Detecting Counterfeit Liquid Food Products in a Sealed Bottle Using a Smartphone Camera

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ABSTRACT

We are witnessing a surge in the reported cases of counterfeit liquid products in the market including olive oil, honey, and alcohol. Counterfeiters often adulterate the liquid products by replacing a large portion of the authentic content with cheaper substitutes (e.g., mixing vodka with cheaper alcohol or potentially toxic methanol). Exacerbating the problem, the counterfeits are packaged and sealed to factory standards, rendering it extremely difficult for an average consumer to identify them. While solutions exist, they are often impractical for the general public as they require specialized and costly equipment. To overcome these limitations, we propose LiquidHash, a novel counterfeit liquid food product detection system. LiquidHash is a practical solution that only requires the use of a commodity smartphone to detect adulterated liquid products without opening the bottles. LiquidHash works by detecting and tracking the shape and movement of air bubbles that form inside the bottles. We implement LiquidHash and evaluate its feasibility with real-world experiments under varying conditions with a total of more than 500 minutes of video recording and observe an overall detection accuracy of up to 95%.

CCS CONCEPTS

- Human-centered computing → Smartphones; Mobile phones;  
- Computing methodologies → Computer vision.

KEYWORDS

Counterfeit, Liquid Testing, Smartphone Camera

ACM Reference Format:


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1 INTRODUCTION

The cases of counterfeit liquid food products are increasing and it is now a major societal concern. The World Health Organization (WHO) estimates that 25% of the alcohol consumed worldwide is counterfeit [57]. There are also many reports of counterfeit liquid food products involving olive oil [7, 12, 14, 30, 46, 52, 60, 72], honey [2, 20, 62, 69], and alcohol [10, 36, 54, 65–67, 78].

The surge in these cases can be attributed to the counterfeiters’ economic benefits as they adulterate, or replace a large amount of authentic liquid contents with cheaper alternatives (e.g., replacing a significant portion of authentic vodka with cheaper alcohol or even potentially toxic methanol). Such adulteration can often cause detrimental health problems leading to fatalities [31, 36, 46, 57, 65, 66]. In addition, the liquid product manufacturers also suffer from significant monetary loss adding up to a total loss of $40 billion globally every year [11, 61, 63].
It is extremely difficult, however, for an average consumer to detect the adulterated liquid contents because the counterfeits are often packaged in authentic bottles which are easily accessible [78], and are sealed to factory standards [19, 73]. Hence, the general public is left vulnerable and relies on the authorities to test the liquid authenticity [57].

There are state-of-the-art solutions that attempt to analyze the liquid contents without opening the bottles. These include Near-Field (NIR) and Raman spectroscopy that utilize absorption of electromagnetic radiation to obtain chemical information of the liquid contents [15, 43, 48]. However, these solutions are not available to the general public as they use specialized and costly equipment. There are also recent research techniques that utilize wireless signals to identify the liquid types. Specifically, they leverage the coupling effect between the liquid content and the radio-frequency (RF) signals to measure electric permittivity [13, 26, 74, 79]. However, these solutions also require specialized equipment and setup. The wireless measurement is also susceptible to environmental effects such as multi-path interference.

To overcome the limitations of the state-of-the-art solutions, we ask the following question – can we achieve a practical solution that only leverages an average consumer’s commodity smartphone to detect adulterated liquid products without opening the bottles? As an answer to this question, we propose LiquidHash, a liquid counterfeit detection system that utilizes a commodity smartphone camera to capture information of the liquid contents sealed inside the bottle. The core idea of LiquidHash is that we can infer liquid properties from the air bubble shapes and movements inside the bottle. This is possible because liquid properties, in particular, density, viscosity, and surface tension influence the radius, aspect ratio, and terminal velocity of bubbles as they rise to the top (See § 2.1). Hence, by quantifying these features from the observed bubbles, we are able to differentiate among different liquid products.

Figure 1 illustrates the process of using LiquidHash to detect adulteration in a liquid product. The user rotates the sealed bottle upside down while recording the bubble shape and movement in slow-motion. LiquidHash then analyzes the recording and processes the images to determine if the liquid product is authentic or adulterated. As an illustration, consider the following use case scenario. Alice enters a shop and wishes to purchase a bottle of olive oil. As a precaution, she wants to check the authenticity of the bottle of olive oil before purchasing. To do this, Alice uses the LiquidHash app installed on her phone to capture the images of the bubble shape and movement in the olive oil after she rotates the bottle. The “signature” extracted from these images are then compared against the “signature” provided by the manufacturer. This process is analogous to a hash checksum verification (hence the name LiquidHash).

Designing LiquidHash, however, comes with the following challenges. First, as the camera placement with respect to the bottles can vary significantly across different rotations, it is difficult to compare across different image captures consistently. To overcome this challenge, we utilize computer vision techniques to normalize the images to be robust against differences in camera distance and angle to the bottle.

Second, LiquidHash requires fine-grained segmentation and tracking of the individual bubbles detected. This is challenging because the shape of a bubble can change as it moves and the outer boundaries may not always be clearly defined. As traditional image processing techniques are insufficient for our purpose, we utilize a fully convolutional neural network (FCN) for bubble segmentation.

Third, based on the extracted features such as radius, aspect ratio, and terminal velocity, we need to infer the authenticity of the liquid. LiquidHash utilizes machine learning classification to train and predict the authenticity of the liquid contents by matching these extracted features to the features of authentic liquids that have been already learned.

We implement LiquidHash and evaluate its feasibility by conducting real-world experiments under varying conditions utilizing three authentic liquid products – i.e., extra virgin olive oil, pure raw honey, and vodka – and eight different adulterants. We invite multiple participants to rotate the bottles containing different liquid contents while recording them with a smartphone camera, and collect more than 500 minutes of recording. Our evaluations show that LiquidHash yields detection accuracy of up to 95%. In summary, we make the following contributions:

- We propose, LiquidHash, a counterfeit liquid detection system that utilizes commodity smartphone camera to detect adulterated liquid contents without opening a sealed bottle.
- We present the design and implementation of LiquidHash that overcomes the challenges of extracting air bubble features in a noisy environment with commodity smartphone camera and utilizing these features to ultimately detect adulterated liquid contents using computer vision and machine learning techniques.
- We demonstrate through a set of comprehensive evaluation that LiquidHash is able to yield high accuracy in real-world settings across different liquid products and adulterants.

