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***Abstract*—One potential way to track or infer the amount of intake of different fluids—ranging from water to caffeinated beverages as well as liquid medication—is to determine the level of these fluids in the containers from which the user may consume them. To do so, we propose four capacitive sensor designs that can be easily added to the outside of containers of different shapes and sizes. Our evaluation of these four sensor designs with containers made of different materials (*i.e.,* ceramic, glass, paper, plastic) show that a multi-layer perceptron model can be learned to accurately predict liquid level with correlation coefficients higher than 0.98 and relative absolute error less than 16%. We then demonstrate that a prototype of this sensor can be constructed and affixed at the bottom of a liquid medication bottom to measure the amount of liquid medication in it.**

Keywords—capacitive sensing; water intake; liquid medication; liquid level; design; measurement; container

I. INTRODUCTION

Although attention is typically placed towards monitoring the amount and type of food that a person eats, it is also important that fluids are consumed at appropriate levels. For example, water is the most important fluid for a person to consume. Insufficient water intake may lead to dehydration, which can result in a variety of symptoms ranging from headache to numb skin and muscle spasm [13]. Reports suggest that 75% of Americans may suffer from chronic dehydration [17]. Chronic dehydration is a prevalent issue because most people simply do not drink enough water [5]. Monitoring water intake throughout the day is one way to estimate a person's hydration level in order to remind her to drink more water as needed. In addition to water intake, the consumption of caffeinated beverages, such as coffee and energy drinks, might also be important to track. A moderate caffeine consumption of up to 400mg/day is considered safe for most healthy adults [28], but excessive caffeine intake may lead to anxiety, headaches and nausea. Yet, data shows that the caffeine intake for adults aged >= 35 is often above the recommended amount (420~467 mg/day) [28]. As a final example, another important type of fluid that must be consumed at an appropriate level is liquid medication. Liquid medication is normally prescribed for people who have difficulty in swallowing tablets or capsules. It is commonly used by young children and the elderly. A common error with liquid medication is taking the wrong dose. Previous studies [41] have shown that 39.4% of parents make an error when administering liquid medication by incorrectly measuring the intended dose for their children. Confusion related to units of measurement accounts for over 10,000 annual poison center calls [6]. Automatically tracking changes to the amount of liquid in a medication bottle can help parents determine if the correct dose is being given.

There are several specially designed bottles sold commercially that support tracking or inferring the amount of fluid that has been consumed [1][11][24][29][35]. One limitation with these products is that the tracking capability is limited to that one container. Unfortunately, the cost of this solution poses scalability problems. From the user's perspective, only the fluid she places into that container can be tracked. However, people regularly consume different fluids— ranging from water to other beverages as well as liquid medication— from a variety of drinkware and containers, such as plastic bottles, glasses, and ceramic cups. Thus, in order to decide if fluids are consumed at appropriate levels, it is important to design scalable sensors that can readily be used for containers varying in shapes, sizes and materials.

In this paper, we investigated how a capacitive sensor can be designed to detect the liquid level held inside any container from outside the container. We examined the efficacy of four capacitive sensor designs to measure the liquid level in containers made from one of the following materials: glass, paper, plastic and ceramic. We built and evaluated two predictive models (linear regression and multilayer perceptron) for estimating the continuous liquid levels in real time based on statistical features extracted from sensor readings. We found that all four designs predicted liquid level with a correlation coefficient higher than 0.98 and less than 16% relative absolute error. We then selected the most compact design and demonstrated that it can be applied as a sensor affixed at the bottom of a bottle to perform liquid medication measurement. In short, this work demonstrates that capacitive sensors can be designed and used to measure liquid level changes in containers of different shapes (such as bottle and glass) and made from different materials (such as ceramic, glass, and plastic) for different health and medical applications.

II. RELATED WORK

Although sufficient water intake is important for maintaining a healthy body, previous studies have shown that people often do not drink enough water [5]. As a result, numerous systems and products have been introduced to remind the user when to drink water, help the user manually keep track of their fluid intake [17], automatically track how much fluid the user has consumed [10][11][24][29][35], and determine what beverages are being consumed [23][26]. Providing users with an awareness of their water intake can encourage healthier drinking behaviour [10][17].

Mobile applications, such as Carboroid [9], Daily Water Free [12], Waterlogged [37], WaterMinder [38], and Water Your Body [39], allow the user to set alerts that remind them to drink water at preset intervals over the course of a day. Many such systems also support manual tracking of fluid intake as a way of setting or dismissing upcoming reminder alerts. WaterJewel [17] is an example of such system which allows the user to manually keep track of their fluid intake. WaterJewel is a bracelet with 9 LEDs which illuminate in succession to represent the user's progress towards successfully drinking eight cups of water each day. The user simply presses a button on the bracelet for two seconds after she drinks a glass of water to indicate to the system her water consumption progress. Fortmann *et al.*'s study [17] shows that WaterJewel's LED visualization provides users with constant awareness of their progress and this can encourage healthier water drinking behaviour.

