PowDew: Detecting Counterfeit Powdered Food Products using a Commodity Smartphone

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ABSTRACT

The prevalence of counterfeit infant formulas worldwide poses serious threats to infant health and safety, a concern highlighted by the notorious *Melamine Milk Scandal* that affected hundreds of thousands of children. The primary challenge in detecting counterfeit formulas lies in their sophisticated *adulteration* and *substitution* techniques. Such detection is feasible only in laboratory settings, making it nearly impossible for average consumers to test the formula before feeding their infants. To address this problem, we propose *PowDew*, a novel and practical system for detecting counterfeit infant formula that utilizes only a commodity smartphone. *PowDew* operates by capturing and analyzing the interaction of a water droplet with the powdered formula, focusing on the *droplet motion*, namely its *spreading* and *penetration*. Our insight is that the droplet motions are governed by powder-specific properties such as *wettability* and *porosity*. *PowDew* analyzes the subtle differences in droplet motions, and infers the formula's authenticity. To demonstrate *PowDew*'s effectiveness, we implement *PowDew* and conduct comprehensive real-world experiments under varying conditions with different brands of powdered infant formula and adulterants. Our experiments result in a total of 12,000 minutes of video recordings of the droplet motions on various infant formulas, including authentic and altered. Our experiments demonstrate that *PowDew* yields an overall detection accuracy of up to 96.1%.

CCS CONCEPTS

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

KEYWORDS

Counterfeit, Powdered Food Products, Smartphone

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1 INTRODUCTION

Powdered food products, ranging from dietary supplements to specialized nutritional formulas, are popular for their convenience, cost-effectiveness, and long shelf life [2, 27, 70, 74, 85]. Infant formulas are a key category within this segment. These products are specifically designed to substitute or complement breast milk and are often available in *powdered form*. Reflecting the advantages, the demand for powdered infant formulas is continuously rising, and their global market value is projected to reach approximately $174 billion by 2032 [21, 69].

Unfortunately, *counterfeit infant formulas* are reported in many parts of the world and pose severe threats to infant health and safety [1, 48, 51, 58, 59, 71, 72, 89]. Specifically, these products are *adulterated* by mixing cheaper, and potentially harmful substances with authentic formulas. An infamous example is the *Melamine Milk Scandal*, where infant formulas were adulterated with melamine, a chemical used in plastics and fertilizers. This scandal impacted approximately 300,000 children, resulting in hospitalization for around 54,000, and tragically led to many fatalities [14, 44, 50]. In other instances, infant formulas have been adulterated with cheap milk powders [9, 30, 49], whey protein [12, 20, 87], or even other lower-grade formulas [17, 51, 59]. Recent reports also indicate a rise in the *substitution* of products, where substandard formulas are falsely packaged with authentic product labels in a sophisticated manner by imitating safety seals, branding, and packaging designs [51, 59, 71, 72, 75, 89].

As such, effectively detecting counterfeit infant formulas is increasingly challenging. Advanced methods predominantly involve chemical analysis techniques such as Near Infrared Spectroscopy

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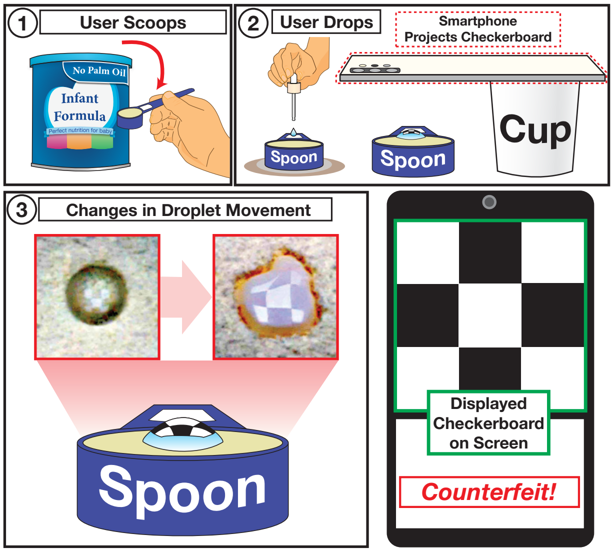

Figure 1: Figure illustrates the usage scenario of *PowDew*. ① The user begins by scooping and leveling the powder using the spoon provided with the infant formula. ② The user aligns the spoon according to the guidance provided by the *PowDew* mobile app. The user then drops water droplets onto the surface of the powder. Following this, the *PowDew* app projects a *checkerboard pattern* onto the droplet from the smartphone's screen. ③ The smartphone captures the *droplet motion* using the front-facing camera.

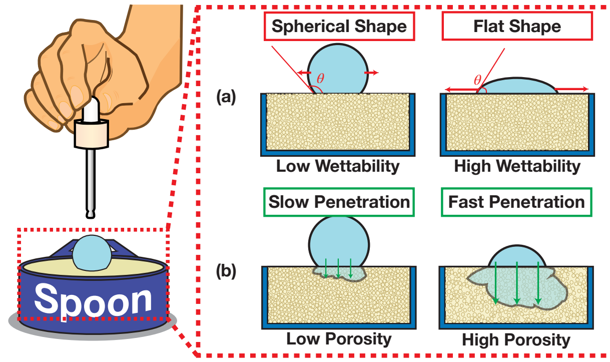

Figure 2: Physical properties of a powder and their impact on the water droplet. Specifically, (a) depicts the impact of *wettability* on how a droplet *spreads out* on the powder surface, leading to changes in its shape (e.g., from spherical to spherical or flat shapes). (b) depicts the impact of *porosity* on the amount, speed, and directions of a droplet *penetrating* into the powder.

(NIRS) or Mass Spectrometry (MS). NIRS analyzes optical absorption, while MS measures the mass-to-charge ratio of ions, both aiming to ascertain the composition, structure, and physical properties of powdered formulas [40, 52, 83]. However, these sophisticated methods typically require specialized, costly lab equipment, making it impractical for everyday consumers to perform quick tests on newly opened infant formula.

To address the challenges of detecting counterfeit infant formulas, we ask a pivotal question: *Can we devise a practical solution* ***using only a commodity smartphone****?* In response, we propose *PowDew*, a system designed to detect counterfeit infant formula utilizing a commercial smartphone, as illustrated in Figure 1. The process involves the user simply dropping a few water droplets onto a bed of powdered formula in a spoon (that comes equipped with the powder container). *PowDew* proceeds to analyze the video captured by the smartphone by observing the behavior of the water droplet – particularly its *droplet motion*, namely its *spreading* and *penetration*, upon contacting the powder. A powder of different composition results in different droplet motions, governed by the powder properties, namely *wettability* and *porosity*. *PowDew* analyzes the subtle differences in droplet motions, and ascertains vital information indicative of the powder's authenticity.

Designing *PowDew*, however, comes with the following challenges. First, accurately capturing the droplet motion poses a challenge, as the camera captures a *two-dimensional view* of a *three-dimensional motion*. To address this, we propose a novel technique of utilizing the smartphone's display to project a checkerboard pattern onto the droplet surface. By recording the dynamic movement changes of this reflected pattern using the smartphone's front-facing camera, *PowDew* achieves a precise depiction of the *droplet motion*.

Second, accurately capturing and tracking the checkerboard movement presents an additional challenge, as *PowDew* must identify subtle differences in powder properties. For this, we employ state-of-the-art object tracking techniques to ascertain the precise movements of checkerboard corners. This process incorporates a corner correction mechanism that addresses incorrectly tracked checkerboard corners (i.e., those wrongly identified or missed). Furthermore, it ensures that even small shifts in corner locations, indicative of changes in powder properties, are accurately captured.

