Hedgehog: Detecting Drink Spiking on Wearables

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ABSTRACT

People increasingly carry wearables and the capabilities of these devices have reached a point where it is increasingly possible to harness the devices to support everyday interactions. We contribute a new use of wearables by demonstrating how they can be used to safeguard against drink spiking, the deliberate act of adding substances to another person's drink. We design Hedgehog, a pervasive sensing approach that re-purposes the optical sensors in off-the-shelf wearables to identify spiked drinks by analysing differences in light reflectivity resulting from small particles inside the drink. We present a wearable prototype inspired by a smart ring design and conduct rigorous experiments that show the Hedgehog reaches up to 89.71% accuracy in detecting drinks that are tampered with. Our work demonstrates how pervasive sensing enables innovative applications and how smart wearables can be re-purposed to support personal safety.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing**.

KEYWORDS

Liquid Sensing, Light Sampling, Wearable, IoT, Smart Ring

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1 INTRODUCTION

Drink spiking, the deliberate act of adding substances to drinks, is a worrisome trend that is being fueled by easier access to substances. Drink spiking is generally perpetrated by someone with the intention to making a victim more vulnerable to assault. A study among student populations showed that almost 8% of all students have had their drink spiked at some point [16], highlighting how drink spiking is indeed a significant and a real threat to people. The public perception is that drink spiking is limited to slipping drugs or sedatives into alcoholic drinks. However, drink spiking can also target non-alcoholic drinks, such as water, soda, soft drinks, or juices. Drink spiking is a critical problem to overcome as it can cause victims severe danger, anxiety, and physical or mental harm [2, 15].

Detecting drink spiking is unfortunately difficult as the spiking typically happens in crowded social occasions where it is impossible to consistently keep a watchful eye on the drink container and its contents. Substances that are commonly used in drink spiking also are not directly visible, making it difficult to realize when the drink has been tampered with. To safeguard individuals against drink spiking, there is a need for solutions that can identify when the drinks have been tampered with. At the same time, these methods need to be unobtrusive to ensure they are acceptable in social contexts. Currently, no such solution exists, and the primary countermeasure has been to design guidelines and advice for raising awareness about the problem. For instance, requesting sealed products when buying them, keeping an eye on the drink, avoiding leaving drinks unattended and so forth. Unfortunately, these methods are ineffective in reducing the issue as people tend to underestimate the possibility of spiking. Indeed, spiking can occur in a short amount of time without the victim realizing it. It is also difficult to visually identify whether a drink has been spiked or not. While drug manufacturers are starting to take steps to reduce the possibility of spiking, e.g., by incorporating a colorant that reacts heavily with water, not all drugs can include colorants. Similarly, while there have been some technological solutions for identifying spiked drinks, e.g., by analysing samples of the drink contents, these are not feasible as a practical solution for everyday interactions as they lack portability and require specialized equipment. Thus, new solutions to overcome these limitations are needed.

We contribute Hedgehog as an innovative pervasive sensing solution for identifying drink spiking. Hedgehog re-purposes optical sensors on wearables, such as smart rings or smartwatches, to identify changes in light reflectance that are caused by small particles inside a drink. Hedgehog identifies drink spiking by first establishing a reference fingerprint of a drink and then monitoring changes in this reference fingerprint. Through rigorous benchmarks that consider different types of drinks and pill-sized doses of compounds being introduced into drinks, we demonstrate that Hedgehog can accurately and robustly identify drink spiking and achieve up to 89.71% accuracy in detecting drinks that have been tampered with. Our results demonstrate a novel use for wearables that can improve

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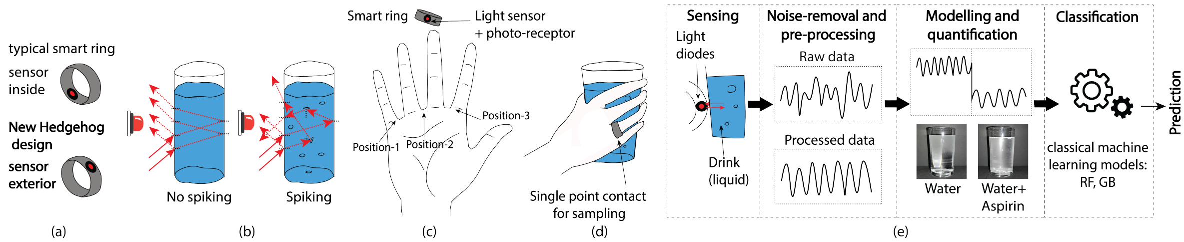


Figure 1: Characterization of drinks with light. (a) Hedgehog design, (b) light reflectivity pattern, (c) Location(s) for sampling, (d) Sampling through a transparent surface, (e) Sensing pipeline for analysis of collected samples.

personal safety and pave the way toward harnessing wearables for supporting everyday interactions.