## 2 BACKGROUND AND FEASIBILITY STUDY

We first present the relevant background information on the physics model of rising air bubbles and capture of slow-motion video using smartphone cameras. We then conduct a preliminary study to demonstrate LiquidHash’s feasibility.

### 2.1 Physics Model of Rising Air Bubbles

Different liquid contents exhibit unique physical properties such as density, viscosity and surface tension [37, 49, 55, 71, 77]. However, these properties cannot be directly measured from sealed bottles. Hence, LiquidHash utilizes the observations of the air bubbles arising inside the bottles to determine the authenticity of the liquid food products. Specifically, we find that the characteristics of the bubbles, namely size and shape (i.e., radius and aspect ratio) and rising speed (i.e., terminal velocity), are correlated with the liquid physical properties [4, 8, 25, 34, 35, 39, 44, 68, 80]. Stokes’ Law [6] and Young-Laplace Law [42, 82] describes the relationship between the characteristics of the bubbles and liquid properties. Specifically, for a spherical bubble, Stokes’ Law describes the relation of terminal velocity \( V \) on the liquid density \( \rho \), viscosity \( \mu \) and bubble radius \( R \) as: \[
V = \frac{2}{9} \frac{\rho g R^2 \mu}{\rho - \rho_l}.
\]
Furthermore, Young-Laplace Law describes the relation of the pressure difference \( \Delta P \) between the bubble and the liquid, the radius \( R \) of a spherical bubble and...
We conduct a feasibility study to test our hypothesis that we can utilize bubble’s characteristics (i.e., radius, aspect ratio, and terminal velocity) to distinguish between different types of liquid. Specifically, we prepare one authentic pure olive oil ($O_{\text{auth}}$) and two adulterated olive oil: $O_{\text{fake}_1}$ (70% $O_{\text{auth}}$ + 30% sunflower oil) and $O_{\text{fake}_2}$ (50% $O_{\text{auth}}$ + 50% sunflower oil). We place each of them in separate bottles as depicted in Figure 2(a). To generate consistent bubbles without adding other sources of noise, we then insert a thin tube into each bottle, and attach a syringe to the other end of the tube. We generate bubbles by gently pressing the syringe, and capture bubbles using a smartphone camera placed on a tripod at a fixed distance from the bottle.

The tube. We generate bubbles by gently pressing the syringe, and capture bubbles using a smartphone camera placed on a tripod at a fixed distance from the bottle.

Figure 2(b) depicts the measured average radius, aspect ratio, and terminal velocity. The measured radius of $O_{\text{fake}_1}$ is higher than that of $O_{\text{fake}_2}$, and $O_{\text{fake}_2}$, despite significant noise in measuring $O_{\text{fake}_2}$. There is a general trend of decreasing aspect ratio as the concentration of sunflower oil increases from 0% to 50%. These observations on radius and aspect ratio correlate with Young-Laplace Law equation because olive oil has a higher surface tension than sunflower oil [55]. Furthermore, the terminal velocity increases as the concentration of sunflower oil increases from 0% to 50%. This observation correlates with Stokes’ Law equation as sunflower oil has a higher ratio of density over viscosity ($\rho_{\text{sunflower}} > \rho_{\text{oive}}$) [55].

From this preliminary study, we demonstrate the feasibility of utilizing bubbles to distinguish different liquid contents.

3 SYSTEM MODEL

We introduce our system model, describing the goal, requirements and assumptions of LiquidHash. The main goal of LiquidHash is to verify the authenticity of a liquid food product in a sealed bottle leveraging observations of air bubbles. We design LiquidHash to fulfill the following requirements: (1) be accurate in classifying...
authentic and fake liquid food products (accuracy), (2) work without opening bottles (usability), (3) work by leveraging commodity devices and real-world sealed bottles (deployability).

To achieve the aforementioned goal while satisfying the requirements, we make the following assumptions: (1) counterfeiters strive for profit gain by replacing a large amount (i.e., at least 30%) of authentic liquid content with cheap alternatives; (2) authentic and adulterated liquids produced by counterfeiters are distinguishable by their properties, namely density, viscosity, and surface tension; and (3) bubbles and liquid contents are semi- or fully transparent to allow observations of the bubbles.

4 SYSTEM DESIGN

We present LiquidHash's design and implementation details.

4.1 System Overview

LiquidHash's goal is to verify a liquid food product in a sealed bottle by leveraging characteristics of rising air bubbles, namely radius, aspect ratio, and terminal velocity utilizing computer vision and supervised learning techniques. LiquidHash is divided into two phases - Bootstrapping and Verification Phases. Bootstrapping Phase occurs offline, where the manufacturers train their liquid content models by collecting a large set of video data, including both authentic as well as adulterated liquid contents, along with ground truth labels. LiquidHash then utilizes the trained model in its Verification Phase, which occurs online as the consumers utilize LiquidHash app on their phone to record videos of unknown liquid food products to verify the authenticity.

Figure 3 illustrates LiquidHash's design overview. LiquidHash takes the recorded video as input to the Pre-processing module (§ 4.2), which selects and processes frames that contain useful bubble information. Next, the processed frames are input to the Bubble Feature Extraction module (§ 4.3), which segments and tracks the bubbles to extract features. The Prediction module (§ 4.4) takes the features as input to train a machine learning model in the Bootstrapping Phase, and predict the authenticity of an unverified liquid food product in the Verification Phase. We now present the details of LiquidHash's design.