We implement and evaluate *PowDew* by conducting comprehensive real-world experiments. We conduct these experiments under diverse conditions with six different brands of powdered infant formula and three different adulterants produced across five countries. We also invite multiple participants to drop water droplets onto the powder while having *PowDew* record the droplet movement using a smartphone camera, demonstrating practical usability of *PowDew*. In total, we collect 12,000 minutes of recording and demonstrate that *PowDew* yields a detection accuracy of up to 96.1%.

2 BACKGROUND, CORE IDEA, AND FEASIBILITY STUDY

In this section, we introduce relevant background information and the core idea of *PowDew*. We then present a feasibility study for *PowDew*.

2.1 Physical Properties of Powders

Powdered food products from different brands exhibit unique physical properties, such as *wettability* and *porosity*, influenced by their manufacturing techniques and ingredient compositions. *Wettability* [54, 73] refers to the ability of powders to interact with liquid, such as water droplets, causing water droplet *spreading* from their original spherical shape to a flat shape on the powder surface. *Porosity* [33] refers to the measure of empty spaces or voids between powder particles, which also affects the powders' interaction with water droplets, namely the *penetration* of droplets into the powders. Figure 2 depicts how powder *wettability* and *porosity* influence the *spreading* and *penetration* of water droplets.

Impact of *Wettability* on Droplet *Spreading*. A powder of low wettability minimally interacts with a water droplet, maintaining the droplet's original spherical shape. In contrast, high wettability destroys the droplet's ability to maintain its shape and causes the droplet to ***spread out*** on the powder surface, creating a flat shape. Figure 2(a) illustrates this phenomenon, which we name as the droplet *spreading*. The amount of *spreading* is governed by the interfacial tensions between the liquid and solid phases (i.e., a force acting on the boundary between the two phases) [24, 66, 82]. The contact angle, θ, between the droplet and the surface of the powder bed is a typical measure of the amount of *spreading*. For example, a powder with high wettability usually causes a small contact angle (i.e., $\theta < 90°$). Young's Equation [96] quantitatively defines the contact angle in relation to the interfacial tensions of the solid-vapor (SV), solid-liquid (SL), and liquid-vapor (LV) interfaces, expressed as $\cos\theta = (\gamma_{SV} - \gamma_{SL})/\gamma_{LV}$, where θ is the contact angle, and γ_{SV}, γ_{SL}, γ_{LV} represent the corresponding interfacial tensions.

Impact of *Porosity* on Droplet *Penetration*. The porosity of powders affects how water droplets ***penetrate*** into the powder. Figure 2(b) illustrates this phenomenon. For example, a powder with high porosity allows a water droplet to penetrate rapidly due to the large volume of pores (or empty spaces) in the powder. The *penetration* of droplets is modeled by Darcy's Law [23, 28], which indicates that the rate of penetration (which refers to the volume of droplet entering per time unit) rises as the pressure for liquid penetration into the pores, denoted as ΔP, decreases. Moreover, $\Delta P = 2(\gamma_{SV} - \gamma_{SL})/R$, where R denotes the radius of the pore [25]. Hence, a high *porosity* leads to a high liquid penetration pressure, which, in turn, increases the volume and speed of a droplet penetrating the powder.

Key Takeaways. The underlying physics reveal that there is a correlation between the *wettability* and *porosity* of a powder and the amount and speed of *spreading* and *penetration* of a water droplet in contact with the powder surface. Thus, *PowDew* employs a smartphone camera to capture these physical behaviors (i.e., **droplet motion**), governed by the powder-specific physical properties, ultimately determining its authenticity.

2.2 Challenges and Core Idea of *PowDew*

Precisely capturing the droplet motion, namely *spreading* and *penetration*, is extremely important for *PowDew* in determining the authenticity of the powder. However, there are two main challenges when utilizing **only a single** smartphone camera for this purpose. First, since a camera only provides a restricted **two-dimensional** view, such as a top-down or side view, it is unable to fully capture the droplet motion in **three dimensions**. For example, *spreading* occurs **on top of** the powder surface while *penetration* occurs **into** the powder. It is difficult to capture both at the same time with a single camera. Second, a commodity smartphone camera may not capture **subtle changes** in the movement and surface morphology (e.g., curvature) of a droplet. This is because these changes may be influenced by lighting conditions and obscured by noises like uneven powder surfaces.

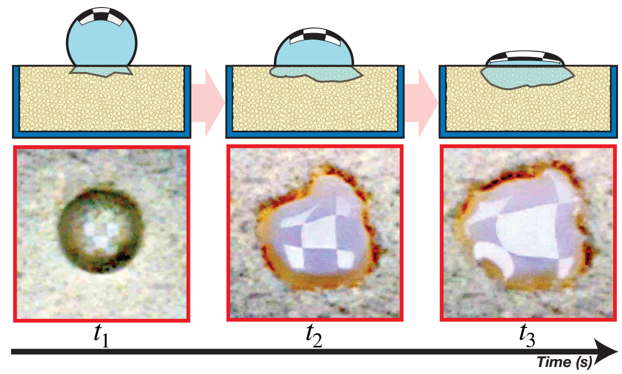

Figure 3: Demonstration of the *droplet motion*, namely the *spreading* and *penetration*. The contrast of the images is exaggerated for visual clarity. As the droplet spreads and penetrates, its upper surfaces become increasingly flatter. This change results in the enlargement of the center square of the projected checkerboard pattern. Moreover, the droplet often spreads or penetrates in random directions, which can cause the checkerboard pattern to appear distorted.

To address the aforementioned issues, *PowDew*'s core idea is to project a checkerboard pattern, from the smartphone's display, onto the surface of a droplet and capture the dynamic changes of the **reflected checkerboard pattern** on the droplet's surface using the smartphone's front camera. Using a checkerboard projection allows us to capture subtle movements and changes in the droplet's surface morphology. This is achieved by analyzing the varying sizes and shapes of the checkerboard tiles, which exhibit **pronounced changes**. This is feasible since changes in the three-dimensional shape of the droplet (due to *spreading* and *penetration*) directly influence the reflection of the checkerboard, causing noticeable changes in the size and shape of the tiles captured at the smartphone camera.

Figure 3 depicts the dynamic changes of the reflected checkerboard with respect to the droplet motion. We observe a drastic change in the ***size*** and ***shape*** of the ***center square***, the largest white square in the center of the reflected checkerboard. When the droplet spreads out and becomes flat, the size of the center square increases. At the same time, as the droplet penetrates the powder, the randomness of pores in the powder causes the different parts of the droplet to penetrate in random directions, leading to distortion of the center square's shape. We can also observe a rapid change in the center square's shape as the droplet penetrates rapidly.

