Low-Cost Produce Quality Monitoring at Scale: A Practical Re-purposing Framework for Pervasive Agriculture

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ABSTRACT

We contribute by presenting a framework that re-purposes off-the-shelf and low-cost components into integrated solutions that are easy to scale and deploy in the wild. We demonstrate the applicability of our framework in the context of produce quality estimation to advance the digital transformation of existing agricultural practices. The deployment of off-the-shelf technologies is critical to foster its large-scale adoption and to accelerate the automation of human manual activities. Through rigorous experiments using our proposed framework, first we demonstrate that individual off-the-shelf light sensors (in three different spectra, green, red and blue) can be easily re-purposed for produce quality estimation, and that this monitoring solution can be further integrated into off-the-shelf nano-drones to support dynamic produce quality estimation at different altitudes without degrading its estimation performance. Our work paves the way towards practical guidelines that can be used to assemble complex off-the-shelf components in a plug and play fashion.

CCS CONCEPTS

• **Computer systems organization** → Robotics.

KEYWORDS

Agriculture, Plug and Play, IoT

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1 INTRODUCTION

Agricultural practices commonly involve considerable amounts of hand work and constant human supervision. For instance, skilled visual inspection from humans is important to estimate the quality of growing produce, such that early diseases and defects can be identified [32]. Improving agricultural practices is critical for sustaining the growing world population, which is expected to increase from 7.3 billion to 9.7 billion people by 2050. A way to achieve this is to embrace the adoption of digital technologies in agriculture practices. Indeed, monitoring solutions enabled by IoT (Internet of Things), and pervasive and ubiquitous technologies can aid in providing more precise, efficient and sustainable quality control for growing produce. This directly translates into better and high quality organic products offered in retail stores to end-customers. While there is a large variety of monitoring solutions to monitor the quality of produce at different stages of the food supply chain [23], a major limitation of those is that they are difficult to scale up [34]. In practice, growing produce in an open field requires the installation of cameras and the establishment of a dedicated infrastructure to enable continuous monitoring [16]. This constraint the amount of produce in the field and introduces higher complexity in its maintainability. As a result, new innovative methods that foster deployments at scale are required.

Existing methods to improve agriculture practices are diverse, mostly requiring a static deployment of specialized infrastructure to support its monitoring. Sensor deployments to monitor the quality of soil have been investigated [21]. Camera-based methods have been explored extensively to support the detection of diseases, deformations and abnormalities caused by the environment as the produce grows [16]. Manufacturing equipment has been integrated with sensors, e.g., thermal cameras, to separate and rank the quality of produce, before dispatching to retailers. A key limitation of these methods is that it is difficult to scale them. Indeed, computer vision methods are power hungry and cannot be executed in constrained devices for running continuously [3]. Their performance also depends largely on the characteristics of the data collected. Besides this, these solutions also required a fixed deployment and specialized hardware, which is bulky and costly. Realizing the vision of digital agriculture at scale requires easy to use technologies that can operate without heavy requirements on processing power and data. At the same time, these technologies should be low-cost to foster large-scale adaptation.

In this paper, we investigate a practical framework that can be used to re-purpose and combine off-the-shelf components (in a play and plug fashion) to support the digital transformation of agriculture. By following the guidelines provided by our framework, we then design a fully off-the-shelf monitoring solution that can be used to estimate the quality of produce. Our monitoring solution

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is built by re-purposing of inexpensive light sensors (three different spectra, green, blue and red) which are also small in size and lightweight to embed anywhere. Moreover, to make our solutions scalable, we analyze how autonomous devices can be augmented with light sensors, such that it is possible to support dynamic deployments that are not tied to a specific fixed location. While there is work that has attempted to augment autonomous vehicles, e.g., AGV, UAVs; with cameras to support agriculture practices, in our work, we take a step further by investigating how off-the-shelf and miniaturized autonomous vehicles (aka nano-drones) can support produce quality estimation. Through rigorous evaluation that considers different produce (fruits and vegetables), our work shows that by re-purposing off-the-shelf technologies and combining them, it is possible to support flexible and scalable solutions that can aid current practices of produce quality monitoring.

Summary of Contributions

- **Off-the-shelf re-purposing** We design a monitoring solution to estimate produce quality using off-the-shelf and low-cost components.
- **Robust estimation** We demonstrate that our solution can monitor a wide range of different produce and generalizes to both, fruits and vegetables.
- **New insights.** We perform rigorous benchmarks that demonstrates that it is possible to estimate produce quality robustly even in the presence of high motion caused by operational navigation of the nano-drones.

2 MOTIVATION

There is a wide range of computer vision methods that can evaluate the quality of produce, either fruits or vegetables. We start by demonstrating that while these methods can detect abnormalities in a variety of vegetables, there are a number of challenges and requirements that prevent these methods to be adopted at scale. We demonstrate this by analyzing a representative application, where computer vision methods are used to detect common diseases that affect produce at any stage of its life cycle.

Dataset: We rely on the PlantVillage dataset [14], which contains samples from common produce that is grown in farms, e.g., tomatoes, potatoes, and spinach to mention some. The dataset comprises 54303 images of 38 classes, containing baseline images of high quality produce and samples from produce affected by different diseases. Sample images are split into 80/10/10 train, validation and test splits respectively. We applied well-known augmentation techniques to our samples to increase the size(horizontal & vertical flips, and brightness) on train and validation splits[33], resulting in around 87K images available to train machine learning algorithms.