A different approach for knowing when to remind a user to drink water is to automatically track or infer water intake. There are many strategies to determine when the user has consumed water. A motion-based approach can be employed by using an accelerometer attached to a drinkware to determine when it has been picked up and tilted and vision-based methods can be used to determine when the amount of liquid inside a container has changed. For example, Playful Bottle [10] is a system which uses an accelerometer and backside camera of a mobile phone attached to a transparent bottle with pattern bars painted on its outer surface to perform motion-based and vision-based detection of water intake. Approaches based entirely on motion may be prone to false detection of water intake and may not be able to accurately determine how much fluid has been consumed. Vision-based approaches, on the other hand, require that a camera must be able to see the fluid inside the container. In the case of the Playful Bottle, the container had to be made of transparent material with patterns marked on it in order for the camera to determine the fluid level. Beyond water, Fan and Truong [18] recently present a small portable acoustic sensor that can be attached to a side surface of a container to infer its content level. They demonstrate the sensor can work for 19 household items of different content types and different container materials.

Capacitive sensing is an alternative approach that is usually more cost-effective than previous approaches. It has been used for liquid level measurement [7][15][21][25][27][31][32][34]. Many of these previous systems [7][25][27][31][32][34] required that the sensors be in contact with the liquid being measured. Goekler [21], on the other hand, proposed a sensor design that can be mounted on an exterior wall of the container. This design is limited to single point sensing of a predetermined level of fluids. Dietz *et al.* [15] explored an external design to measure continuous liquid level in glassware. The design required that the sensor fully enclosed the external surfaces of the glass. While this solution can work from the outside of a glass, this made the sensor a specially designed container itself.

HydraCoach [24], Vessyl [35], OCup [29] and Cuptime [11] are examples of commercial products for measuring liquid level inside a bottle. These products use different methods, such as capacitive sensing or liquid flow metering, that do not require sensors be placed inside the liquid itself. Instead, the sensors are designed to be a part of a specially designed bottle, which means that the user would not be able to track her intake from any drinkware other than that bottle. All approaches discussed here use changes in fluid levels to infer consumption.

Besides water, people may also consume other types of liquid. Previous research has suggested that 21% of people's caloric consumption comes from what they drink [16]. Thus, it is potentially important to track what a person consumes because even beverages, such as diet soft drinks, can cause weight gain [20]. As a result, researchers have explored different ways of detecting the type of liquid inside a container. For example, Lester *et al.* [26] designed a classification system which uses spectroscopy and Ion Selective Electrodes to classify 68 different types of drinks with up to 79% accuracy. Hirano *et al.* [23] implemented a method which uses a gas sensor to distinguish different categories of drinks over larger distances with the help of a fan that draws the odors towards the sensor. Capacitive sensing can potentially be designed to work together with these liquid-type detection sensors to track the amount of different fluids consumed.

Finally, an important type of liquid that people sometimes consume is liquid medication. Many approaches have been proposed for detecting solid medication intake, such as using computer vision [4], motion sensors [8], and specifically designed pill bottles [1][2][22][30]. However, most of these solutions do not work for liquid medication or do not sense the amount of medication being taken. One notable exception is AdhereTech [1] which has designed a pill bottle that uses capacitive sensing to measure the amount of pills or liquid medication inside it. The pills or liquid medications must be stored in this specially designed bottle. The cost of the solution can become an issue if a person takes more than one medication and has to purchase multiple bottles to track each. In this paper, we explore different capacitive sensor designs that can be easily added to any container as a way of inferring liquid medication intake without requiring a special bottle to track this information.

III. THEORY OF OPERATION

Capacitive sensing is a method that most commonly has been used in tablets and phones to detect the user's finger proximity and touch input. Touchscreens typically have a conductive layer under the top layer of the touch screen (*i.e.*, a protective coating layer). When a finger comes close to or actually touches the screen surface, the capacitance formed by the conductive layer and the human body changes the electrostatic field of the screen. This allows an embedded circuit to sense the position of the touch point.

