinking events and 75% accuracy in estimating the volume of fluid intake. Liu et al. uses a 3D printed smart cup attached with a single accelerometer which can detect drinking events and recognize complete periods of drinking. Soubam et al. proposed a sensor- instrumented base that can be attached to a water bottle.

The system can also be linked to a smartwatch to detect drinking motion with an accuracy of 93.53%. Although the above-mentioned prior research has been successful in detecting fluid intake using various types of sensors embedded in water bottles, most of the systems focus on estimating the volume of consumed fluid. There is a gap in our knowledge on how to develop technologies that can monitor both the type and volume of the fluid consumed by the user in a minimally-invasive manner. The proposed technology in this paper, LIDS, bridges the gap by introducing an integrated system that can monitor the type and volume of the liquid inside a bottle based on an array of sensors, including accelerometer, ultrasonic distance, and RGB color sensors. Furthermore, LIDS also monitors activities, such as whether a user drinks from the bottle or opens the lid, or whether the bottle is positioned stationary or moving (e.g., walking), which are used to opportunistically sample sensor data and further optimize the power efficiency of the system. The proposed system is complemented by utilizing machine learning algorithms for detecting drinking activities, classifying the type of liquid content, and estimating its volume.

3. EXISTING SYSTEM

Ultrasonic rangefinder depends on the Time-of-Flight (ToF) of the signal to measure distance. The distance D is calculated from the ToF using the equation, $D = (ToF * c)/2$, where c is the speed of sound (m/s). The speed of sound in dry air at Standard Temperature and Pressure (STP) is 331.45 m/s ± 0.05. (STP: 273.15 K, 1.01325×105 P a = 1 atm)

Most important environmental parameters that affect the speed of ultrasonic sound waves in air are temperature, relative humidity and to a lesser extent other gases present in the medium. Acoustic noise also has a major effect on ultrasonic sensor operation and distance measurements. Both environmental parameters and acoustic noise induce uncertainty in ultrasonic sensor-based distance measurements. Nowadays, water is scarce and a more valuable resource as the gap between demand and supply increases day by day. Thus, proper management of water resources using required technology is the need of the hour. Storage tanks are used to store bulk water and monitoring water level in storage tanks is very important for efficient water management. The water level can be determined using the following equation $L = H - D$ (1) where L is the water level, H is the height of the tank measured from ultrasonic sensor position to zero level, $D = (ToF * c)/2$, represents the distance from measuring device (ultrasonic sensor) to water level or surface.

Speed of sound in a medium increase as the temperature of the medium increases and it will lead to incorrect distance or level measurements [8]. The effect of temperature and relative humidity can be compensated using observations of temperature and humidity sensor along with the ultrasonic sensor. Ultrasonic level measurement system will yield noticeable accuracy if temperature and relative humidity remain constant between sensor position and the water level. Despite this, there still exists error in the measurement which is significant for many level measurement applications. This error is due to uncertain parameters like electronic noise and the variation (gradient) of temperature and relative humidity throughout the ultrasonic signal travel path between sensor position and water level. Especially, when the water tank diameter is larger, a small variation in level measurement will result in erroneous volume measurement of water contained in the tank. When the tank is exposed to sun, the temperature and relative humidity gradient induces significant error in level measurement.

Most of the existing works done so far in this field focused on compensating the effect of temperature [10]–[12]. In this paper, an extensive review of existing ultrasonic measurement techniques for liquid level monitoring is presented and a novel Artificial Neural Network (ANN) technique to compensate the environmental perturbations that affect the accuracy of ultrasonic measurement is also proposed. The main objective of this work is to improve the accuracy of ultrasonic based measurement system, which is adaptive to the environmental changes in the measurement medium. We propose a modified ANN based UMS, which can minimize the error substantially. The same model is also used to extend the operating range of the ultrasonic sensor.