2.3 Feasibility Study

We conduct a feasibility study to validate our two main hypotheses: (1) using a checkerboard projection can facilitate effortless capture

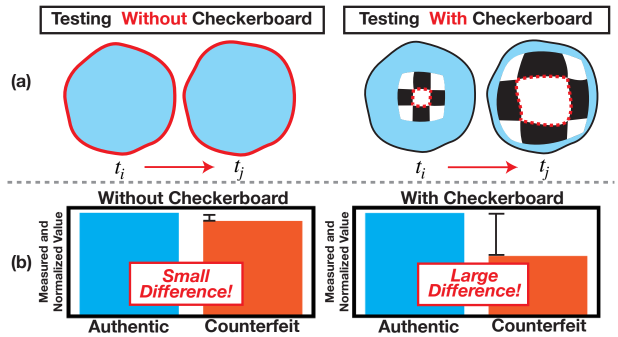

Figure 4: Illustration of changes in droplet shape over time and the effect of using reflected checkerboards. (a) illustrates the aid of the checkerboard projection on the droplet. (b) demonstrates a large, amplified difference in observing the droplet with the assist of a checkerboard reflection.

of droplet motion by a single smartphone and (2) dynamic changes of the checkerboard's center square can be used to determine the authenticity of a powder.

Setup. We prepare two off-the-shelf powders, namely an authentic infant formula (i.e., Authentic) and a budget milk powder. We adulterate 50% of infant formula with 50% of the budget milk powder which acts as a counterfeit here. We capture the droplet motion with and without the checkerboard projection using a smartphone's front camera.

Hypothesis (1): Assistance via Checkerboard. Figure 4(a) illustrates the differences in the captured water droplets when testing an authentic powder with and without the checkerboard projection. Note that we purposefully present hand-drawn illustrations instead of real photos, due to the limitation that it is impossible to reproduce an identical shape of droplets across two conditions. Hence, Figure 4 is to convey the key principles, while Figure 3 depicts how an actual droplet and the center square spread over time, respectively. In Figure 4, the red solid lines indicate the area of a water droplet and the red dotted lines indicate the area of the center square as the droplet spreads and penetrates. Over time (from t_i to t_j), we can observe notable changes in the area of the center square, while only subtle differences in the droplet's area. Figure 4(b) illustrates the normalized change in the captured area from t_i to t_j for both authentic and counterfeit powder cases. The difference in the center square area with the checkerboard is significantly more distinguishable compared to the whole droplet area without the checkerboard. Consequently, the checkerboard's presence enables the smartphone camera to more easily observe the droplet motion.

Hypothesis (2): Powder Authenticity. Figure 4(b) illustrates the distinction between authentic and counterfeit powders based on the rate at which the center square area of the checkerboard increases. A large difference demonstrates the feasibility of using a checkerboard projection (like the center square area) to determine the authenticity of powders. In addition to the area, *PowDew* extracts other critical features to improve its performance and robustness (see §3.4).

3 SYSTEM DESIGN

We now present the details of *PowDew*'s design.

3.1 System Overview

We design *PowDew* to verify the authenticity of powdered food products by employing a smartphone screen to project a checkerboard pattern onto a water droplet's surface once dropped onto the powder. Subsequently, *PowDew* captures the reflected pattern using the smartphone's camera for further analysis. *PowDew* consists of two distinct phases: *Training* and *Verification* phases. During the *Training Phase*, *PowDew* undergoes machine learning model training with a large collection of video recordings consisting of authentic and counterfeit powders, each appropriately labeled as such. Counterfeit conditions include various levels of adulteration or substitution with cheaper alternative powdered food. In this phase, *PowDew* processes these videos to extract salient features, which are then used to train a machine learning model. We note that this can be a one-time process and envision the infant formula manufacturers or government regulatory agencies (e.g., FDA), to perform such offline training and store the trained model on their cloud. In the *Verification Phase*, users are instructed to drop a water droplet on a leveled powder bed. Then, using their smartphones, they capture a video of the water droplet spreading over or penetrating the powder while projecting the checkerboard pattern onto the droplet. With this video, *PowDew* operates the pre-trained model to verify the authenticity of the power. This process is designed to be simple and quick, enabling average parents to easily perform this verification step with their smartphones upon opening a new container of formula.

Figure 5 illustrates an overview of *PowDew*'s system design. Specifically, the *User Guidance and Data Collection* module (§3.2) guides the user to record a video of a water droplet being dropped onto the powder. These captured videos are then input to the *Preprocessing* module (§3.3), which segments the region of interest displaying the droplet with the checkerboard reflection and enhances the contrast of video frames. Subsequently, the *Checkerboard Feature Extraction* module (§3.4) extracts crucial features related to the dynamic changes in the checkerboard's size and shape. Finally, the *Training and Verification* module (§3.5) verifies the authenticity of the powder with a trained machine-learning classifier.

3.2 User Guidance and Data Collection

Maintaining a consistent *distance* and *angle* between the camera and the spoon powder bed is crucial when capturing the video, as the checkerboard pattern's reflection on the water droplet is influenced by these factors. Figure 5(a) illustrates a user-friendly setup keeping constant distance and angle using a typical household item such as a paper cup. To further help with horizontal alignment, *PowDew* offers user guidance to direct the user to place the powder spoon at the optimal location with respect to the camera. However, as the smartphone screen projects the checkerboard onto the droplet, the user cannot directly view the smartphone screen for alignment. To address this issue, we design and implement two assistant features. The first involves using an auxiliary display, such as a smartwatch, iPad, laptop, or smart TV, to mirror the smartphone's screen. This method provides the user with a clear view, aiding in the accurate placement of the spoon at the optimal location. In the case where an auxiliary device is not an option, the user can also utilize voice-over

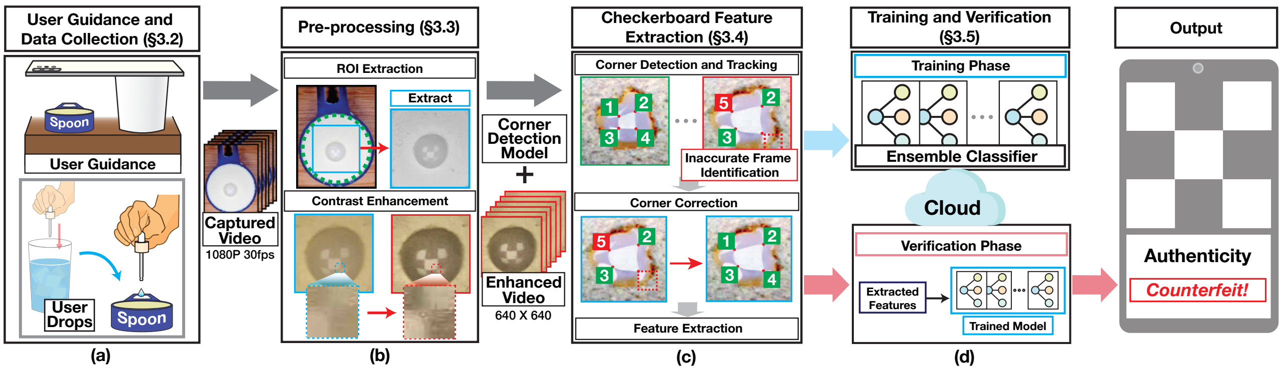

Figure 5: Figure depicts the flowchart of *PowDew*. During the *Training Phase*, relevant parties such as infant formula manufacturers or government regulatory agencies (e.g., FDA) train the model. This is performed by using the video recordings that capture both authentic and counterfeit products with various adulterants. During the *Verification Phase*, the user drops the droplet onto the powder bed and records the video. *PowDew* then analyzes the droplet motion to determine the authenticity of the infant formula.

feedback, with instructions such as "move left" or "move up", to assist the user in correctly positioning the spoon within the image.

3.3 Pre-processing

In the pre-processing module, *PowDew* first identifies and extracts the region of interest (ROI), which includes the droplet and its checkerboard reflection in each video frame. Following this, *PowDew* enhances the contrast within this ROI. This is crucial in reducing the effect of external environmental factors, such as varying lighting conditions. Figure 5(b) depicts the processing pipeline of this module.