We use the same underlying principle in this paper for detecting liquid level. It works by leveraging the concept of capacitive coupling. Capacitive coupling is the transfer of energy within electrical networks by means of the electrical charge of the conductive or dielectric material [3]. In the liquid level sensing application, the liquid typically acts as the conductive or dielectric material. There are many possible capacitor designs, however, a simple parallel plate capacitor design has two conductive electrodes (or plates) separated by a dielectric material (*e.g.,* air, water). A capacitor has certain capacitance C, which can be expressed in the following equation: $C = \frac{\varepsilon * A}{d} C = \frac{Ɛ * A}{d}$, where A is the area of the plate, d is the distance between the two plates and Ɛ is permittivity of the dielectric material. Change in any of the three factors will cause the capacitance to change. For liquid level sensing, the area of and the distance between the plates are kept constant. Therefore, any change in the liquid level changes the permittivity of the medium, leading to a change in the overall capacitance of the system. By observing the change in the system capacitance, one can estimate the corresponding liquid level change.

Measuring the liquid level inside a container using capacitive sensing from the outside requires treating the container and its content as a part of the capacitor. Here, the liquid acts as one of the dielectric materials that exist between the two conductive surfaces of a capacitor; other dielectric materials include the air itself as well as the material used to make the container. As the liquid level changes, the amount of dielectric materials between the conductive plates is affected. Because different dielectric materials have different permittivity, the capacitance will change correspondingly. The sensor values for the different amounts of liquid in a container can be collected and used to develop a prediction model for estimating the liquid level automatically.

As mentioned in the related work, there are several examples of previous work which have also explored the use of capacitive sensing for liquid level measurement [7][15][21][25][27][31][32][34]. Many of these previous systems [7][25][27][31][32][34] require the sensors to be in contact with the liquid. The sensors in these instances either can be a probe that is placed inside the container along with the liquid [25][27][31][32][34] or are attached to the interior surfaces of the container [7]. For example, Reverter *et al.* [32] measured liquid level in a grounded metallic container using two stainless probes placed in the container along with the tap water being measured. Canbolat's design [7] on the other hand includes three pairs of conductive surfaces that are placed at the top, bottom, and along one vertical wall of the container. The conductive surface placed along the vertical wall is the main sensor, while the surface placed at the bottom acts as a reference point and the top one senses the amount of air in the container. This multi-capacitor design can minimize the effect that extraneous factors might have on the individual sensor readings.

Most similar to the work described in this paper is probably Dietz *et al.*'s system [15], which consists of one conductive surface at the bottom of the glassware and another single conductive surface wrapped fully around the entire vertical exterior of the glass. Although the wrapped conductor facilitates continuous liquid level detection, it limits the flexibility of the design. In a way, this sensor is a specially designed container itself.

In this paper, we address the limitations in previous systems by proposing designs that can be easily added externally to containers of different shapes. We further investigate the efficacy of our designs across containers made from different materials.

IV. HIGH-LEVEL DESIGN & IMPLEMENTATION DETAILS

We divide our exploration of using capacitive sensing to externally measure the liquid level inside a container into two phases. First, we explore the efficacy of different capacitive sensor designs with containers made from different materials. To do so, we consider different designs for such a capacitive sensor with respect to the number, size and placement of the conductive surfaces in relation to the dielectric materials (comprised of the container and the liquid inside it). We hold the shape and form of the container constant as a 20 oz. cup to test if different capacitive sensor designs can work with the different materials—paper, plastic, glass and ceramic. This allows us to understand which design can be applied to other common drinkware and container types based on the materials that they are made of, such as ceramic mugs, wine glasses, and plastic bottles. Second, we then use findings from the first exploration to test the effectiveness of a specific capacitive sensor design to externally measure the level of liquid medication contained in a plastic bottle. This allows us to test if findings from the first phase can be applied to measure a different type of liquid when it is inside a container that is of new shape and size.

Figure 1 shows the four capacitive sensor designs for liquid level measurement and how they could be placed on a cup. The first design (Figure 1a) places two equal-sized conductive surfaces on opposing sides of a container spanning the height of the cup. The second design (Figure 1b) extends the first design. Instead of having just two conductive surfaces on opposing sides of the container, it has multiple pairs of conductive surfaces. Each pair of conductive surfaces forms a capacitor. Therefore, the second design actually consists of several individual capacitors that are vertically stacked. This design explores whether having multiple capacitors can help to improve the accuracy of liquid level measurement. The third design (Figure 1c) places one conductive surface at the bottom of the cup and one along the side of the container. Finally, the fourth design (Figure 1d) contains just one conductive surface at the bottom of the container and works in a manner similar to how touchscreens do.

Figure 2 shows the implemented versions of the four sensor designs placed on a cup. Although we implemented them as cup sleeves (for Designs 1 & 2), coasters (Design 4), or a combination of both (Design 3), we envision that potentially

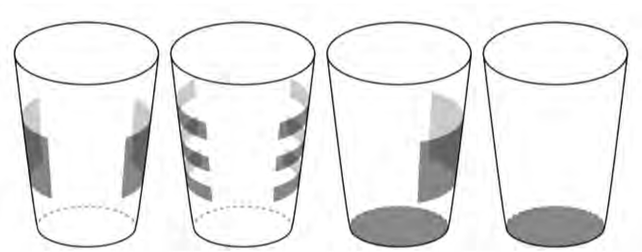

Fig. 1. Sketch of four capacitor designs and their envisioned placements to measure the liquid level in a cup.