2 IDENTIFYING DRINK SPIKING

Hedgehog smart ring design: Figure 1 (a, top) shows a classical smart ring design where sensors collect measurements from the individual's skin to derive metrics, such as skin temperature or heart rate [20]. Figure 1 (a, bottom) shows the design of Hedgehog, which re-purposes the light sensor by placing it on the exterior of the ring to collect light reflectance measurements from liquid containers. This requires the sensor to be placed on the surface of the liquid container and the container to be transparent or translucent. One key design challenge is how to optimally position the sensor to take high quality measurements. Our experiments consider drinks in glass containers and demonstrate that measurements can be taken robustly on a smart ring.

Theoretical foundation: Hedgehog exploits the principle of light scattering and reflectivity to assess changes in drinks [1, 22]. First, when the user touches a liquid container, light measurements are taken to establish a reference fingerprint of the liquid inside the glass (drink characterization, Figure 1(b)-(d)). The contents are then continuously monitored and changes in the fingerprint are used to determine if the drink has spiked. The fingerprint consists of parameters that characterize the distribution of light intensity values, and thus in practice Hedgehog operates by monitoring changes in the distribution of the light intensity values. This requires measurements to be collected over a sufficiently long period to ensure the distribution can be estimated consistently. This, in turn, depends on the sampling frequency of the underlying sensor and the stability of the measurement context. In practice, 50-100 measurements (10-20 seconds depending on sampling frequencies) suffice.

Sensing pipeline: The sensing pipeline used to process measurements is summarized in Figure 1(e). First, light measurements are cleaned using median filtering and convolution smoothing. Next, the reference fingerprint is established and assigned to a specific liquid-filled container. Successive fingerprints are then compared to the reference fingerprint, and these fingerprints are used as input for machine learning classifiers to determine whether the drink has been spiked or not. We consider two simple and easy-to-implement classifiers: Random Forest (RF) and Gradient Boosting (GB).

3 EXPERIMENTS

We evaluate Hedgehog through four experiments which focus on (i) characterizing different drink contents, (ii) detecting mixtures of soluble compounds, (iii) detecting compounds and (iv) demonstrating practicability in the field. In all experiments, measurements are taken using a smart ring prototype that integrates a red light sensor; see Figure 1. Measurements were taken from three different fingers: little finger (Position-1), middle finger (Position-2), and index finger (Position-3), as shown in Figure 1(c). In all experiments, 225 milliliters of the given liquid were poured into a transparent glass (cup1), and we conducted 4 trials per drink per position, with each trial consisting of 6 one-minute measurement periods. We collected data for one minute to ensure the data is representative data and the impact of micro-hand movements, re-adjusting of the grip, and other sources of noise are mitigated throughout the experiments. We separately carry out further evaluations that consider the effect of ambient luminosity, and different cups and drink types. Below we detail our experiments.

Apparatus: We built a smart ring prototype that embeds the light sensors on a ring and connects to a computing board that analyses the light values; see Figure 2(a). The prototype uses a wireless M5StickC PLUS ESP32 development board that controls the sampling frequency of the light sensor and uploads the samples to a server in real time. It is also possible to use a smartphone for analysing the measurements. The M5StickC Plus contains an inbuilt Wi-Fi connection facility, battery supplies (120 mAh @ 3.7V), and an LCD screen to externalize the activities of the board. Moreover, it is lightweight (21g) and portable, such that it can be placed in a wristband (65 mm $\times$25 mm $\times$15 mm). A light sensor is integrated through a separate wire that is attached to a plastic ring. The ring is made from an elastic wire which makes it easy to adjust it to different fingers. Our prototype takes light measurements using a red laser diode (650 nm, 5 mW, $3-5$V) and a photo-resistor (5MΩ). The photoresistor measures the intensity of light reflected back from the beam produced by the laser diode. The photoresistor captures analog voltage measurements, which are converted to digital voltage representations. The output value of ADC (analog to digital conversion, with 12-bit resolution) is used as the physical unit for reflected light intensity. The sample rate is configured at 5 Hz frequency, and on average, 50 samples are needed to characterize a drink with light measurements at 97.5% confidence.