The components/hardware used are:

1. **Arduino UNO** – The micro controller that processes the data obtained from the sensors and send necessary information when connected to a communicative device/module
2. **Ultrasonic sensor (HC-SR04)** - An ultrasonic sensor is an electronic device that measures the distance of a target object by emitting ultrasonic sound waves, and converts the reflected sound into an electrical signal.
3. **Temperature and Humidity sensor (DHT22)** – It is used for sensing temperature and humidity. It gives an analog voltage output that can be processed further using a microcontroller
4. **Bluetooth module (HC-05)** – A connectivity module that can be used to communicate in between a micro controller and a smartphone/PC
5. **Mobile/PC** – These are the devices used to receive information from the Microcontroller

4. PROPOSED SYSTEM

The proposed system consists of a hardware platform that integrates various electronics and an algorithm suite that uses sensor data for fluid intake monitoring. Our state machine and algorithms for bottle state recognition, volume estimation, and fluid type detection are discussed thoroughly.

Design Considerations:

The major design principle of this system is supporting the usability of the system for everyday use. People use different bottles or cups for drinking water or other fluids in a daily basis. Our principle is to design a system in such a way that it can be used for different containers. For instance, most people may drink tea in a cup and drink water from a bottle. As a result, having a system which can be used for both scenarios is desirable. Furthermore, we envision a sensing system that is low-cost, small in size, and light-weight, such that it can be conveniently installed as a lid on a fluid container. Having the ability for LIDS to be used with different bottles in different conditions brings the challenges associated with the adaptability and robustness. As the ultimate goal of our system is to be deployed in end-user settings, we need to assure that it is effective in such settings where uncertainties due changes in the reusable bottle (e.g., bottle color) and environment (e.g., ambient light) are taken into consideration during the system design.

Moreover, computational models need to be able to utilize the movement readings to effectively distinguish the fluid intake action from other movements such as refilling the bottle that may occur. In addition, the system needs to correctly classify fluid intake activities from many different users who may have varying signal patterns and signatures. LIDS needs to adapt itself to different conditions such as different brightness conditions, or using LIDS with transparent, translucent, or opaque containers.

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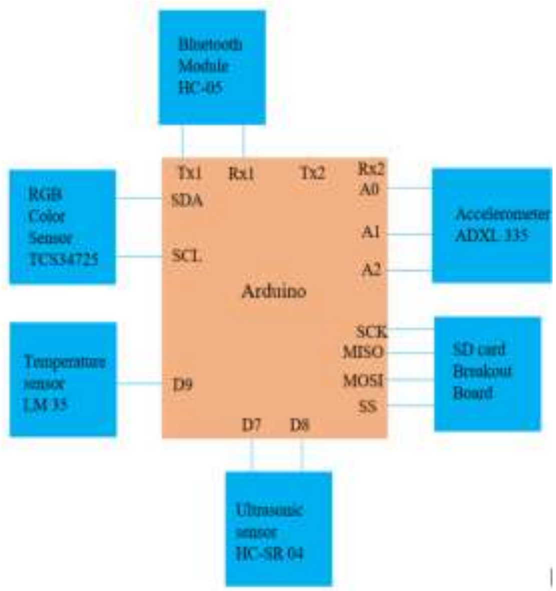

Fig 4.1: Block Diagram of proposed system.

As a result, based on RGB color sensor, we propose a comprehensive data collection process which includes different scenarios such as environments with different light intensities, different fluid volumes and different bottle colors. Power efficiency is another concern which is vital for a health monitoring system that is going to be used throughout the day. Therefore, the minimization of the energy consumption while maintaining the performance is crucial in designing LIDS. Energy efficiency is important to ensure long-term continuous functionality of the system and enhance adoption of the system

In particular, the system collects and processes various sensor data including an ultrasound and RGB sensors which consume a significant amount of power. As a result, we propose a signal processing methodology based on the accelerometer sensor that identifies the optimal times for volume and fluid type detection to drastically decrease the duty cycle of the sensors by putting them in sleep mode while not in-use. This includes an array of sensors The array of sensors:

- Ultrasonic sensor
- RGB color sensor
- Infrared temperature sensor
- An accelerometer to monitor the volume and type of the fluid inside the container, as well as important motions related to drinking activities (i.e., stationary, closing the lid, drinking from the bottle, or ambulating)

Hardware Platform:

Fig 1 shows various hardware components used in designing the proposed system. The diagram also shows the circuitry of the hardware components and how each module is connected to the main controller. We utilize four different sensors including accelerometer (ADXL335), ultrasonic (HC-SR04), RGB color (Adafruit TCS3200), and temperature (DS18B20) sensors. Most of the electronic components are installed inside a box to protect them from water and other fluid.