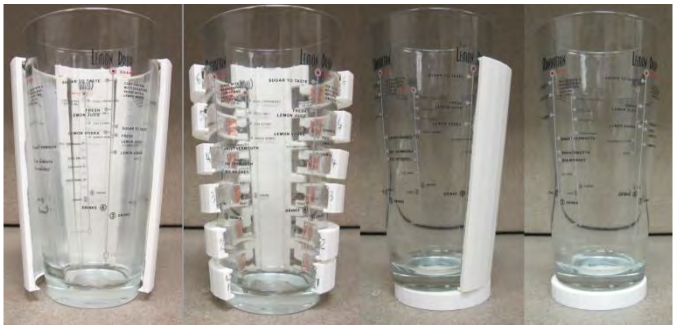

Fig. 2. Implementation of four capacitor designs and their placements on a glass cup.

they can also be implemented as decals or materials that can be easily stuck on or affixed to and removed from any liquid container in the respective positions depicted in Figure 1. For prototyping and testing purposes, we 3d printed parts to act as these different sleeve and coaster designs. Although it would have been possible to implement these designs as decals, these 3d printed parts allowed us to simulate the placement of the conductive surfaces on a container in a more rapid and consistent manner. In all four implementations, we constructed the conductive surfaces out of aluminum foil. The conductive surfaces were then wired to form a resistor-capacitor (RC) circuit that was connected to an Arduino to sense the capacitance change based on the liquid level found in the cup. For the capacitor designs comprised of two conductive surfaces, one surface is connected to the ground, and the other one is connected to the Arduino twice: once directly and the second time through a connected 10M Ohm resistor. These two connections are the sensor pin and the signal pin respectively in the RC circuit. Figure 3 shows how Design 2 is connected to an Arduino to form an RC circuit.

To use any of the implemented sensors, initially we set the signal pin to output a high voltage with the sensor pin in a low voltage state. Electrical charge will then flow into one conductive surface of the capacitor and charge it until the sensor pin reaches the same voltage as the signal pin. Next, we set the sensor pin to output a high voltage with the signal pin in a low voltage state. Electrical charge will flow out of the conductive surface of the capacitor until the sensor and signal pins reach the same voltage. Effectively, the capacitor is charged and then discharged. The time taken for charging and discharging is determined by the RC time constant tau, which can be expressed as $R \times C$. In our sensing system, the resistor value R is fixed, but the capacitance C of the capacitor is affected by the dielectric materials between the two conductive surfaces. Therefore, by

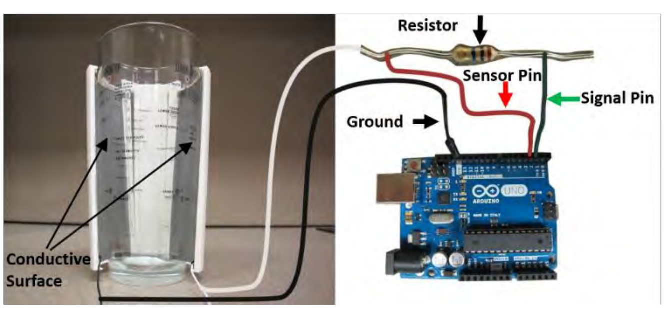

Fig. 3. The RC circuit connection of a prototype of Design 1 on a glass cup.

Fig. 4. A soft sleeve design with paper and electric tapes as the main support materials.

measuring the time of the aforementioned charging and discharging phases and repeating the two phases periodically, it is possible to determine changes to the dielectric materials in real time.

To demonstrate that the designs do not require the 3d printed cases, we have also implemented a sleeve prototype made of paper and electric tape as a proof of concept (see Figure 4). In developing this prototype, we show that a flexible (non-rigid) prototype of the capacitive sensors can also be constructed. Although this prototype is a large sleeve, we could have easily created it as a decal as well. Tests with this prototype show that it functions in a comparable manner to the prototype constructed using the 3d printed parts. The paper prototype lacks elasticity and therefore could only fit to the shape of the cup it was constructed to wrap around. Reusing it with cups made of different materials was not possible because even though cups may be of the same height and volume, their shapes may vary slightly. To accommodate the slight differences in the cup shapes, we connected the 3d printed parts holding the conductive surfaces to an additional 3d printed "spine" part and we added torsion springs (to Design 1 and 2) to force the 3d printed parts to naturally cling onto cup. This allowed the designs to work on different cup shapes. In this paper, we only report and analyze the data collected with the 3d printed prototypes.