(i) Characterizing Drinks: We first assess whether light reflectance measurements can be used to characterize and identify different types of drinks. We consider six commonly available and consumed drinks that can be easily manipulated in social contexts [17]. The drinks are shown in (1) of Figure 2(b) and comprise (A) water, (B)

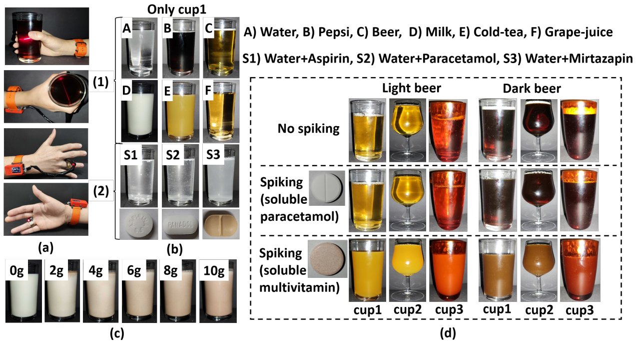


Figure 2: (a) Smart ring prototype from different angles; (b)(1) Drink characterization; (b)(2) Drink spiking with common pills; (c) Milk drink with aggregated compound mixture; (d) drink spiking with soluble pills.

carbonated soft drink, (C) beer (5.2% alcohol), (D) milk, (E) cold tea, and (F) grape juice. We refer to this setup as DRINKS.

(ii) Soluble Compound: The second experiment (MIXTURE) incrementally mixes a soluble compound – instant cocoa powder – into milk. The powder was added in increments of 2 g until a total of 10 g had been added. After each increment, the mixture was stirred for about a minute and left untouched until the liquid reached a stable state (no motion) for light fingerprint measurement; see Figure 2(c).

(iii) Medical Compounds: The third experiment (PILLS) evaluates water that has been spiked with medical pills. We consider three different pills: aspirin (500 mg), paracetamol (500 mg) and mirtazapine (30 mg). The first two are generic, freely available, over the counter painkillers. The last one is an antidepressant that has mild sedative effects and can only be obtained with a prescription. The pills were ground into powder and mixed with a glass of water; see (2) in Figure 2 (b). The resulting mixture is stirred thoroughly prior to taking measurements.

(iv) Practicability: The final experiment assesses factors affecting the light measurements. These experiments only consider measurements from the middle finger (position-2) as the other experiments demonstrate this position to provide the best performance (see below). We carry out experiments with different cups, pill types, types of drinks, and ambient luminosity levels. We consider transparent and translucent glass cups: cup1 (2 mm thickness, baseline), cup2 (1 mm thickness, goblet) and cup3 (2 mm thickness, tinted cup); with additional soluble pills: paracetamol (500 mg, no color change) and multivitamin (color change); luminosity: indoor dark (Dark), indoor ambient light (IAL) and outdoor ambient light (OAL); and drink types: light beer (4.7% alcohol) and dark beer (5% alcohol); see Figure 2(d).