4.2 Pre-processing

The goal of this module is to process the frames such that (1) the bubbles are comparable despite the differences in camera distance and angle; and (2) it reduces redundant information from input video. It takes as input the video recordings and outputs the processed frames and a reference ratio (i.e., a ratio inversely proportional to the distance to the camera), as depicted in Figure 4. We first select the frames that contain bubble information in the Frame Selection stage (§ 4.2.1). We then ensure the viewing angle from the camera to the bottle is correct in the Pre-screening Test stage (§ 4.2.2). If ensured, we proceed to the following stages in parallel. In the Frame Processing stage (§ 4.2.3), we process the selected frames to output the processed frames. Simultaneously, in the Distance Estimation stage (§ 4.2.4), we extract the distance to the camera as a reference ratio.

4.2.1 Frame Selection. In this stage, LiquidHash aims to select frames that contain bubble information. It takes raw input frames and outputs bubbles' moving direction (i.e., bubble vector), positions of pre-determined markers (i.e., bottle markers) and steady frames. We define steady frames as frames in which the bottle is inverted and the impact of bottle rotation to the bubbles is minimal. We select steady frames by using an object detector, a computer vision technique, to recognize pre-determined markers on bottle and bubbles' moving direction. We train the Faster-RCNN [50] object detector with annotated bottle and bubble images. Faster-RCNN is a real-time object detection neural network. Using transfer learning, we augment a pre-trained Faster-RCNN network with around 200 annotated images of bottles and bubbles to implement our object detector. LiquidHash samples one in every 60 frames of input video recorded at 240fps, and process sampled frames to obtain (1) bubble vector, (2) bottle markers and (3) steady frames.

1 Bubble vector. We use the object detector to obtain a set of bubble positions and compute the best-fit line of the bubble positions to represent bubble’s moving direction, \( l_{\text{bubbles}} \). We compute the average of square distances, \( d \), between each bubble position and \( l_{\text{bubbles}} \).

2 Bottle markers. We use the object detector to obtain a set of marker positions, \( P_{\text{markers}} \). As a proof-of-concept, we utilize a black square on the bottle, and define the four vertices as markers. In practice, LiquidHash can also be extended to utilize different logo and the product description texts on commodity liquid bottles.

3 Steady frames. For each sampled frame, we use (1) bubble vector to check bubbles’ moving direction and (2) bottle markers to check bottle orientation to select steady frames. First, we ensure that bubbles move in a straight line which indicates that bubbles are minimally affected by liquid perturbation. When the liquid is recently perturbed by bottle rotation, bubbles move erratically in curved trajectories. Such bubbles are undesirable as they exhibit noisy characteristics. As the liquid sets, bubbles tend to move in a straight line. We select the frame, if \( d < d_0 \), where \( d_0 \) is an empirically set threshold, to ensure trajectories of bubbles are straight. Second, a subset of bottle markers is always positioned in the lower half of the frame, or below other markers when the bottle is inverted. We compare the positions of these markers to determine if the bottle is inverted and discard frames where the bottle is not. We output bottle markers (\( P_{\text{markers}} \)), bubble vector (\( l_{\text{bubbles}} \)) and steady frames to the next stage.

4.2.2 Pre-screening Test. Subsequently, LiquidHash validates each trial to ensure camera angle is correct. It takes as input bottle markers (\( P_{\text{markers}} \)), bubble vector (\( l_{\text{bubbles}} \)) and steady frames from the Frame Selection stage, and outputs them to the next stage if a trial is valid. Recall from § 2.2 that the viewing angle from the camera to the bottle may affect the sizes and shapes of the captured bubbles due to refraction through the bottle. LiquidHash rejects a trial when a subset of markers is occluded and cannot be detected by the object detector. We also utilize the pixel distances between markers to further examine the viewing angle. In addition, we require the number of selected frames to be large to contain sufficient bubble information. LiquidHash requires the user to retry if the trial fails the pre-screening test.

4.2.3 Frame Processing. LiquidHash then removes redundant information. It takes as input bottle markers (\( P_{\text{markers}} \)), bubble vector (\( l_{\text{bubbles}} \)) and steady frames from the Pre-screening Test stage, and
Figure 3: Figure depicts the flowchart of LiquidHash's design. During the Bootstrapping Phase, liquid manufacturers train models with video data from authentic products and different types of adulteration, and save the model in the cloud. During the Verification Phase, the user records a slow-motion video of rotating the bottle. LiquidHash analyzes the recorded video by detecting the bottle and rising air bubbles. LiquidHash processes the bubbles to determine if the liquid food product is authentic or adulterated.

Figure 4: Figure depicts LiquidHash's Pre-processing (§ 4.2) and Bubble Feature Extraction (§ 4.3) module pipelines. Pre-processing module processes raw input video frames, and extracts a reference ratio containing distance information. Bubble Feature Extraction module extracts features from processed frames, and normalizes them using the reference ratio.

outputs the processed frames. We locate a small region in steady frames to contain only bubble information, by adding offsets to $P_{markers}$. In this region, bubbles are mostly visible to the camera because regions between bottle labels generally do not occlude the liquid content. We crop the region and rotate it to align $b_{bubbles}$ and the vertical axis of the image. We output the processed frames to the Bubble Feature Extraction module.

4.2.4 Distance Estimation. LiquidHash mitigates the impact of the distance of the camera to the bottle. It takes as input bubble markers ($P_{markers}$) from Pre-screening Test stage, and outputs a reference ratio, $R_{ref}$, the ratio of an object’s size measured in the real-world to that in the image. We compute $R_{ref}$ as the ratio of a real-world distance between markers, $L_{actual}$, to detected pixel distance, $L_{pixel}$, by $R_{ref} = L_{pixel}/L_{actual}$. This ratio is inversely proportional to the distance. We output $R_{ref}$ to Bubble Feature Extraction module.