V. Data Collection and Evaluation

To understand how well the four different capacitive sensor designs estimate the liquid level in a container, we collected sensor data for each design on four different types of containers: plastic, glass, paper and ceramic. We then analyzed the collected data to build a prediction model to estimate the liquid level in a container from sensor readings in real time.

We then further evaluated the use of one sensor design (Design 4) for measuring the level of liquid medication inside a bottle. Again, we collected sensor data for different levels of Cold & Flu liquid medication found inside a bottle to build a prediction model.

A. Data Collection

For every possible container type (paper, plastic, glass, and ceramic cup) and capacitive sensor design (Designs 1-4) pairing, we collected sensor data for different liquid levels using following protocol: **1**) start with an empty container; **2**) measure 15 milliliter (ML) amount of liquid and pour into the container; **3**) once the liquid settles, press a button to start the collection of sensor data; **4**) let the Arduino microcontroller collect sensor data and transmit it to a PC via serial port in real time for the next 10 seconds; **5**) run a program on the PC monitoring that serial port log the sensor values along with the current liquid level into a file; **6**) repeat from step 2 until the target amount of liquid has been reached in the cup.

B. Feature Extraction & Prediction Model Learning

To build and test a prediction model for each sensor design, we first processed the collected data. The raw data sample for sensor Designs 1, 3 and 4 is collected in the following format: $< ts_i, x_i, y_i >$, where ts_i is a timestamp, x_i is a raw sensor value; and y_i is the amount of liquid inside of the container. Because Design 2 has 6 pairs of capacitive sensors that sense independently, the *i*th raw data format includes 6 sensor readings: $< ts_i, x_{1,i}, ..., x_{6,i}, y_i >$. In order to reduce the effect of noise in the raw data, we calculated 4 statistics (mean, median, mode and standard deviation) using a 1 second window as the final features for training the prediction model. We chose a 1 second window in order to develop a prediction model that can determine the current liquid level at a 1 second frequency. Because the prediction target y_i is a continuous value, learning the prediction model is a regression problem. We explored two regression models. The first is the linear regression model for its fast performance and the ability to handle the linear relationship between features and the target. The second is the multi-layer perceptron for its ability to handle both linear and non-linear relationship between the features and the target.

The four statistical features for the data samples collected with four sensor designs on the glass container are illustrated in Figure 5. The data collected from the other three types of containers follow the same trend. In Figure 5, for Design 2, we averaged the readings from the six individual sensors. The raw sensor readings from the six individual sensors in Design 2 are shown in Figure 6.

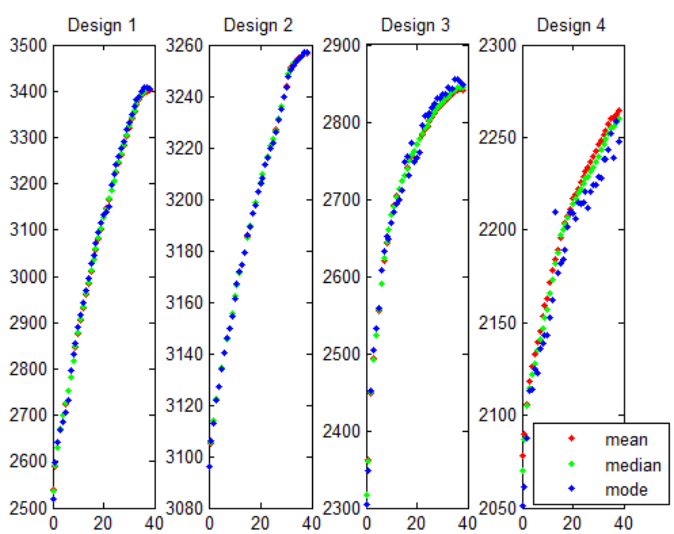

Fig. 5. Plot of processed sensor data for four sensor designs on a glass container. Horizontal axis is the volume of liquid (unit: 15ML); Vertical axis is sensor value.