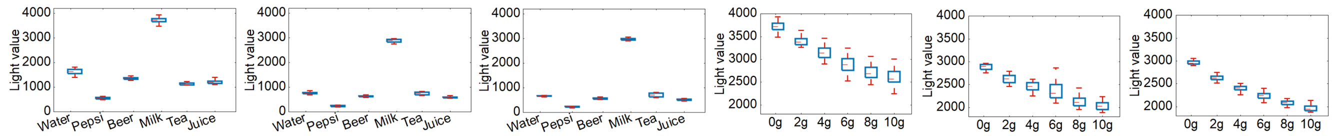
4 RESULTS

Drink characterization: We start by demonstrating that individual drinks have light reflectance fingerprints that are unique to the contents. This is essential for establishing reference fingerprints that can then be used to determine whether the contents of the drink have been tampered with or not. Figure 3 (a)-(c) shows the results for having the ring on different fingers. There are clear differences between the drinks, but these also differ according to the contact point. Kruskal-Wallis tests [10] demonstrated that light reflectivity in different positions could characterize different drinks that are poured into a standard transparent glass (Position-1: $\chi^2 = 131.12, \eta^2 = 0.94, p < .05$; Position-2: $\chi^2 = 131.12, \eta^2 = 0.94, p < .05$; Position-3: $\chi^2 = 131.93, \eta^2 = 0.92, p < .05$). Pairwise post-hoc comparisons for each sensor and drink indicated significant differences in all but three cases. The exceptions were cold tea and grape juice measured on the little finger ($\chi^2 = -1.30, p > .05$), and cold tea and water measured on the middle ($\chi^2 = 0.35, p > .05$) or index finger ($\chi^2 = -0.16, p > .05$). The index and the middle finger typically result in a stronger grip than the little finger, which tends to improve the quality of the measurements. Even then, however, the quality depends on how the container is held and how exactly the fingers are positioned. Our prototype is capable of piggybacking measurements from multiple contact points and angles over time, and taking advantage of this helps to improve the robustness of the measurements. The results also demonstrate that, while differences in contents can be clearly observed, identifying the exact liquid type is challenging. We next demonstrate that the granularity of these differences is sufficient for identifying drink spiking.

Aggregated drink mixture: Figure 3 (d)-(f) demonstrate how the fingerprints of milk change as dissoluble compound (cocoa powder) is added. Friedman test [6] verifies the differences in reflectance to be statistically significant for all fingers (Position-1: $\chi^2 = 115.26, W = 0.96, p < .05$; Position-2: $\chi^2 = 111.71, W = 0.93, p < .05$; Position-3: $\chi^2 = 120, W = 1, p < .05$). Pairwise post-hoc comparisons using Wilcox-Bonferroni tests [18] further proved that all differences in light values are statistically significant for all compound amounts ($p < .05$) and each finger. These results were also supported by visual inspection as the drink (naturally) became darker. This result demonstrates that Hedgehog is capable of detecting changes in drink characteristics.

Drink spiking: Figure 4 (a) shows the light reflectance measurements when medical pills are added to water. Both the 500 mg compounds (painkillers) and the 30 mg one (antidepressant) are easily identifiable. Note that the pills are not designed to be soluble, and on visual inspection, it is possible to see small particles in the water. These particles cause the light to refract in different directions, changing the way in which the light is captured by the photoreceptor and causing significant alternations in the overall fingerprint of a drink. From the figure, we can also observe that, while the light intensity values vary across different sensor positions, the changes in contents are consistent across all positions.

Friedman tests in all the sensor positions demonstrated significant differences for all the spiked drinks ($p < .05$). Placing the sensor on the middle finger (position-2) provided the best results overall ($\chi^2 = 51.05, W = 0.71, p < .05$). Pairwise post-hoc comparisons (Wilcox-Bonferroni) proved that the differences in light values are statistically significant for all the pairs ($p < .05$) except the two painkillers, aspirin and paracetamol in position-1 ($Z = -0.04, p > .05$) and position-3 ($Z = -1.67, p > .05$). These results indicate that *drink spiking can be detected robustly* but the *exact compound may be difficult to identify*, especially if the compounds have a similar structure (e.g., distinguish between the two



(a) Position-1 (b) Position-2 (c) Position-3 (d) Position-1 (e) Position-2 (f) Position-3

Figure 3: DRINKS and MIXTURE results; (a)-(c): Drinks identification; (d)-(f): Milk mixed with powder.

painkillers). The middle finger (position-2) provides the best individual position for detecting changes, but overall using measurements from multiple contact points is preferred as it improves detection when the spatial distribution of the particles changes, e.g., the compound can initially be mixed with the drink and slowly fall to the bottom as it interacts with the liquid. This suggests that even partial changes, such as the formation of sediments, could be detected as long as multiple contact points are used for the sensors.

Spiking over time: After a drink has been spiked, many compounds gradually sink to the bottom of the container over time. Note that this does not hold for all substances as some can remain submerged or float on the surface of the liquid, depending on their density relative to the liquid and their chemical properties. We next demonstrate that gradual changes also alter the light fingerprint of a drink sufficiently to allow Hedgehog to detect the changes in contents. To accomplish this, after a drink is spiked (S), we leave it motionless for an hour and collect measurements (SN). We then shake the spiked drink (SS) to verify whether it returns to its original value after spiking. Figure 4 (b) shows the results, and a water reference baseline is also included in the figure to facilitate its comparison. After an hour, the light fingerprint of the spiked drink changes, returning to a characterization value close to the water baseline. However, it goes back to its original spiked range as the drink is shaken. This suggests unattended drinks need measurements from multiple contact points, or they need to be shaken to monitor whether they are spiked or not.