4.3 Bubble Feature Extraction

Utilizing the processed frames and the reference ratio ($R_{ref}$), this module extracts features corresponding to the bubble characteristics, including radius, aspect ratio, and terminal velocity, in addition to $V-R$ ratio (See § 2.1), to perform machine learning training and prediction through the following stages as depicted in Figure 4. During the Bubble Segmentation stage (§ 4.3.1), we utilize the instance segmentation technique to accurately segment bubbles in each frame, and extracts each bubble’s radius and aspect ratio. During the Bubble Tracking stage (§ 4.3.2), we devise a tracking algorithm to
obtain bubbles’ unique trajectories across frames to obtain bubble’s terminal velocity and reduce measurement errors in segmentation. We then take average values of radius, aspect ratio and terminal velocity as bubble features. In addition, we also extract statistical features computed based on the bubble features, namely, the standard deviation, harmonic mean, minimum, and maximum, to reveal the impact of rotation to bubble characteristics.

4.3.1 Bubble Segmentation. In this stage, LiquidHash segments pixels containing the bubbles from the background in each frame, and estimates the radius, and aspect ratio of the bubbles by proceeding with the following steps.

- **Enhancing frames.** We first enhance the images to increase the contrast between bubble and background pixels to aid the segmentation. For each pixel with value $c_{\text{pixel}}$, we scale the value using $\tilde{c}_{\text{pixel}} = \alpha \cdot c_{\text{pixel}} - \beta$, where $\alpha$ and $\beta$ are empirically set values of 2 and 200, respectively.

- **Segmenting bubbles.** We segment the bubble from the background pixels using U-Net, a neural network frequently used in biomedical image segmentation [53]. We utilize U-Net for its performance even with relatively small training dataset. We train the U-Net bubble segmentation with only 200 annotated bubble images.

- **Fitting an ellipse.** To mitigate segmentation errors due to intermittently bright pixels within the bubble, we approximate an ellipse that spans the bubble region. We choose an ellipse because only spherical and ellipsoidal bubbles obey the aforementioned physics model (See § 4.2.4) and their cross-sections are in the form of ellipse.

- **Extracting bubble information.** Based on the correctly segmented bubble pixels, we extract bubble radius, aspect ratio and position in the following steps. First, we estimate the bubble radius using the *oval equivalent radius* [70] that captures the pressure and resistance experienced by ellipse shaped objects in the liquid. Specifically, we use width ($w$) and height ($h$) of the fitted ellipse normalized by the *reference ratio* ($R_{\text{ref}}$, See § 4.2.4), respectively, to compute the radius. Second, we approximate the bubble aspect ratio ($E$) to capture the overall shape of the bubble [44]. We compute $E = \min(w, h)/\max(w, h)$. $E$ is always between 0 and 1, and decreases as the circularity of bubble decreases (i.e., bubble becomes flatter). Third, we calculate bubble position using the *topmost* pixel position of the segmented pixels because the shape change at the top is almost negligible whereas the tail of the bubble experiences significant shape changes [44]. Finally, we output bubble radius, aspect ratio and position of all bubbles in each frame.

4.3.2 Bubble Tracking. In this stage, we aim to track bubbles across frames to identify unique bubble trajectories, using bubble radius, aspect ratio and position from the previous stage. This is to obtain bubble’s terminal velocity and reduce measurement errors in radius and aspect ratio arising from bubble segmentation. However, it is challenging as bubbles may overlap with each other and may not be visible or detected in some frames. To overcome this challenge, we devise a tracking algorithm based on the observation that the same bubble appearing in consecutive frames has a small travelled distance and small changes in the radius and aspect ratio. The tracking algorithm consists of two parts, namely (1) tracking a single bubble from a given starting position, and (2) tracking all unique bubbles.

(1) **Tracking a single bubble.** The tracking algorithm takes as input an initial bubble position and searches for similar bubbles in subsequent frames to output a bubble trajectory. For an initial bubble position $P_t$ at frame $t$, we search the bubbles in the next $k$ frames such that the distance between two bubbles are sufficiently small, i.e., $||P_{t+k} - P_t|| < dk$ where $d$ is an empirically set threshold representing the maximal distance per frame. We find the smallest $k$ and continue searching from bubble position $P_{t+k}$.

(2) **Tracking all unique bubbles.** We identify all unique bubble trajectories by repeating part (1) on unique starting bubbles. If a bubble is already in the trajectory of another bubble, it is no longer a unique bubble. Thus, we use a set, $S_{\text{visited}}$, to keep track of all previously tracked bubbles to avoid repetitive tracking.

4.4 Prediction

In this module, LiquidHash performs training and prediction using features extracted from the Bubble Feature Extraction module. LiquidHash takes video data of authentic liquid food products and target types of adulteration, with their ground truth labels (i.e., authentic and fake), to train a machine learning classifier in the Bootstrapping Phase. In the Verification Phase, LiquidHash tests newly collected video data to predict the authenticity of an unverified liquid. However, it is challenging to rely on a traditional classifier due to uneven number and weightage of bubble features (i.e., radius, aspect ratio, terminal velocity and $V$-$R$ ratio) extracted from each bubble and statistical features extracted by combining information across all bubbles. To overcome this challenge, we ensemble two classical machine learning classifiers, $C_{\text{bubble}}$ and $C_{\text{stats}}$, for training and prediction. For prediction, each classifier predicts the a probability (i.e., $P_{\text{bubble}}$ and $P_{\text{stats}}$) for each class (i.e., authentic and fake). We add the probabilities to obtain the final probability, $P_{\text{final}}$, and make a decision by taking the class label of the highest probability (i.e., output is authentic when $P_{\text{final}}(\text{authentic}) > P_{\text{final}}(\text{fake})$, and fake otherwise). In our implementation, we use Adaptive Boosting (AdaBoost) [17, 28], a statistical classification meta-algorithm, as our classifier. An AdaBoost classifier adjusts weights of incorrectly classified instances to focus on difficult cases where extracted features of different types of liquid are numerically similar to each other.
### Table 1: Table depicts the list of liquid food products and adulterants in our experiments.