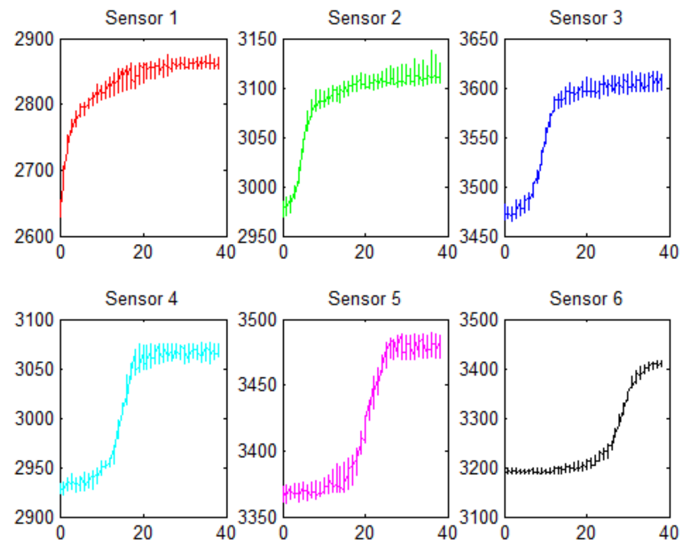

Fig. 6. Plot of six sensor readings of Design 2. Sensor 1 is at the bottom while the sensor 6 is at the top of the container. Horizontal axis is the volume of liquid (unit: 15ML); Vertical axis is sensor value.

C. Performance Results of the Different Sensor Designs

A common approach to evaluating the generalization ability of a prediction model is cross-validation. In k-fold cross validation, the data set is randomly divided into k equal partitions. One partition is used as the test data and the rest k-1 partitions are used as the training data. The training procedure repeats k times (folds) and each time one of the k partitions is chosen exactly once as the test data. The k testing results are then averaged to produce a single evaluation result. We performed a 10-fold cross validation on the linear regression and multilayer perceptron models respectively. The results are shown in Table 2, with the best performances for different container materials under each prediction model highlighted.

The four designs fall roughly into two groups based on their performances: Designs 1 and 2 perform better than Designs 3 and 4. For the linear regression model, Designs 1 and 2 outperform much more than Designs 3 and 4. With a multi-layer perceptron model, the performances of all four designs are comparable to each other, but Designs 1 and 2 still perform better than Design 3 and 4. With more sensors embedded, Design 2 outperforms Design 1 in most cases. This implies that having more sensors placed around a container can potentially help determine the liquid level more accurately. However, the trade-off is the increased complexity of the sensor design. From the results of this evaluation, Design 3 may not offer any clear benefits over Design 4. Given its simplistic design and promising prediction performance, Design 4 is an ideal one because it could be implemented as a decal or a component that could easily be attached to the bottom of a variety of containers of different shapes and sizes. With regard to the container materials, both prediction models work better on the paper and plastic containers than the glass and ceramic ones. The thickness of the glass and ceramic could have potentially been the cause for this, but further experiments should be conducted using different containers made at the same thickness. With regard to the performance of two regression models, Multilayer perceptron outperforms linear regression in most cases. This

TABLE I. PERFORMANCE OF FOUR SENSOR DESIGNS, WITH THE BEST PERFORMANCES FOR DIFFERENT COTNAINER MATERIALS UNDER EACH PREDICTION MODELS HIGHLIGHTED

Design	Cup Material	Linear Regression				Multi-layer Perceptron			
		Correlation Coefficient (CC)	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)	Relative Absolute Error (RAE)	Correlation Coefficient	Mean Absolute Error	Root Mean Squared Error	Relative Absolute Error
1	Ceramic	0.9837	24.54	30.39	16.69%	0.9974	9.46	12.49	6.43%
1	Glass	0.9896	19.06	24.29	13.03%	0.9989	5.68	7.96	3.88%
1	Paper	0.9983	7.99	9.77	5.44%	0.9998	2.83	3.59	1.93%
1	Plastic	0.9952	13.74	16.51	9.42%	0.9997	3.38	4.14	2.31%
2	Ceramic	0.9963	10.28	14.46	7.02%	0.9989	5.83	8.10	3.99%
2	Glass	0.9979	7.42	10.81	5.08%	0.9995	3.72	5.31	2.55%
2	Paper	0.9994	4.83	5.99	3.22%	0.9995	4.36	5.44	2.91%
2	Plastic	0.9997	3.05	3.97	2.08%	0.9997	3.15	3.97	2.15%
3	Ceramic	0.8687	65.66	83.72	44.78%	0.9839	23.36	30.62	15.93%
3	Glass	0.8967	61.88	74.84	42.2%	0.997	10.04	13.3	6.85%
3	Paper	0.929	48.68	62.66	33.14%	0.9982	6.81	10.12	4.63%
3	Plastic	0.9142	55.51	68.32	37.89%	0.9991	4.84	7.04	3.3%
4	Ceramic	0.9938	13.56	18.74	9.28%	0.9993	4.51	6.57	3.08%
4	Glass	0.9746	21.04	26.81	20.25%	0.997	6.52	9.41	6.27%
4	Paper	0.9287	44.55	62.6	30.41%	0.9844	18.37	29.66	12.54%
4	Plastic	0.9927	14.10	20.39	9.63%	0.9974	7.61	12.06	5.2%

suggests that Multi-layer perceptron can better handle the non-linear relationship between the sensor values and the liquid level than a linear regression model.