Classification performance: Hedgehog also supports binary classification of spiked drinks. We used 5-fold classification to train two simple classifier models: Random Forest (RF) and Gradient Boosting (GB). When only the light reflectivity values in one position capturing drink spiking are considered, the average estimation accuracy is 89.71% from the middle finger. The index finger results in 82.24% performance, whereas the little finger results in only 48.64% accuracy. The reason for the poor performance of the little finger comes from the grip of the user. Specifically, the grip force exerted by the little finger is typically smaller when the user holds an object, which results in the ring having weaker contact with the glass container than when the middle or index finger is used. When the diode is not tightly pressed against the container, the gap between the diode and the container surface can reflect some of the light back, causing noise in the light measurements. For the index and middle finger, this noise is not present. The difference between middle and index fingers, in turn, results from the middle finger being more firmly planted on the surface of the container, resulting in less noisy light measurements. These variations can also be detected by examining characteristics of the light signals, and the classification can target situations where the signal is clean,

Test conditions		Trial1	Trial2	Trial3	Trial4	5-CV
IAL	L,C,B	87.97	89.35	95.37	95.37	92.25
	L,C,B,U	88.89	90.74	90.74	93.98	91.21
Dark	L,C,B	100	98.14	99.07	97.69	99.30
	L,C,B,U	100	98.14	99.07	97.69	99.30
OAL	L,C,B	93.52	93.52	93.06	96.76	94.80
	L,C,B,U	94.44	93.52	92.60	96.30	94.91
All	L,C,B	83.64	83.03	82.72	85.03	85.92
	L,C,B,U	93.98	92.44	91.67	94.75	94.29

Table 1: Drink spiking classification performance(%). Features: light reflectivity value (L), glass cup type (C), beer type (B) and light intensity LUX (U).

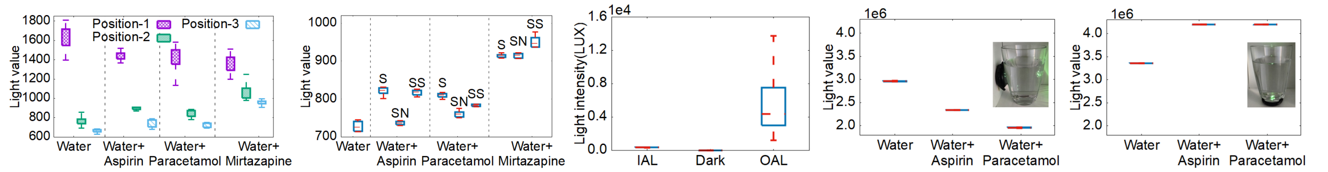
suggesting that over 80% accuracy is very much achievable as long as poor quality signals are filtered out.

Practicability results: We also analyzed additional factors that can influence the performance of Hedgehog. Figure 4 (c) shows variations in ambient light intensity. Both indoor ambient light (IAL) and dark have small variations in the light, but outdoor ambient light (OAL) can result in additional reflections that impact the detection. Figure 5 shows the results for different cups and drink types under different light conditions. The results largely mirror those before, showing that it is possible to distinguish spiked drinks from those that are not spiked across all conditions. We also re-trained the classification models to analyze how the new features affect classification performance. As the features we consider the light intensity captured by the photoreceptor (L), ambient light intensity (U); drink type (B) and glass cup type (C). We train and test using both 5-fold cross-validation and leave-one-trial-out cross-validation to assess impact of training data and the robustness of the models. Table 1 shows the overall average classification results. The effect of luminosity is generally minimal (IAL: 92.25%, Dark: 99.30%, OAL: 94.91%). From the table, we observe the variations between lit and dark environments to be minimal, indicating Hedgehog is resilient to changes in the luminosity of the ambient environment. The best performance is obtained when all ambient conditions are considered, resulting in an accuracy of 94.29%. A model that considers only the light reflectivity values in different settings results in about 61.65% accuracy, i.e., needs enough other ambient light conditions for better classification performance.