However, sensors such as RGB color, ultrasonic, and temperature sensors remain outside of the box to monitor the fluid. We use a waterproof ultrasonic sensor, shown in Fig 1, to ensure sensor operation in proximity of the fluid. We use epoxy to cover the circuits of RGB color sensor and temperature sensor to prevent the direct contact between the fluid and the sensors. Following our design principles, all the sensors need to function on a lid of a bottle and in a non-contact way. Therefore, for volume

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measurement through lid of a bottle we need a non-contact proximity sensor. There are three types of noncontact proximity sensors including capacitive, photoelectric, and ultrasonic sensors. However, capacitive sensors' sensing range falls short for our application. Their typical measurement ranges are between 1 and 60 millimeters. In addition, the shape and the color of the object can affect the readings of photoelectric sensors. Therefore, we choose ultrasonic method which can measure distance up to 3 meters. For temperature measurement, we use DS18B20 which is an infrared thermometer designed for non-contact temperature sensing. An Arduino micro-controller samples each sensor and transmits the sensor readings via Bluetooth (Sparkfun Bluetooth Mate Gold) to a mobile device for data processing. LIDS is also capable of logging the collected data on an SD card (via Adafruit Micro-SD card breakout board). A rechargeable LiPo battery with the capacity of 500 mAh is used to power the entire hardware board. In order to construct an affordable prototype for fluid intake monitoring, all the components of the sensing system cost less than two thousand.

Method of operation:

In this section we explain the design flow of LIDS and how it monitors fluid intake. We begin with an overview of the various procedures and computational tasks, which are needed for LIDS to compute fluid intake features. We then focus on each computational task and describe bottle-state recognition, volume estimation, and type detection algorithms.

5. RESULTS

We conducted a comprehensive set of experiments to evaluate the performance of LIDS. The analysis focused on performance evaluation of various machine learning algorithms used for fluid volume estimation, type detection, and bottlestate recognition. In addition, we experimentally measured the power consumption of the system for various combinations of the sensors that can be included in the prototype system. We installed LIDS on commercially available water bottles for validation.

Accuracy Results:

For color accuracy:

Table 8.1: Accuracy based on different Illuminance conditions

Light setting	Illuminance	Accuracy (%)
Dark	0	93.81
Medium	200	96.61
Extreme	1000	98.81

Absolute relative errors in LOVO approach:

Table 8.2: Relative absolute error approximated based on inputs

Volume range	Test set(mL)	Relative absolute error(%)
150,300,450,600	0	7.32
0,300,450,600	150	4.16

0,150,450,600	300	3.80
0,150,300,600	450	2.73
0,150,300,450	600	1.52

6. CONCLUSION

We designed, developed, and evaluated a low-power and portable sensor system for detecting fluid type and volume using low-cost, commercially available sensors including accelerometer, RGB, ultrasonic and temperature sensors which cost less than $50. We have implemented feature engineering and machine learning algorithms to process raw sensor data to detect fluid volume, fluid type and bottle state. Using Random Forest Regressor and Feature Embedding method, the system can estimate the fluid volume with a RAE of 1.1% while detecting the fluid type of 10 different fluids with an accuracy of 97.6% for previously seen bottle. In addition, fluid type detection accuracy for unseen bottles using feature embedding method obtained the average of 84.8%. LIDS is also able to identify the bottle state as expressed by movements of the lid with an accuracy of 98%. In this paper, we provided the results of fluid type classification, fluid volume estimation, drinking event recognition, consumed calorie estimation through fluids and current draw of the system.

Infusion device is a means for injecting certain chemical fluids, nutritional fluids, blood transfusions and chemotherapy to patients. The fluid enters the body through veins. The use of infusion is actually not so problematic if the patient can be controlled and monitored periodically for a short time by the nurse. Some problems present when there is lack of human resources in the hospital or nurse's negligence. One of the problems is the

administration of intravenous fluids. When the fluid runs out, there is no sign or warning directly sent to the nurse.

Therefore, a system to control and monitor the level of infusion fluid is necessary to design. The system is designed to detect the level of infusion fluid using a level sensor and a microcontroller as the data processor and hardware regulator. This system sends messages to nurses by short message text application.

The result of the research showed that when the infusion fluid is about to finish, the system notifies the nurse by sending an SMS.

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