<table>
<thead>
<tr>
<th>Use Case</th>
<th>Authentic Product</th>
<th>Adulterant</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Olive Oil</td>
<td>O_A Naturel Extra Virgin</td>
<td>O_F1 Knife Groundnut Oil</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>O_A Naturel Extra Virgin</td>
<td>O_F2 Golden Circle Sunflower Oil</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>O_A Naturel Extra Virgin</td>
<td>O_F3 OKI Premium Soybean Oil</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>O_A Naturel Extra Virgin</td>
<td>O_F4 Golden Circle Corn Oil</td>
<td>30</td>
</tr>
<tr>
<td>Honey</td>
<td>H_A Balparmak Pine</td>
<td>H_F1 Little Bee Golden Syrup</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>H_A Balparmak Pine</td>
<td>H_F2 Wescobe Australian Honey</td>
<td>30</td>
</tr>
<tr>
<td>Vodka</td>
<td>V_A Smimoff Red</td>
<td>V_F1 Chamsul Soju Fresh</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>V_A Smimoff Red</td>
<td>V_F2 Water</td>
<td>30</td>
</tr>
</tbody>
</table>

5.4 Enhancing Bubble Generation

Recall that LiquidHash relies on features extracted from bubble characteristics to determine the authenticity of liquid food products. To further improve LiquidHash’s usability and capability of differentiating authentic and adulterated liquid food products, we devise a bubble generation mechanism, as an accessory to a bottle cap, to assist users to generate a large number of consistent bubbles. Figure 5(a) depicts the design of our proposed bottle cap accessory (See § 6.1 for practical considerations). Specifically, the accessory has a small bubble aperture (i.e., an opening to allow air to flow out) to constrain the size of bubbles to a small range, and slow down the rate of bubble generation to ensure that most bubbles are generated after liquid stabilizes. When a bottle is inverted, the air is released slowly via the small bubble aperture in a steady stream of regularly shaped spherical and ellipsoidal bubbles. The proposed accessory helps LiquidHash to address two practical issues. First, large bubbles arise due to insufficient collision forces to break the air gap in the bottle. Large bubbles have non-spherical shapes (e.g., spherical-cap and irregular shapes) and significant shape changes during the rising process. LiquidHash discards these bubbles which do not obey the physics model (See § 2.1). Second, bubbles are generated before the liquid stabilizes, and are significantly affected by the liquid perturbation due to the bottle rotation. LiquidHash discards video frames containing these bubbles. Figure 5(b) illustrates examples of undesirable bubbles discarded by LiquidHash.

5 EVALUATION

We now present LiquidHash’s comprehensive evaluation.

5.1 Experiment Setup

Apparatus. Figure 6 illustrates our experimental procedures. We evaluate LiquidHash in three use cases, namely olive oil, honey and vodka, with authentic liquid food products and corresponding common off-the-shelf adulterants [2, 7, 10, 46, 60, 65, 69, 72]. In total, we have 11 instances of liquid content enumerated in Table 1. Note that the three chosen types of liquid are representative of a wide range of common liquid food products with viscosity in the range from less than one centipoise (i.e., vodka) [45] to 10,000 centipoises (i.e., honey) [51]. In addition to the three authentic liquid food products (i.e., O_A, H_A, V_A), we prepare four adulterated instances of olive oil (i.e., O_F1, O_F2, O_F3, O_F4), two adulterated instances of honey (i.e., H_F1, H_F2), and two adulterated instances of vodka (i.e., V_F1, V_F2), all packaged in their corresponding authentic bottles. We use the original packaging for these bottles without removing any brand covers, printed labels, and stickers. We prepare all adulterated liquid food products by replacing 30% of the authentic liquid content with adulterants, to represent majority of reported real-world incidents [46, 65, 69]. In this experiment setup, we demonstrate the sensitivity of LiquidHash to various amounts of differences in liquid properties. Despite the 30% adulterant added, the difference in liquid properties between authentic and adulterated liquid contents is in a wide range. For example, the difference in viscosity is in the granularity of millicentipoise, centipoise and several hundred centipoises in the use cases of vodka, olive oil, and honey, respectively. Furthermore, we also apply the proposed bottle cap accessory when conducting the experiments (See § 4.5).

Data Collection. We recruit five participants (two female and three male) to perform two tasks under a room lighting condition and a constant temperature of 25°C. We limit the participant numbers due to COVID-19 restrictions. We ask each participant to rotate each of the 11 liquid contents up to eight times. The total number of trials is over 400 in our experiment, exclusive of the controlled experiments. It is important to note that the rotation pattern is different across trials (even performed by the same participant). Participants record slow-motion videos of each rotation with a smartphone placed on a tripod with an additional light source (i.e., a table lamp) to illuminate the liquid content. Overall, we have a total of more than 500 minutes of slow-motion video recording. Figure 6 illustrates this experimental setup. To ensure that each collected video data passes LiquidHash’s pre-screening test (See § 4.2.2), each participant undergoes a five-minute training session. We conduct this study upon the approval of our institution’s Institutional Review Board.

Evaluation Metrics. We define the metrics to evaluate LiquidHash’s performance. We define A_t and A_f as correctly and falsely classified authentic liquid food products, respectively, and F_t and F_f as correctly and falsely classified fake liquid food products, respectively. Accuracy refers to the percentage of correctly classified instances in all tested authentic and fake liquid food products (i.e., Accuracy = (A_t + F_t) / (A_t + F_t + A_f + F_f)). Precision is the percentage of correctly classified fake instances in all tested fake liquid food products (i.e., Precision = F_f / (F_t + F_f)). Recall is the percentage of correctly classified authentic instances in all tested authentic liquid food products (i.e., Recall = A_t / (A_t + A_f)). When we evaluate LiquidHash’s performance on a specific class (i.e., authentic or fake), we use Accuracy_auth and Accuracy_fake to represent the percentage of correctly classified authentic and fake instances in the tested liquid food products of the same class, respectively (i.e., Accuracy_auth = A_t / (A_t + A_f) and Accuracy_fake = F_t / (F_t + F_f)).