5 GREEN LIGHT RE-PURPOSING

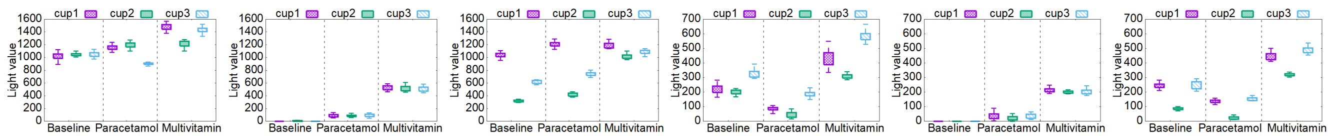
We next show that Hedgehog is not limited to rapid prototyping devices by re-purposing a commercial off-the-shelf smartwatch to capture light reflectance.

Apparatus: We use a Samsung Gear S3 Frontier smartwatch that integrates two green LED lights and a photo-receptor, which it uses for measuring heart rate data. We re-purpose the green light sensor



(a) (b) (c) (d) (e)

Figure 4: PILLS results, ambient light values and smartwatch sensor re-purposing; (a) Water spiked by different pills, (b) Spiked drink (Position-2 sensor only). S: Spiked, SN: Spiked-nomotion (for an hour), SS: Spiked-shaken (after an hour), (c) Light intensity (LUX) in different environments; (d) Sensor at one side. (e) Sensor at the bottom.



(a) Light beer: IAL **(b) Light beer: Dark** **(c) Light beer: OAL** **(d) Dark beer: IAL** **(e) Dark beer: Dark** **(f) Dark beer: OAL**

Figure 5: Drink spiking with different soluble pills in different beers under different cups and environments.

of our smartwatch to identify spiked drinks by wearing the watch with the clock-face down.

Setup: We replicated the third experiment (see Section 3) where different dosages of pills are mixed with water. We used aspirin (500 mg) and paracetamol (500 mg). We took measurements both from the side and the bottom of the glass container.

Results: Figure 4 (d-e) shows the results for the smartwatch experiments. The results mirror the characterization and the relative order of those obtained for red light with the smart ring prototype. This indicates that off-the-shelf sensors can easily be re-purposed to detect spiked drinks. Friedman test indicated significant differences for measurements collected at the side of the glass: ($\chi^2 = 4796, W = 1.0, p < .05$) and at the bottom of the glass ($\chi^2 = 5598, W = 1.0, p < .05$). In both cases, pairwise post-hoc comparisons using Wilcox-test (with Bonferroni correction) indicated significant differences for all pairs ($p < .05$) in both conditions. This implies that the relative position of the device with the container affects measurements. This can be detected using inertial sensors embedded in the smartwatch.

6 DISCUSSION

Room for improvement: Our work demonstrated that light reflectivity could be used to both characterize drinks poured into different transparent glasses and to accurately detect drinks that are spiked. Further work is needed to generalize the method, particularly when the ambient environment frequently changes. For instance, in a social gathering an individual can move through rooms that are differently lit and be exposed to different types of drinks and containers. To ensure accurate performance in these kinds of dynamic settings, it is necessary to evaluate and ensure the consistency of the fingerprints of drinks to minimize unwanted false positives. This requires further measurements, which could be collected by taking advantage of participatory crowdsensing. Specifically, individuals can be probed (e.g., using experience sampling) to provide measurements for drink profiles that then help to identify drinks in diverse real-world settings, e.g., diverse luminosity, different hand movements, or sensor angles. We are also interested in evaluating the method from the top of the glass as not all glasses are transparent [4], e.g., mugs.

Other methods: Hedgehog considers light measurements taken during natural hand interactions with drinks using a smart ring. Sensor modalities used by state-of-art methods, such as RF sensing [14] or audio sensing [12], could also be re-purposed to operate in everyday settings. Compared to these alternatives, a key benefit of Hedgehog is that it can be used without need for specialized measurement setup, whereas further work would be needed to design ways to integrate other modalities into wearables or other devices that support everyday interactions. Indeed, unlike the sensors needed by other state-of-the-art approaches, wearable devices are already equipped with the sensors to detect drink spiking, which makes it easy to adopt and scale up the use of our Hedgehog.

Chemical effects of spiking: The presence and quantity of small particles is commonly detected using light (scattering) refraction, e.g., this principle is used to detect particulate matter in air and to identify plastic pollutants [22]. We are interested in developing models that can identify chemical effects caused by tampering, e.g., using light refraction to detect particles that gradually sink to the bottom or the formation of crystallized structures or to detect soluble compounds that are mixed with drinks by stirring them.