Region of Interest Extraction. In each video frame, *PowDew* focuses exclusively on the spoon powder bed region, eliminating all other areas. This approach significantly enhances image processing efficiency, as the ROI is much smaller (i.e., 4.3% in area) compared to the full video frame. Additionally, this method helps reduce human errors that may arise in various tests or with different users, such as inconsistent positioning of the droplet or variations in the distance between the camera and the powder bed. To achieve this, *PowDew* operates an edge detection algorithm [77] to determine the powder bed boundaries (e.g., edge of a spoon). It then exploits the Hough circle detection algorithm [43] to pinpoint the powder bed's exact location. When a circle is consistently identified in n successive frames ($n = 10$ in our implementation), *PowDew* confirms the area as the powder bed (marked with a green-dotted circle in Figure 5(b)). Following this identification, *PowDew* crops a square area encompassing the powder bed (indicated by a blue-lined square), based on a pre-determined size that reflects the powder bed's actual dimensions. The cropped region is then resized to a normalized dimension of 640x640 pixels to generate the ROI.

Contrast Enhancement. Subsequently, *PowDew* performs operations to enhance the contrast of the extracted ROIs. The checkerboard pattern, composed of black and white tiles, inherently has a high contrast in luminance (i.e., brightness or intensity of light reflected). However, external factors such as ambient lighting and powder colors can reduce this contrast, making it difficult to distinguish between the black and white tiles. To address this, *PowDew* employs contrast enhancement methods to clearly define the boundaries. Specifically, *PowDew* converts the *RGB* color space to *Lab*. In the *Lab* space, L represents luminance, while a and b denote the color components, specifically red/green and blue/yellow, respectively. The next step enhances the contrast of the L component. Specifically, we use a tile-based local contrast histogram equalization algorithm [67] with a clip limit to prevent over-enhancements. Finally, *PowDew* converts the ROIs back to *RGB* space and feeds this result to the *Checkerboard Feature Extraction* module, as depicted in Figure 5(c).

3.4 Checkerboard Feature Extraction

In this module, *PowDew* extracts features from the dynamic changes in size and shape of the checkerboard, as observed in the preprocessed video frames. These changes are indicated by the checkerboard corner movements, and accurately capturing these movements is vital for differentiating powder products with subtle differences in their physical properties. To achieve this, we devise a novel corner detection and tracking technique. Figure 6 details the processing pipeline. Initially, *PowDew* detects corners of the checkerboard in each frame, which is followed by the tracking of their movements over successive frames in the *Corner Detection and Tracking* step (§3.4.1). In the next step, *PowDew* identifies frames containing incorrectly detected and tracked corners in *Inaccurate Frame Identification* (§3.4.2). Then *PowDew* corrects the errors in *invalid frames* using *Corner Correction* (§3.4.3) to ensure corner movements are accurately captured. Finally, in the *Feature Extraction* step (§3.4.4), *PowDew* analyzes the statistical features of corner movements.

3.4.1 Corner Detection and Tracking. In this step, *PowDew* first detects the locations of checkerboard corners in each of the preprocessed frames and then identifies the movement of each corner across frames. Figure 6(a) depicts an example of detected and tracked corners in each frame.

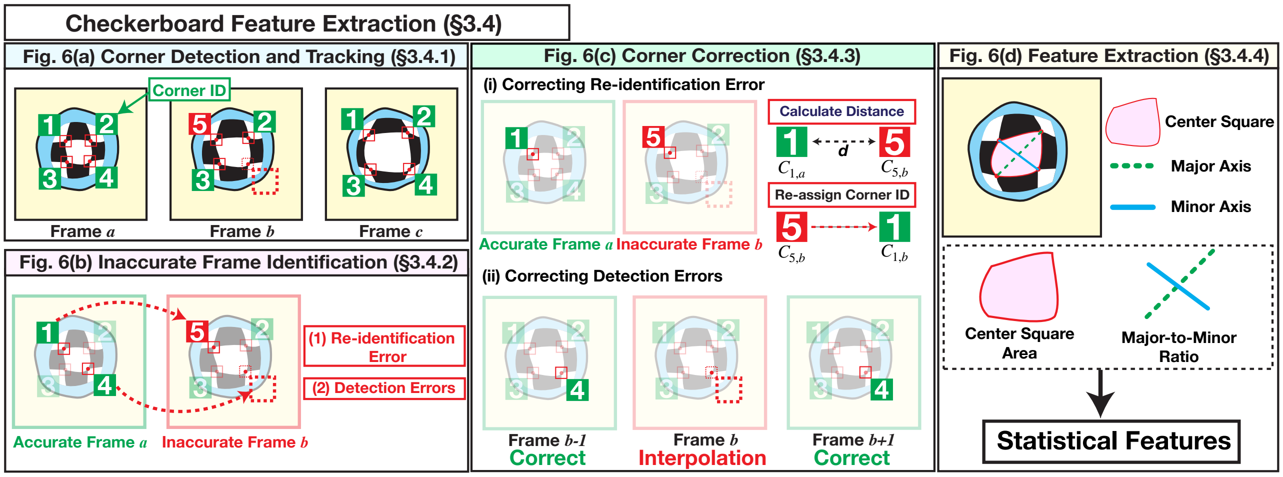

Figure 6: Figure depicts the detailed processing pipeline of the *Checkerboard Feature Extraction* module (§3.4). Specifically, *Corner Detection and Tracking* (§3.4.1) locates the corners across video frames. *Inaccurate Frame Identification* (§3.4.2) identifies frames that contain incorrect corners. *PowDew* then corrects the errors in these frames in *Corner Correction* (§3.4.3). Finally, *Feature Extraction* (§3.4.4) extracts statistical features using the corners of the checkerboard.

Corner Detection. We leverage the state-of-the-art object detection technique to determine the locations of corners in the checkerboard. Due to limited image resolution and rapid corner movements, the checkerboard is often observed blurry. Hence, it is difficult to identify the exact location of each corner. We resort to utilizing a deep-learning object detection model, namely YOLOv8 [68, 91]. However, a publicly available pre-trained YOLOv8, despite being trained with large-scale datasets, lacks specialization in detecting corners of a checkerboard. Thus, we fine-tune the model using checkerboard images, with manually annotated corners, to improve the detection accuracy. We obtain a bounding box around each corner and compute the centroid of the bounding box as the corner location.

Corner Tracking. Subsequently, we track the movement of each detected corner across frames. We assign an ID to each corner and re-identify the same corner appearing in subsequent frames. We obtain a list of locations to represent each corner movement. For example, we obtain the locations of each corner (indicated with a red box in Frames *a*, *b*, and *c*) and assign corresponding IDs (i.e., 1, 2, 3, 4) to these corners in Frame *a*. For this task, we adopt DeepSORT [93], a computer vision tracking algorithm for tracking objects while assigning an ID to each object. We use DeepSORT because of its outstanding tracking accuracy and real-time performance.

3.4.2 *Inaccurate Frame Identification.*

Recall that *PowDew* requires accurate corner location and movement detection to differentiate powders with minute differences in their physical characteristics. In this step, *PowDew* identifies *inaccurate frames* that contain incorrectly detected corners.

Errors in Corner Detection and Tracking. We observe two main sources of errors as depicted in Figure 6(b). First, ***re-identification error*** occurs when the same corner in different frames is assigned with two different IDs. Second, ***detection error*** occurs when the corner is not detected in certain frames. The combined effect of these two errors results in inaccurate capturing of the corner movement.