5.2 Overall Performance

Data Preparation. To evaluate the overall performance of LiquidHash, we collect 125, 120 and 120 video clips for the olive oil, honey, and vodka along with their corresponding adulterants, all packaged in their corresponding authentic bottles. We utilize the data for cross validation across the five participants – i.e., training with four participants’ data and testing on the remaining participant’s data at a time.
§5.4 Differing Conditions

- **$\S5.4.1$ Adulterant Concentration**
- **$\S5.4.2$ Bottle Shape**
- **$\S5.4.3$ Distance**
- **$\S5.4.4$ Bottle Cap**
- **$\S5.4.5$ Frame Rate**

Figure 6: Figure depicts the setup of our experiments. We evaluate the accuracy of LiquidHash across different liquids and adulterants when used by different participants. We also vary experimental and environmental conditions to comprehensively evaluate LiquidHash.

Figure 7: Figure depicts the accuracy of LiquidHash in three use cases, namely olive oil, honey, and vodka, compared to the accuracy of No Assistance method.

Figure 8: Figure depicts the accuracy, precision and recall of LiquidHash in three use cases, namely olive oil, honey, and vodka.

Figure 9: Figure depicts the accuracy breakdown in different types of authentic and adulterated liquids.

**Baseline.** We resort to No Assistance method as our baseline by simply asking the participants to identify authentic liquid products without any assistance, resembling consumers point-of-view in the real-world – i.e., they interact with the liquid food products freely without opening the bottles. We allow participants to use their smartphones to obtain additional information of the products, such as referencing online images to compare the appearances and using the flashlight to compare the liquid colors.

**Results.** We illustrate the overall results in Figure 7, where we observe that LiquidHash achieves an accuracy of 93.9%, 95.0% and 86.0% for the use cases of olive oil, honey and vodka, respectively, significantly outperforming the No Assistance method by 33.9%, 17.2%, and 30.4%, respectively. On the contrary, the No Assistance method only yields an accuracy of 60.0%, 77.8% and 58.3%, respectively. On average, 60%, 40% and 70% of fake olive oil, fake honey and fake vodka, respectively, are misclassified as authentic while only 20% of authentic vodka is misclassified as fake and none of authentic olive oil and honey is misclassified. These results indicate that participants are more biased toward authentic bottles (i.e., classifying as authentic when they are unsure), leading to higher false-positive rates (i.e., fake samples misclassified as authentic). Furthermore, as we simply mix authentic liquids and adulterants without adding any colorant, visible difference in the color of the adulterated liquid is unavoidable, especially for honey adulterated with syrup (i.e., $H_A + H_F$) which all participants can observe the color difference. This explains the higher accuracy of the No Assistance method than that of a random guess (i.e., 50%) in all use cases.
Detecting Counterfeit Liquid Food Products in a Sealed Bottle Using a Smartphone Camera MobiSys ‘22, June 25–July 1, 2022, Portland, OR, USA

5.3 Performance of System Modules

We evaluate the internal modules of LiquidHash to compare between alternative designs.

5.3.1 Deep Learning Models for Bubble Segmentation. Recall that we utilize U-Net for bubble segmentation in § 4.3.1. We now evaluate different deep learning models and compare the performance. Specifically, we evaluate the effect of the models on the measurement errors of bubble radius, aspect ratio and position in ten representative bubble images, compared to ground truth values from manual annotations. From Figure 10, we observe that U-Net has the lowest error rates compared to Mask-RCNN [29] and a hybrid approach (i.e., Faster-RCNN for object detection and U-Net for segmentation). Note that high error rates in the measurement of bubble characteristics are detrimental to LiquidHash’s performance, because the numerical difference in these characteristics may not be large enough between authentic and adulterated liquids, and large measurement errors can easily result in misclassifications.

5.3.2 Classifiers for Decision Making. Recall that we utilize Adaptive Boosting (AdaBoost) for prediction in § 4.4. We also evaluate other widely adopted classifiers including Random Forest (RF), Gaussian Naive Bayes (Gaussian NB), Support Vector Machine (SVM) and K-Nearest-Neighbours (KNN). Figure 11 demonstrates that AdaBoost outperforms other classical machine learning classifiers. This is attributed to the fact that AdaBoost is more likely to distinguish between numerical features than other classifiers as it adjusts weights of incorrectly classified instances to tackle boundary cases.

5.4 Impacts on Experimental Conditions

We now evaluate LiquidHash under varying experimental and environmental conditions. We conduct the experiments using olive oil and its adulterants, namely corn, soybean, sunflower and peanut oil as depicted in Table 1.

5.4.1 Varying Concentration of Adulterants. Adulterated liquid food products are made by replacing a percentage of authentic liquid content with a fake liquid. As the amount of the fake liquid added per unit volume increases (i.e., concentration of adulterant), the difference in liquid properties between the mixture and authentic liquid also increases. We evaluate LiquidHash’s performance against varying concentration of common adulterants of olive oil, namely corn, soybean, sunflower and peanut oil, from 10% to 50%, all packaged in the authentic olive oil bottles.

We note that the majority of reported real-world incidents witness adulteration of at least 30% concentration [46, 65, 69].
We prepare two types of liquid (i.e., $O$ and $A$) with and without our cap accessory. The height of the bottle increases, a bubble travels a longer distance after reaching its terminal velocity. Second, as the diameter decreases, the liquid turbulence propagates through the bubble in a larger number of frames. We propose two reasons to explain this trend.

The accuracy remains below 90% even if the concentration of peanut oil increases to 50%. We attribute this to the liquid properties. For example, the concentration of corn oil is above 20%. However, we also observe that LiquidHash has the lowest accuracy in detecting the adulteration with peanut oil. The accuracy remains below 90% even if the concentration of peanut oil increases to 50%. We attribute this to the liquid properties of peanut oil being relatively similar to those of olive oil, as explained previously in § 5.2.