In addition to continuous liquid level prediction, the separated multi-sensor design of Design 2 also provides an opportunity for predicting discrete liquid levels, *i.e.,* based on which sensor the water level is the closest to. We extracted the mean from a 1 second window for each of the six sensor readings and trained a Decision Tree classifier based on these six features. The 10-fold cross validation results are shown in Figure 7. The prediction accuracy is above 0.95, with misclassifications to only directly adjacent levels. Thus, Design 2 can predict discrete liquid level reasonably well.

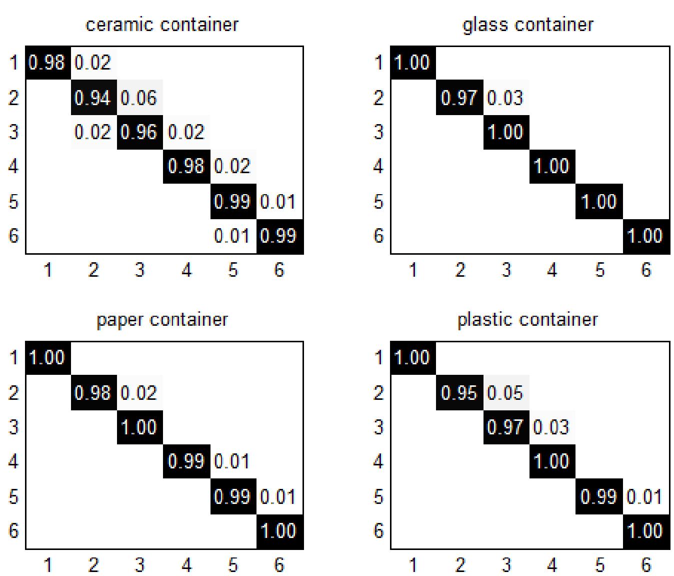

Fig. 7. Confusion matrix of discrete liquid level detection using Design 2. Horizontal axis: classification results; vertical axis: actual labels.

D. *Performance Result of Liquid Medication Level Sensing*

Results from above show that a single conductive surface capacitive sensor design (Design 4) can determine the liquid level from the bottom of a plastic container reasonably well. We chose to test this design further because it can be created ideally as a small decal-like component affixed at the bottom of any container, thereby not interfering with existing stickers identifying the product and providing instructions on how to administer the medication. To test Design 4's ability to predict the amount of liquid medication found in a bottle of cold and flu relief liquid medication (Figure 8), we 3d printed a triangle shape part that fits under the bottle. The total amount of liquid inside the bottle is 355ML.

To build a regression model, we started by emptying the liquid medication into another container and placed the sensor prototype under the empty bottle. We then followed the same protocol as described in the *Data Collection* section. We poured 15ML medication (the smallest recommended dosage) into the medication bottle each time. An Arduino Micro was connected to the sensor that sent the readings to a PC where another program received the data and logged them into a file.

The collected data show that there is a rough linear relationship between the sensor values and the liquid level. We again trained two regression models by following the same

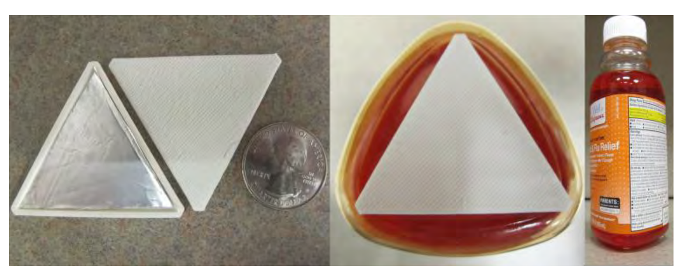

Fig. 8. 3d printed triangle coaster for liquid medication measurement (left); the coaster is placed at the bottom of the bottole (middle and right).

TABLE II. PERFORMANCE OF LIQUID MEDICATION LEVEL PREDICTION

Linear Regression				Multi-layer Perceptron			
CC	MAE	RMSE	RAE	CC	MAE	RMSE	RAE
0.96	15.24	31.78	16.17%	0.9829	11.83	20.00	12.56%

procedure described in *Feature Extraction & Prediction Model Learning* section. The 10-fold cross validation results are shown in Table 2. The prediction models can accurately predict the liquid level (with correlation coefficients being above 0.96). The multi-layer perceptron model can achieve less than 15% Relative Absolute Errors.

VI. DISCUSSION

In this section, we explore three additional questions surrounding the use of capacitive sensors to determine the amount of content inside a container.