Identification of Frames. We first identify the ***accurate frames*** (i.e., frames with all four correctly detected corners without any errors) across all video frames. For example, in Figure 6(b), frame *a* and frame *c* are accurate, while frame *b* contains both re-identification and detection errors. Note that the ID of the four corners is auto-generated based on their relative locations, with an ID of 1, 2, 3, 4 for the top-left, top-right, bottom-left, and bottom-right corners, respectively. The remaining frames are considered as *inaccurate frames* and we correct the errors in the subsequent steps.

3.4.3 *Corner Correction.*

In this step, *PowDew* corrects both re-identification and detection errors in the inaccurate frames. Figure 6(c) details the processing pipeline.

(i) Correcting Re-identification Error. For the *inaccurate frames*, we first correct the *re-identification error*, which causes wrongly assigned IDs. For example, a corner may be assigned with an ID of 5 while only IDs of 1 to 4 are expected. Hence, we re-assign these corners with correct IDs by matching their locations with those in the nearest *accurate frame*. For example, for a corner, $C_{5,b}$, assigned with ID of 5 in an inaccurate frame, b, we compare this corner with all four corners in the nearest accurate frame, a. We calculate the Euclidean distance, $Dist$, between the locations of these corners (i.e., $Dist = \sqrt{(Loc_{C_{5,b}} - Loc_{C_{1,a}})^2}$ where $C_{1,a}$ is the nearest corner in the accurate frame, a). If $Dist$ is within a threshold, we re-assign the ID of $C_{5,b}$ from 5 to 1.

(ii) Correcting Detection Error. Subsequently, we correct the *detection error* in *inaccurate frames*. Since the difference between locations of the same corner in adjacent frames is minimal, we can obtain the location of a missing corner by interpolating between the locations of the corner with the same ID in adjacent frames. For example, in frame b, we have a missing corner whose ID is supposed to be 4. We can obtain its location by interpolating between corners with an ID of 4 in frames $b-1$ and $b+1$.

3.4.4 Feature Extraction. In this step, *PowDew* extracts relevant features from the corner movements to effectively capture changes in the size and shape of the checkerboard's center square. Figure 6(d) depicts examples of the extracted features. Specifically, *PowDew* computes ***area*** and ***major-to-minor-axis ratio*** of the checkerboard's center square to measure its size and shape, respectively, using four corners in each frame. We calculate *area* as the cross-product of the vectors along two diagonal axes, and *major-to-minor-axis ratio* as the length ratio between the longer diagonal axis and the shorter one. Before computing the two features, *PowDew* performs z-score normalization to further reduce the variances of scale across different trials. Furthermore, we derive statistical features from these two features, including mean, variance, skewness, and kurtosis. These statistical features effectively capture the overall movement of corners and hence the dynamic changes in size and shape of the checkerboard's center square. Finally, *PowDew* inputs the statistical features to its machine learning classifier.

3.5 Training and Verification

In the final phase, *PowDew* utilizes machine learning techniques to predict the authenticity of a powder using the features extracted from the video frames. Specifically, *PowDew* trains its machine learning model in the *Training Phase* to optimize the model's performance and robustness. It then utilizes the trained model for prediction in the *Verification Phase*, as depicted in Figure 5(d).

While *PowDew* is designed to be flexible and can employ various machine learning models as its classifier for identifying counterfeit infant formulas, we choose to use the XGBoost model. XGBoost provides a scalable, portable, and distributed gradient-boosting approach for classification via an ensemble architecture [19]. Among many possible alternatives, we select XGBoost due to its high classification performance stemming from its capability to optimize its model based on its additional regularization. We note that for improved robustness, despite XGBoost being an ensemble model itself, we further ensemble multiple versions of XGBoost with different initialization parameters. This is to assure that we mitigate the risk of overfitting to specific patterns (or outliers) in the data.

4 EVALUATION

We now present an extensive evaluation of *PowDew* using comprehensive real-world experiments.

4.1 Experiment Setup

Apparatus. Figure 7(a) illustrates our experimental setup. In our evaluation of *PowDew*, we use six distinct commercial infant formula products from various manufacturers around the globe: Similac [7] (made in Ireland), Aptamil [8] (made in the Netherlands), HiPP [41] (made in Germany), IMNZ [46] (made in New Zealand), Namyang Goat Milk [64] (made in Korea), Golden Jersey [47] (made in France but sold as a Korean brand). These products are prominent in global or regional markets.[1] Recent reports indicate that counterfeiting methods in infant formulas have increasingly involved either *adulteration* (mixing with cheaper alternatives) or *substitution* (complete replacement with cheaper alternatives). To mimic these real-world scenarios, we select three different adulterants – *milk powder (MP)*, *whey protein concentrate powder (WP)*, and a different but *cheaper brand of infant formula (CF)*. For the *adulteration* experiments, we prepare mixtures containing 50% of each adulterant with the authentic powder. For the *substitution* experiments, we completely replace the authentic powder with the adulterants.

Prototype Implementation. To demonstrate the feasibility of our idea, we implement a preliminary version of *PowDew* on Android devices. Specifically, we implement a mobile app for user guidance and data collection and transfer the video data to a cloud-based server, equipped with a 3.0 GHz CPU, 64 GB memory, and RTX 4090 GPU, for preprocessing, feature extraction, training, and verification.

Data Collection. We perform our data collection in a controlled environment with standard room temperature and humidity level of 25°C and 55%, respectively. Given the potential inconsistencies across different infant formula containers, we collect data from multiple containers of the same brand (i.e., make-and-model). Furthermore, to minimize oxidation effects, we only use formulas that are opened on the day of the experiment. Note that this would be a practical use case as users would likely test the authenticity of a formula upon opening a new container.

For consistency, we employ a Samsung Galaxy Note 10+ for data collection (except for experiments with varying smartphones in Section 4.3.2). We record videos in Full High Definition (FHD) with a resolution of 1920x1080 pixels at 30 frames per second. Each recording session lasts three minutes, capturing subtle dynamic changes in the checkerboard pattern. Finally, we conduct our experiments adhering to our Institutional Review Board (IRB) approval.

Evaluation Metrics. We evaluate the performance of *PowDew* using the following metrics.

- *Accuracy* is the percentage of correctly classified instances (including both authentic and counterfeit) among all tested products (i.e., $Accuracy = (Auth_T + Counter_T) / (Auth_T + Counter_T + Auth_F + Counter_F$, where $Auth_T$ and $Auth_F$ are authentic products that are correctly and incorrectly classified, respectively, while $Counter_T$ and $Counter_F$ are counterfeit products that are correctly and incorrectly classified, respectively).
- *Recall* is the percentage of correctly classified counterfeit instances among all counterfeit instances (i.e., $Recall = Counter_T / (Counter_T + Counter_F)$).
- *Precision* is the percentage of correctly classified counterfeit instances among all instances classified as counterfeit (i.e., $Precision = Counter_T / (Counter_T + Auth_F)$).

4.2 Overall Performance

Data Preparation. To evaluate the overall performance of *PowDew*, we collect 240 videos for each brand of infant formula. This includes 120 videos of authentic products, and 120 videos of counterfeit products (20 videos each for both 50% adulterated products and substituted products across three adulterants) ensuring a balanced dataset. For all evaluations in this section, we employ a five-fold

[1] For example, Similac is the leading baby formula (21.2%) in the U.S. market in 2016 [26]. Aptamil is the leading brand (52%) in the U.K. in 2018 [60].