Usage performance: Drink spiking can occur in a matter of seconds and individuals only shave 5 to 20 minutes before the first symptoms appear. This suggests warnings and possible alerts should be presented as soon as possible. The measurement time of our approach can be further reduced by increasing the sampling frequency of the sensors or by integrating models that predict the behavior of compounds in drinks. Other alternatives to improve the safety of individuals are to connect our solution with third-parties, e.g., police or relatives. Indeed, Hedgehog can automate the process of requesting third-party help immediately when it recognizes that a user gets in contact with drinks that have been tampered with.

Complex drink mixtures and other factors: Given the large spectrum of different drinks, drug substances and combinations, it can be challenging to determine whether an unknown drink has been spiked or not. Further work is needed to generalize our approach for more drink types and different concentrations, e.g., different drug dosages or alcohol percentages. Besides this, drinks that combine different sources, e.g., cocktails, may first require characterization of their contents before drink spiking events can be detected. In addition, other factors can influence the identification of drink spiking; for instance, objects inside the drinks can significantly modify their measurements, e.g., ice, carbonation level, spoons and straws. We are also interested in investigating whether our method can be used with hot beverages as hot contents may provide better means for dissolving foreign compounds.

Databases and models: Similarly to manufacturer databases and online dictionaries that provide detailed specification about drugs, Hedgehog provides a way to collect data about drink spiking, such that drink spiking databases (or datasets) can be created. These databases can provide details about the type of drink (mixed details) and substances (drug concentration and type) that were used. These databases can also collect information from symptoms faced by individuals while spiked. In parallel to this, AI models can be trained from this data, such that robust detection and actionable recommendations can be provided. As wearable devices continue to evolve and change over time, the easy access to these databases and models can also help in reducing false positives in drink spiking for new wearables.

The road for new innovative applications: Besides drink spiking detection, our developed method, and smart ring prototype can enable new types of applications. For instance, the light sensor can be re-purposed further to estimate the quality of vegetables [22]. Another example is to extend the light characterization to support human recycling practices. This further highlights the potential of our wearable design.

7 RELATED WORK

Light reflectivity methods in the green spectrum are mostly used in photoplethysmography to estimate heart rate via propagation of light through the body [3]. Several works have investigated approaches to re-purpose sensors from smart devices to identify liquids and materials. For instance, alcoholic drinks, sugar, liquid density, liquid surface tension and liquid viscosity [5, 7–9, 19, 21] are some of them. Drink spiking has been investigated mainly by analyzing the chemical composition of liquids. For instance, a method using rapid capillary zone electrophoresis was proposed to identify benzodiazepine drugs (aka benzos) in (spiked) beverages that include Coca-Cola, orange juice, beer, bourbon, and Bacardi [17]. Spectroscopy also has been used to identify spiked drinks. For example, a fluorescence spectroscopy method was investigated to detect flunitrazepam (Rohypnol benzodiazepine) in color-less alcoholic liquids such as vodka and tequila [11]. Other methods have also studied the use of ultraviolet and electrochemical approaches for detecting benzodiazepines in liquids [13]. While these works demonstrated that spiked drinks could be detected, those require specialized and expensive instruments, which cannot be easily integrated into wearables, or deployed at large-scale. In parallel to this, industrial manufacturers, such as DrinkSavvy, have designed specialized cups, glasses and straws that instantly change the color of a drink as it gets spiked. While the approach is convenient for continuous monitoring, it can be easily disguised just by using similar utensils. Moreover, the product just works for a limited set of drugs. Unlike others, we developed a sensing method and a new smart ring wearable to identify drink spiking.

8 SUMMARY AND CONCLUSIONS

We contributed Hedgehog, an innovative sensing method that can be integrated into wearables for identifying drink spiking. Through rigorous experiments, we demonstrated that Hedgehog can be used to identify different types of drinks from specific light reflectivity fingerprints, and to identify drink spiking robustly and accurately (up to 89.71% accuracy). We also show that our proposed method can be easily implemented using existing off-the-shelf commercial smartwatches and that it works for different cup types, drinks, and ambient luminosity conditions. Our research paves the way for new innovative solutions for harnessing wearables to support personal safety and identify spiked drinks.

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