A. Different Content Types

The first question that we explored further was whether a model developed for a container with one type of fluid and can be used to measure the liquid level when that same container contains a different fluid. To answer this question, we followed the same data collection protocol described earlier in the paper to collect 10 different liquid levels (15ML × 10 = 150ML total amount of liquid) for four types of liquids (*water, coke, milk, orange juice*) in a glass cup using Design 4 (the last image in Figure 2). The collected sensor readings for different levels of these four types of liquid are similar to those for water and therefore one prediction model can be learned and applied for any of them. However, because the ranges of sensor values for these four types of liquids are roughly the same, it would be hard to distinguish them using only capacitive sensing.

Although this paper explores the efficacy of different sensor designs on measuring liquid level, a natural question that arises is: can capacitive sensing be used to measure the level of solids in a container as well? We again performed the same data collection procedure described above, but with three different types of solid content: *rice, salt, and flour*. As expected, for each solid content type, the sensor values increased as the amount of content increased. However, the amount of the change in the sensor value for every 150 cubic centimeters' worth of solid content is much smaller than that for the same volume of liquid. Thus, although capacitive sensing can work for solids, the sensing granularity for solids is lower than for liquids. Furthermore, the models trained for one type of solid cannot be used to determine the level for a different type of solid. This is perhaps because the granularity of each type of solid differs significantly (*e.g.,* flour is much finer grained than rice). As a result, for example, a container filled with rice might have more air in it than the one filled with flour. Additionally, each type of solid might also have a different permittivity as well.

B. Different Temperatures

Next, we investigated if the temperature of the liquid inside a container affects the model. We addressed this question by comparing the sensor values for cold water (water sitting in ice) and hot water (water that has been brought to a boil). Again, we followed the same procedure to collect data samples in a glass using Design 4 (Figure 2). We ran two sample t-tests on sensor values (V) for the same amount of cold water and hot water: V= 100ML, $t(1205) = -20.20$, $p < .01$; V= 200ML, $t(1199) = -19.90$, $p < .01$; V = 300ML, $t(1194) = -28.51$, $p < .01$. The results indicate the temperature of the liquid affects the sensor readings significantly. In this instance, water at a warmer temperature produces higher sensor values than those for the colder one. This suggests that a model trained at one temperature level might not work when the content is being measured at another temperature (for example, a water bottle that is sitting inside a fridge might not have the same sensor value as one resting at room temperature).

C. Different Container Shapes

Finally, we investigated if the shape of a container affects the model. We 3d printed three different cups to ensure that they were made from the same material. The cups have the same height. The bottom of all three cups are the same size. However, each cup grows wider at different rates as the cup gets taller—making them different in shape (Figure 9). Again, we followed the same protocol to collect data for different amounts of liquid. Even when the cups were empty, the sensor values were already different, which suggests that the shape of the cups might have an effect on the sensor data. To understand the extent of the effect, we offset the data collected with the baseline value for each cup (*i.e.,* the sensor value at empty for each cup). We then performed a one-way ANOVA on the sensor values of at the same volume (V) in the three cups. The results are: V = 100ML, $F(2, 1210) = 1855.12$, $p < .01$; V = 200ML, $F(2, 1205) = 2574.16$, $p < .01$; V = 300ML, $F(2, 1201) = 934.46$, $p < .01$. The mean values of the sensor values recorded with the same amount of liquid in three cups are statistically different. This suggests that the shape of the container affects the model.

Fig. 9. 3d printed cups with the same size bottom and the height

VII. CONCLUSION AND FUTURE WORK

In this paper, we explored four different capacitive sensor designs, made of aluminum foil and 3d printed components, for liquid level prediction. We evaluated the four sensor designs on four different types of container materials (*i.e.,* ceramic, glass, paper and plastic) with two prediction models and found that the multi-layer perceptron model learned based on four statistical features of the collected data can predict the water level with correlation coefficient higher than 0.98 and less than 16% relative absolute error. We then demonstrated an application of this work, by developing and attaching a simple decal-like sensor prototype to the bottom of a medication bottle, to predict liquid medication level with less than 16% relative absolute error.

One challenge that we encountered while implementing the different sensor designs was removing noises that can affect the sensor data. Because our designs were instrumented on the outside of a container, a user's hand may touch or come close to the sensors. The capacitance of the user's body can affect the sensor values (essentially, for the same reason why touchscreens works, the human body can also introduce noise in the sensors discussed in this work). Our solution was to add an additional metallic layer on the outside surface of each 3d printed part in the prototypes, ground that additional metallic surface and then insulate it with electric tape. Such a design shielded the sensor from interferences introduced from capacitive coupling with the human body as well as nearby objects. Future work should explore additional ways to address noises that can be introduced. Additionally, instead of using 3d printed parts, a flexible structure design could be interesting to explore as well because it can be thinner, lighter, and attached much closer to the surface of a container which might improve the sensitivity of the sensor.

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