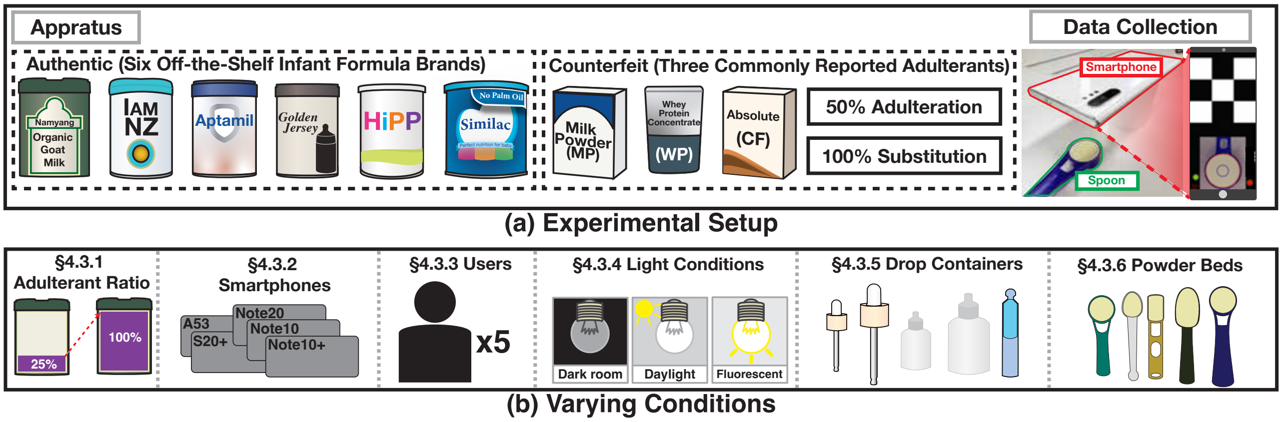

Figure 7: Figure depicts the setup of our experiments. (a) We evaluate the effectiveness of *PowDew* by comparing different infant formulas and their counterfeits, including the tests for *adulteration* (where counterfeit substances are added) and *substitution* (where the authentic ingredients are completely replaced with the counterfeit substances). (b) We also comprehensively evaluate *PowDew*'s performance under varying experimental conditions.

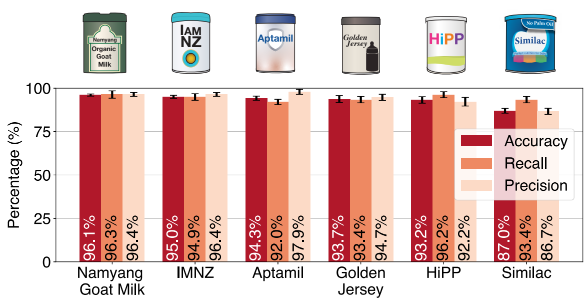

Figure 8: Overall performance of *PowDew*, namely the accuracy, recall, and precision across six distinct brands of infant formula.

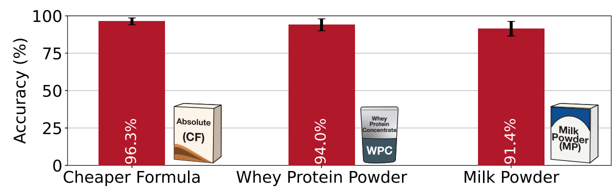

Figure 9: Accuracy for different types of adulterants.

cross-validation, which involves training *PowDew* with a randomly selected set of 192 instances and testing it with the remaining 48 instances.

Results We illustrate the overall results in Figure 8. We observe that *PowDew* achieves an **overall accuracy of 92.31%**. Specifically, *PowDew* yields an accuracy of 96.1%, 95.0%, 94.3%, 93.7%, 93.2% for Namyang Goat Milk, IMNZ, Aptamil, Golden Jersey, and HiPP, respectively. However, we note that *PowDew* yields a relatively lower accuracy of 87.0% for Similac. We attribute this performance degradation to missing information on the *initial movement* of the droplet immediately after it contacts with the powder, caused from the inevitable occlusion taking place from the user hand. While the same phenomena is acceptable for other formulas, Similac shows high wettability and porosity; thus, the droplet spreads and penetrates rapidly. This limits *PowDew* in accurately capturing the powder characteristics. Nevertheless, despite missing a few frames embedding the initial movement, *PowDew* is still capable of achieving a reasonable accuracy for practical use.

Furthermore, Figure 8 presents results for *PowDew* in different performance dimensions, namely recall, and precision. *PowDew* yields a high recall, indicating that *PowDew* can successfully detect counterfeit products in most cases. Focusing on the results for Similac once again, while showing a relatively lower precision of 86.7%, in which authentic cases are misclassified as counterfeit, the recall rate, indicating the rate of wrongly-classified counterfeit samples, is high (93.4%). This is important to emphasize given that reducing the misclassification of counterfeit products (i.e., maintaining high recall) is critical in our use case to minimize the chances of detrimental consequences (e.g., illnesses or even fatalities). Overall, *PowDew* achieves high recall (i.e., 92.0% - 96.3%) and precision (i.e., 92.2% - 97.9% except Similac) in classifying authentic and counterfeit powdered food products.

We further break down *PowDew*'s performance according to different adulterant cases. Figure 9 shows the average accuracy of *PowDew* for the aforementioned six original powders and three adulterants. We observe that *PowDew* generally yields high accuracy in detecting most types of adulterants (i.e., 50% mix). Specifically, *PowDew* yields an average accuracy of 96.3% and 94.0% in detecting adulteration of cheaper formulas, and whey protein powder, respectively. We attribute the high accuracy to the differences in the wettability and porosity of powdered food products between authentic products and adulterants. However, in the case of milk powder (MP) as an adulterant, we observe a relatively low classification accuracy since the core powder properties such as wettability and porosity of milk powder are more similar to the infant formulas.

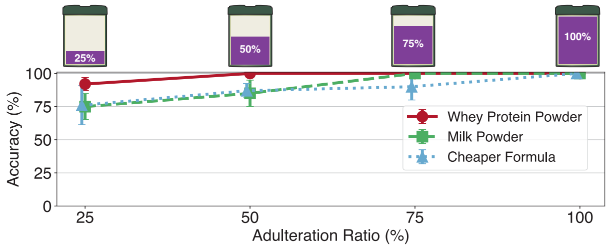

Figure 10: Accuracy with varying adulteration ratios.

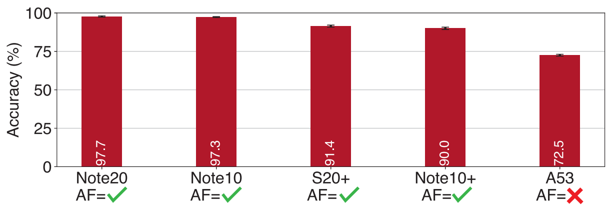

Figure 11: Accuracy for different smartphone models with varying specifications such as the autofocus (*AF*).

Overall, *PowDew* remains accurate in detecting counterfeit products across different types of adulterants.

4.3 Differing Conditions

To demonstrate *PowDew*'s practicality and robustness, we evaluate its performance under varying environmental and experimental conditions, as depicted in Figure 7(b). For experiments from §4.3.1 through §4.3.6, we select Namyang Goat Milk as the authentic product and a budget milk powder (*MP*) as the adulterant. We choose this configuration to design a self-challenging scenario since *MP* shows similar physical properties to the authentic product. Unless specifically noted, we evaluate *PowDew* using three cases: authentic, 50% adulterated, and completely substituted.