5.4.2 Varying Bottle Height and Shape. Liquid food products have standard volumes (e.g., 350ml, 500ml, 750ml) but often packaged in bottles of various dimensions. To simulate this scenario, we evaluate LiquidHash’s performance in five 3D-printed bottles of different heights ($H$) and diameters ($D$) but a constant volume ($V$) of 500ml. We prepare two types of liquid (i.e., $O_A$ and $O_A + O_F$), and conduct ten trials per liquid per bottle. For each bottle, we perform cross validation using the leave-one-out approach (i.e., train on nine trials and test on the remaining trial). Figure 13 illustrates the accuracy to classify authentic and fake olive oil products. Figure 14 illustrates the accuracy to classify authentic olive oil and adulteration, respectively. With the original cap, LiquidHash is capable of achieving an accuracy of 81.3%, a precision of 74.3% and a recall of 95.0%. However, this is still much lower than the accuracy using the modified cap with the accessory proposed in § 4.5. The original cap has an inner tube with a diameter of approximately 50mm, which is significantly larger than the diameter of 2mm in LiquidHash’s design. This causes the number of valid bubbles extracted per trial to be extremely small (i.e., only one to two bubbles per trial), and the velocities of bubbles are significantly affected by the turbulence in the liquid as the bubbles are most likely to rise in curved trajectories.

5.4.3 Varying Bottle Caps. Recall from § 4.5 that the physical design of bottle caps affects bubble generation, and regularly shaped spherical and ellipsoidal bubbles are desirable to LiquidHash. To demonstrate the practicality of LiquidHash, we evaluate the performance with the original olive oil bottle cap. Figure 14 illustrates the accuracy to classify authentic olive oil and adulteration, respectively. With the original cap, LiquidHash is capable of achieving an accuracy of 81.3%, a precision of 74.3% and a recall of 95.0%. However, this is still much lower than the accuracy using the modified cap with the accessory proposed in § 4.5. The original cap has an inner tube with a diameter of approximately 50mm, which is significantly larger than the diameter of 2mm in LiquidHash’s design. This causes the number of valid bubbles extracted per trial to be extremely small (i.e., only one to two bubbles per trial), and the velocities of bubbles are significantly affected by the turbulence in the liquid as the bubbles are most likely to rise in curved trajectories.

5.4.4 Varying Camera-to-Bottle Distance. We evaluate LiquidHash against changing the distance of the bottle to the camera. The camera-to-bottle distance affects the quality of bubbles captured because as distance increases, the number of pixels per bubble decreases proportionally. Figure 15 illustrates the effect of distance on the accuracy to classify authentic and fake olive oil products. LiquidHash achieves the highest accuracy within a distance of 20cm, but the accuracy drops below 80% when the distance is above 30cm. We attribute this performance degradation to the significant reduction in the number of pixels of both the bottle and bubbles. Specifically, as the distance increases from 20cm to 30cm, the measured width of a bottle and a bubble decreases from around 300 pixels and 25 pixels to around 200 pixels and 16 pixels, respectively. A small number of pixels do not contain sufficient image details, leading to errors in the marker positions (See § 4.2.4) and bubble radius and aspect ratio (See § 4.3.1). It is important to note that when the distance is
We present discussions on work when frame rate is below 240fps in this case. On the contrary, video frame rates.

**5.4.5 Varying Video Recording Frame Rate.** We evaluate LiquidHash against different video frame rates. The video frame rate of the smartphone camera affects the capability of capturing bubble trajectories with sufficient information. This experiment simulates recording the bubbles in different smartphones with standard frame rates at 240fps, 120fps, 60fps and 30fps [1, 64] while maintaining the resolution at 1080p. Most commodity smartphones support the frame rate of 240fps, but for some low-end smartphones, such as Xiaomi Redmi Note 10S, Samsung Galaxy A12 and Vivo Y20s [22–24], only slow-motion recording of 120fps and normal video recording of 30fps and 60fps are supported. Figure 16 illustrates the effect of decreasing frame rate on the accuracy to classify both authentic and fake olive oil products. We observe a general trend of decreasing accuracy as the frame rate decreases. We attribute the performance degradation to the reduction in number of frames available to capture a bubble, hence introducing noise to extracted features (See § 4.3), and making the distinction between different liquids unclear. It is important to note that a high frame rate is required to obtain sufficient number of frames per bubble in the use case of vodka, where bubbles move extremely fast. LiquidHash does not work when frame rate is below 240fps in this case. On the contrary, LiquidHash achieves a high accuracy when the frame rate is only 30fps in the use case of honey.

### 6 DISCUSSION

We present discussions on LiquidHash’s deployment considerations and its limitations.

#### 6.1 Deployment Considerations

**Bottle cap accessory.** Recall from § 4.5 that we design a bottle cap accessory to further improve the detection pipeline. We envision that this cap accessory can be attached to the original bottle cap with no modification needed to the original packaging, and can be peeled off upon opening of the bottle. To enable this, we are inspired by commodity bottle cap and lid designs. For example, many olive oil bottles ship with tube-like cap (depicted in Figure 5(b)) [3] to slow down the pouring process. Similarly, we are also inspired by the commodity peel-off lids, which is an additional layer in between the liquid content and the bottle cap [9, 47, 59]. Furthermore, we envision that more manufacturers may adopt the bottle cap accessory as there are economic benefits for manufacturers to be compliant with LiquidHash, which ensures liquid authenticity and may enhance consumers’ trust in the products.

**Extending LiquidHash to other applications.** While we propose LiquidHash as an aid for the average consumers for verifying authenticity prior to purchasing liquid food products in offline stores, we envision other potential use cases. For example, different stakeholders within a product supply chain – from production, distributor, retailer, and logistics – may utilize LiquidHash as a proof to verify the integrity of the product.

**Complementing other solutions.** Many existing works propose to measure liquid properties using smartphone in-built sensors [32, 83], but requires opening the containers. LiquidHash could rely on these techniques to identify untrained types of adulteration after opening the bottle.