4.3.1 Varying Adulteration Ratios. Since counterfeiters may produce counterfeit products using various percentages of adulterant, we evaluate *PowDew*'s performance with different percentages of adulterant (i.e., adulteration ratio). In Figure 10, we observe an increasing trend in *PowDew*'s accuracy as the adulteration ratio increases (i.e., less authenticity). We attribute this trend to the increasing disparity between counterfeit products and authentic products. However, we observe that the accuracy is ~75% when the adulteration ratio is as low as 25%. Yet, this scenario is unlikely in reality as counterfeiters tend to lean towards higher adulteration ratios to maximize their profits [32, 84, 94]. Overall, *PowDew* is effective and robust in identifying counterfeit products across different adulteration ratios.

4.3.2 Varying Smartphone Models. Given the diversity of smartphone models, variations exist in both the users' cameras and displays. We evaluate *PowDew*'s performance across five smartphone models with varying specifications. Notably, we focus on evaluating with *unseen phones that PowDew has not been trained with.* To this end, we adopt a leave-one-out approach, where we train on four

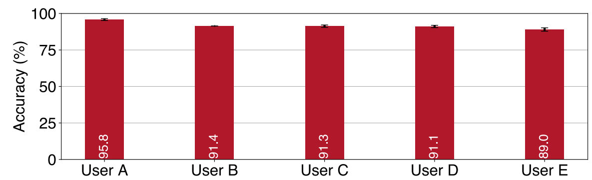

Figure 12: Accuracy for five different users operating *PowDew.*

smartphone models and test on the remaining one. We also ensure that the checkerboard appears of the same size on all smartphones (e.g., 2.5cm × 2.5cm for the center tile of the checkerboard) and that the camera-to-powder distance and position are consistent. Figure 11 depicts *PowDew*'s performance using each smartphone. We observe that smartphones equipped with auto-focus (i.e., Samsung Galaxy Note 20 [36], Note 10 [34], S20+ [37], and Note 10 [35]) achieve an accuracy of over 90%. On the contrary, Galaxy A53 [39], which lacks auto-focus features on its front-facing camera, yields the lowest accuracy of 72.5%. Without auto-focus, A53 fails to capture a clear image at close distances, causing blurry video frames and hence inaccurate detection and tracking of the checkerboard corners. To alleviate this constraint, we observe that attaching a simple and cheap off-the-shelf external lens (e.g., a macro lens) could significantly increase the sharpness of the video frames (see §5).

4.3.3 Varying Users. As *PowDew* involves user interaction to dispense droplets onto the powder, we evaluate *PowDew*'s robustness across different users. In particular, we invite five participants, all males in their twenties, and allocate a ten-minute practice session to each. This allows them to acquaint themselves with the system. This includes tasks such as aligning the spoon and dispensing water droplets. Then, each participant operates *PowDew* to collect data over a total of 60 trials, including 20 for authentic products, 20 for adulterated samples, and 20 for substitutions. We also adopt the leave-one-out approach. Figure 12 depicts the accuracy across different users. We observe that all five participants obtain a high accuracy of over 89.0% with slight variations in the accuracy. We attribute this variation to varying tilt levels and the force applied when dispensing water droplets from the dropper. We conjecture that we could further improve the accuracy by providing a comprehensive user guide, possibly in the form of a tutorial video, demonstrating common mistakes, including incorrect tilting angles. For a more fundamental improvement of *PowDew*'s usability, we envision automating the process by incorporating *PowDew* into commercial infant formula dispensers (see §5).

4.3.4 Varying Light Conditions. Given that *PowDew* captures the reflected checkerboard on water droplets, *PowDew* is sensitive to variations in lighting conditions. We evaluate *PowDew*'s performance in three lighting conditions: (1) Dark room (no lighting), (2) Daylight, and (3) Fluorescent light. We note that fluorescent lighting can occasionally create intense spot reflections on the droplet's surface, overwhelming the checkerboard's reflection. To prevent such exceptional scenarios, we position obstacles using common items like boxes and file folders around the smartphone and spoon

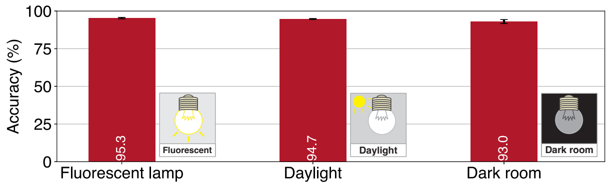

Figure 13: Accuracy under varying light conditions, namely Fluorescent lamp, Daylight, and Dark room.

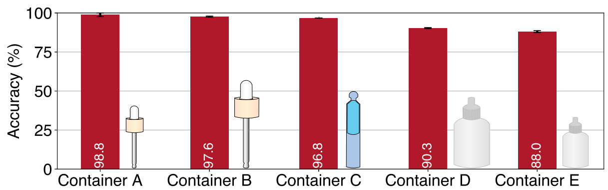

Figure 14: Accuracy with varying drop containers. Containers A and B are amples with different volumes. Container C is an eyedrop. Containers D and E are droppers with different volumes.

to block intense direct lighting. Figure 13 depicts *PowDew*'s accuracy in three lighting conditions. We observe that *PowDew* achieves a high accuracy of over 93% in all conditions. Note that *PowDew* works well even without external lighting as the smartphone's display itself illuminates the droplet. Overall, *PowDew* demonstrates its robustness to varying lighting conditions that are common in typical home environments.

4.3.5 Varying Drop Containers. Various dispenser types feature distinct tip shapes that impact the volume and velocity of the dispensed droplets. Hence, we evaluate the impact of the drop containers on *PowDew*'s performance. Specifically, we utilize five distinct drop containers as depicted in Figure 14. Note that these containers are easily accessible either online or offline. However, we observe that certain containers generate extremely small droplets, making it difficult to capture the reflected checkerboard. For such cases, we resort to dropping ***multiple droplets*** to form a larger droplet. From Figure 14, we observe that droplet containers have minimal impact on *PowDew*'s performance. Despite slight variations in droplet volume, *PowDew* consistently achieves high accuracy, surpassing 88.0% across all five containers. Overall, *PowDew* is robust to different types of drop containers.

4.3.6 Varying Powder Beds. Powdered food products like infant formula usually come equipped with spoons to maintain consistent nutrient intake. However, the size and shape of spoons vary across different brands. Hence, we evaluate *PowDew*'s performance using five distinct spoon designs from authentic infant formulas. For all spoons, we scooped a spoonful of formula and leveled the surface, which is the standard practice in preparing the formula for feeding. Figure 15 depicts *PowDew*'s accuracy for each spoon and a corresponding picture of its design. We note that *PowDew*'s performance varies slightly across spoons with different shapes and sizes, but it generally achieves a high accuracy of above 90%

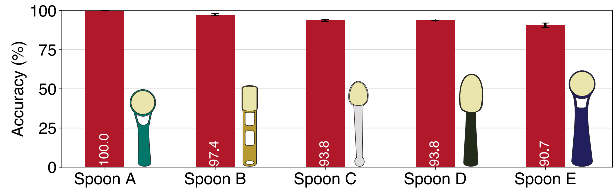

Figure 15: Accuracy under varying powder bed conditions. Spoons A to E have different sizes and shapes: circle, square, and ovoid.

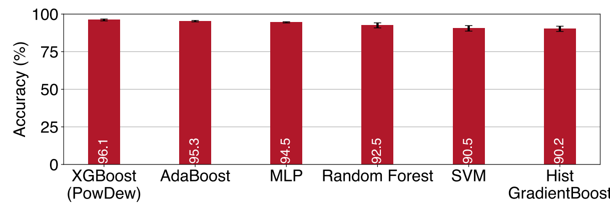

Figure 16: Accuracy of various machine learning classifier options.

for all spoons. However, we note that Spoons C, D, and E yield a relatively lower accuracy of 93.8%, 93.8%, and 90.7%, respectively. We attribute this to their relatively large size and asymmetrical shape. Instinctively, when the user uses a large and asymmetrical spoon to scoop the powder, ensuring uniform powder density throughout the entire spoon becomes challenging. As density can notably impact the powder's porosity, it results in a decline in *PowDew*'s performance. Therefore, for optimal performance, we suggest users adopt relatively small and symmetrical spoon designs like Spoon A and B. Nevertheless, our results suggest that *PowDew* is still robust to different types of powder beds.

4.4 Classifier Comparisons

Finally, we present evaluations on the impact of using different classifiers in *PowDew*. Specifically, we examine the performance of *PowDew* when employing widely used machine learning classifiers including AdaBoost [31], Random Forest [15], SVM [13], MLP [22], and HistGradientBoost [65]. Note that *PowDew* chooses to use an ensembled XGBoost model as its classifier (see §3.5). For fairness, we ensemble three versions of each classifier (with varying initialization parameters) for all cases presented in this experiment.

Figure 16 presents the classification results. We observe that XGBoost, which *PowDew* adopts, generally yields higher accuracy than other classifiers across all six infant formula products. At the same time, one important observation to make from this plot is that alternative models also show a reasonably high performance. This hints on the robustness of *PowDew*'s core functionalities. While we adopt XGBoost as the main classifier, our results suggest that other classifiers can also be used when they show higher performance with new (or different) infant formula products.

5 DISCUSSION

We now present some interesting discussion points we extract from our experience in designing and developing *PowDew*.

• **Deployment Considerations.** Recall that the current implementation of *PowDew* is limited to using only the front-facing camera, as displaying the checkerboard pattern requires the smartphone's screen. This constraint is particularly disadvantageous for phones lacking auto-focus features on the front-facing camera, such as Galaxy A53 (see § 4.3.2). To alleviate this constraint, we empirically observe that attaching a simple and cheap off-the-shelf external lens [3, 5, 6] significantly enhances *PowDew*'s performance. Furthermore, the use of foldable smartphones, like the Galaxy Z Flip [38], could enable *PowDew* to utilize rear cameras, which generally possess more advanced camera hardware.

• **Model Training in *PowDew*.** We foresee a variety of stakeholders showing interest in adopting *PowDew*. For instance, infant formula manufacturers are likely to have strong incentives to implement *PowDew*. Similarly, government agencies, such as the FDA or Customs Service, and law enforcement agencies might also consider adopting it. We anticipate that the entity adopting *PowDew* would be responsible for pre-training a target model with accurate ground truth information. Nevertheless, despite a pre-trained model, the practicality of preparing the model for all potential adulterants is implausible. Thus, to fortify the model's ability to detect counterfeit products containing unseen adulterants, strategies to mitigate this challenge must be devised. While we leave this as part of future work, a plausible direction of research could be integrating an uncertainty-based module [62, 92], which can assess uncertainties within the model's predictions to identify potential anomalies that align with previously unseen adulterants. For example, such a module could flag items where the model's confidence levels are notably low for further inspection.

• **Process Automation.** To automate the process of detecting counterfeits, we envision incorporating *PowDew* into commercial automatic infant formula dispensers [10]. These dispensers, which are becoming increasingly popular, operate similarly to an espresso machine, requiring users to simply refill the powder and water. We envision equipping these dispensers with a small camera that would deploy *PowDew* to automatically verify the authenticity of the formula before feeding the infants.

• **Extending *PowDew* to New Applications.** While we initially propose *PowDew* as a solution to detect counterfeit infant formula, its application may certainly be extended to other domains. For instance, numerous powdered food products, such as powdered milk [63, 88], spices [11, 57, 78, 79], and dietary supplements [4, 53, 86], are also vulnerable to counterfeiting [90, 99]. Furthermore, the scope of *PowDew* could be expanded to include the detection of counterfeit or substandard medicines that are in granular form, such as capsule pills. The production of these powdered food products involves complex manufacturing processes to maintain uniform nutrition and physical properties, making them suitable for use in our system. The design and experimental results for *PowDew* presented in this work suggest *PowDew*'s generalizability in a variety of sectors where product authenticity is critical.

• **Limitations of *PowDew*.** We demonstrate the robustness of *PowDew* through comprehensive evaluations involving diverse controlled variables, yet limitations may exist. Sophisticated counterfeiters emulate authentic powdered food products by employing identical manufacturing processes and ingredients. Moreover, *PowDew*'s effectiveness might diminish with extremely low concentrations of adulterants. Nevertheless, the suggested mechanisms entail significantly higher costs compared to mere adulteration or substitution, opposing the objectives of counterfeiters.

6 RELATED WORK

We now present related research in this domain and position *PowDew* among previous work.

• **Laboratory-based Solutions.** Conventional laboratory-based material testing, such as near-infrared spectroscopy (NIRS) and mass spectrometry, involves analyzing the chemical composition of substances. Researchers have explored the use of NIRS [16, 29, 40, 52, 55, 61, 97, 100] and mass spectrometry [42, 56, 83] for verifying the authenticity of various types of powdered food products. However, these methods require costly equipment and a high level of expertise, rendering them practically inaccessible to average users. In contrast, *PowDew* offers a low-cost, pervasive alternative that requires only a commodity smartphone.

• **Smartphone-based Solutions.** Recent studies explore techniques that utilize smartphones to verify counterfeit commercial products [18, 45, 81, 95, 98]. For example, *LiquidHash* [81], *CapCam* [98], and *Vi-Liquid* [45] utilizes the unique characteristics of bubbles, capillary waves, and vibration, respectively to determine liquid authenticity and physical properties such as surface tension, and viscosity. However, these approaches require transparent liquids, while powdered food products dissolve in water and result in opaque solutions. Furthermore, *MobiSpectral* [76] leverages a smartphone's infrared sensor for hyperspectral imaging to detect food fraud. However, the modern smartphone hardware does not support sufficiently high wavelengths of infrared light to detect adulteration in powdered food products. In contrast, *PowDew* employs only a single smartphone by leveraging the analysis of droplet motion on the powder bed. In addition, *FilterOp* [80] uses smartphone's display light to verify filtration efficiency of a mask. However, this method does not fit to powdered food products, since it is difficult to make powder layer consistently thin enough for light to pass through. This method also requires two smart devices unlike *PowDew*.

7 CONCLUSION

We present *PowDew*, a novel system designed to detect counterfeit powdered infant formulas using only a commodity smartphone camera. *PowDew* capitalizes on the principle that different powdered formulas exhibit unique properties upon contact with liquid, discernible through the water *droplet motion* interacting with the powder. Specifically, *PowDew* analyzes the droplet's *spreading* and *penetration*, to infer information correlated to the powder properties such as *wettability* and *porosity*, which are key indicators of the formula's authenticity. We evaluate *PowDew* with comprehensive real-world experiments under varying conditions to achieve an overall detection accuracy of up to 96.1%.

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