#### 6.2 Limitations and Future Work

**Experiment setup.** Despite adopting background lighting in our experiments, it is not always necessary as LiquidHash only requires additional lighting in the use cases of honey, which is a dark-colored liquid. Furthermore, lighting conditions may affect the performance of bubble detection and segmentation. However, with more training bubble images under various lighting conditions, LiquidHash would be robust against different lighting conditions. Furthermore, we evaluate LiquidHash using a tripod as a proof-of-concept. However, we note that the tripod may not be required when the container has labels acting as reference markers. The relative positions of bubbles with respect to the bottle can be obtained. This can handle the case when the camera is moving. In addition, there are many other methods to rest the camera in a stationary position (e.g., resting the smartphone on a shelf).

**Bottle and liquid content transparency.** LiquidHash requires semi- or fully transparent bottles to allow observations of the bubbles. While many liquid food products satisfy this requirement, there are many products that come in opaque bottles. From our on-going explorations with many non-transparent liquid contents, we find that additional lighting (e.g., flashlight and lamps) significantly help to enable LiquidHash to observe bubbles. Furthermore, we envision adopting different light sources to help in observing the bubbles that may transmit through dark or opaque materials (e.g., utilizing light sources outside the visible light spectrum, such as infrared).

**Powerful counterfeiters.** Recall that LiquidHash distinguishes the adulterants based on the differences due to liquid properties. However, powerful counterfeiters may carefully mix various types of adulterants to try and match the properties with authentic liquid product. While this is possible in theory, it is an extremely difficult, time-consuming, and expensive process. On the contrary, many reported real-world incidents are attributed to economic benefits of the counterfeiters, who strive to gain profit by mixing cheap adulterants.

**Measurement of liquid properties.** Recall that LiquidHash utilizes machine learning techniques to obtain classification results. To further extend LiquidHash, we envision building and training an improved machine learning model to increase the detection accuracy on a smaller amount of adulteration (e.g., less than 30%), estimate the liquid properties (i.e., viscosity, density, and surface tension), and compensate on temperatures, by providing the ground truth values of the liquid properties measured by laboratory equipment such as a rheometer.
Impact of LiquidHash. LiquidHash demonstrates the feasibility to detect differences in liquid contents by simple human interaction to induce a physics phenomenon, and video analysis to extract useful information. Through LiquidHash, we aim to inspire the research community that physical interactions can augment computer vision and mobile sensing to uncover hidden information to solve many important and practical problems, especially with the increased processing power of mobile devices. We hope that this paper would encourage the mobile computing community to explore other directions of research that leverage physical interactions to augment sensing in mobile devices.

7 RELATED WORK

We now present related work on liquid testing and how LiquidHash could complement these solutions. Laboratory Setting-based Solutions. Conventional laboratory-based techniques, such as viscometer, rheometer, refractometer and chromatography, test physical properties from liquid samples which require opening of bottles and costly equipment [40, 41, 56]. Recent works on Near-Field (NIR) and Raman spectroscopy test liquid properties without opening bottles by utilizing absorption of electromagnetic radiation to obtain chemical information of the liquid contents [15, 43, 48]. However, these solutions are not available to the general public as they also require specialized and costly equipment. On the contrary, LiquidHash is a pervasive and low-cost method that the general public can utilize to perform early testing on liquid food products, and send the detected counterfeit products to the authorities for more comprehensive testing in the laboratory setting.

Ubiquitous Sensing-based Solutions. Recent research studies techniques that utilize wireless signals to identify the liquid types utilizing interactions between liquid content and radio waves [13, 16, 26, 27, 74, 75, 79, 81, 84]. However, these solutions also require specialized equipment and setup such as large antennas which are not portable. The wireless measurement is also susceptible to environmental effect such as multi-path interference. For example, LiquidID [13] tries to identify liquids using the liquid’s electric permittivity, which would not be hindered by dark bottles or liquids as long as the container is not metallic. However, it requires a specific container and has not shown in-bottle identification abilities. RF-EATS [26] attaches a radio-frequency identification (RFID) tag to the bottle and utilizes the coupling effect between the liquid content and radio-frequency (RF) signals to detect counterfeit liquid food products. However, it requires stable placement of the RFID reader and small differences between how the RFID tag is placed could affect its accuracy. It could be a viable solution to complement LiquidHash in the cases of opaque bottles or dark-colored liquids. Another body of research utilizes commodity devices (e.g., smartphones) to test liquid properties such as surface tension and viscosity [21, 32, 33, 76, 83]. However, these solutions require opening of bottles to transfer liquid content to controlled settings, rendering the solutions impractical in our setting. For example, CapCam [83] uses a smartphone camera to estimate liquid surface tension by capturing the capillary waves induced by smartphone vibrations. However, it requires transferring the liquid content to a paper or plastic container for desirable capillary waves. Similarly, Vi-Liquid [32] utilizes a smartphone vibro-motor and accelerometer to induce and receive vibrations from liquids, to estimate liquid viscosity. It requires transferring the liquid content to a specific container to transmit strong vibration signals and optimize smartphone placement. On the contrary, as LiquidHash does not require the opening of bottles and transferring of liquid contents, it is more practical for consumers to verify liquid authenticity prior to purchasing liquid food products in offline stores and for different stakeholders within a product supply chain to verify the integrity of the product. After purchasing, consumers could then rely on CapCam and Vi-Liquid to identify untrained types of adulteration after opening the bottle.

8 CONCLUSION

We present LiquidHash, a novel counterfeit liquid food product detection system that uses a commodity smartphone camera to detect adulterated liquid products without opening the bottles. LiquidHash leverages the physical phenomenon that different liquid contents exhibit unique properties, which can be inferred by the shape and movement of the air bubbles forming inside the bottle. We evaluate the performance of LiquidHash with real-world experiments under varying conditions with a total of more than 500 minutes of video recording and observe an overall detection accuracy of up to 95%.

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