Methodology: After our dataset is prepared for training, we next trained two CNN-based models: MobileNetV2 and InceptionV3. These models are selected as their performance have been reported by other work [36], making it suitable to replication. Both models were trained for 10 epochs, and the performance of the models is evaluated using different configurations, 1) training all layers from scratch; 2) training all layers from pretrained weights on ImageNet and 3) fine tuning the last linear layers from pretrained weights on ImageNet. We analyzed these configurations to have a robust characterization of performance for both models.

Results: Our results indicate that models trained with InceptionV3 generally performs better than models trained with ImageNetV2, suggesting that while InceptionV3 resulting models are more advanced for prediction, those require higher demand on (storage space) resources when compared with MobileNetV2 models, making them less suitable for constrained devices. Table 1 shows the performance of both models and compares the accuracy to detect diseases with different adopted configurations. The highest accuracy is achieved for configuration 3 that involves fine tuning of pretrained layers, this configuration also shows to be lighter in terms of resource requirements when compared to the others.

Model	Model Size (MB)	Configuration 1	Configuration 2	Configuration 3
MobileNetV2	14	0.151	0.601	**0.955**
InceptionV3	92	0.738	0.865	0.951
Total Average		0.4445	0.733	**0.953**

Table 1: Comparison of models and configurations.

Insights: Advanced machine learning models can be used to detect abnormalities in produce. However, the models that perform the best are typically pretrained suggesting that the overall pipeline and data collection cannot be handled by constrained devices. While these devices can connect to remote (Cloud-Edge-Fog) infrastructure to offload processing, this introduces higher complexity in the deployment of monitoring solutions as it becomes dependent on connectivity and availability of remote resources. Hence, existing methods can be easily used to monitor produce quality, however, its deployment in practice is difficult. Thus, solutions cannot be easily deployed nor scaled.

3 OFF-THE-SHELF PERVASIVE AGRICULTURE: PRACTICAL GUIDELINES

A key challenge for the digital transformation of agricultural practices is its large-scale deployment. Indeed, while existing monitoring solutions for agriculture have reached a good enough performance, their deployment and usage in practice requires considerable effort and large amounts of human involvement. In the following, we start by describing our vision for digital transformation of agriculture. After this, we describe the process of re-purposing off-the-shelf devices. With this information, we then show that while individual re-purposing is feasible, the integration of different off-the-shelf components is challenging, requiring to assess different characteristics of the components before re-purposing. We thus propose a framework that can aid in the integration of off-the-shelf components for practical use.

Vision: Our vision for large-scale produce quality estimation using off-the-shelf components is shown in Figure 1. In our vision, off-the-shelf nano-drones are equipped with sensing devices that are lightweight, such that they can be deployed and powered by constrained devices. Nano-drones are low-cost, have low energy footprint and their small size makes it suitable to operate and maneuver with flexibly and ease. Nano-drones can perform produce quality estimation in open fields or indoors such as greenhouses.

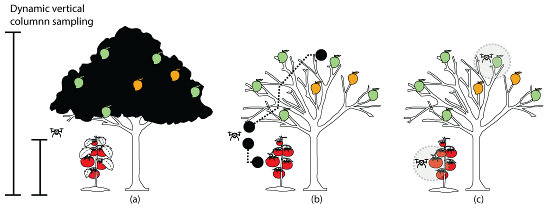


Figure 1: Vision of off-the-shelf sensors and nano-drones for produce quality estimation at scale.

Since nano-drones are equipped with all the required monitoring functionality, the deployment is dynamic and not linked to static infrastructure. Another benefit of using this solution is that monitoring is not tied to a specific view or angle, instead, nano-drones can explore and sample different vertical column heights, making it suitable for a wide range of produce at different altitudes, e.g., avocado vs tomatoes. Moreover, the complexity of performing produce quality monitoring can be reduced dynamically based on the number of flying nano-drones that are deployed.

Practical framework: Our proposed framework is shown in Figure 2 and consists of three phases, 1) off-the-shelf component selection; 2) off-the-shelf re-purposing and 3) off-the-shelf integration. Our framework provides general practices and steps that can be followed to build solutions with heterogeneous components. We next describe each of the phases in detail.

Off-the-shelf component selection: In the first phase, objectives of the application to be designed are stated along with the definition of the task. With this information, it is possible to identify available off-the-shelf components to define a comprehensive pool of different technologies that can be used. Generally, off-the-shelf components are ranked based on their flexible usage and available tools to configure and develop applications on them, e.g., APIs, IDEs, to mention some. Another key aspect that is considered is the cost of the components and availability in the market. Components that are approaching obsolescence are not taken into account, as replacing such components could necessitate restarting the entire process of integrating off-the-shelf components. As different factors can influence the selection of an off-the-shelf component, our framework defines a list of factors, which can be used to filter off-the-shelf components. This set of factors depends on the characteristics of the applications that is being developed, requiring an individual using the framework to select the most relevant factors that he or she considers important for their prototyping. Currently, our framework defines factors for energy consumption, physical dimensions, weight and sensor re-purposing complexity. The outcome of this phase is a set of off-the-shelf candidate devices that can be integrated.

Off-the-shelf re-purposing: Once off-the-shelf candidate components are selected, the second phase involves to apply re-purposing approaches on the type of sensor/device considered for the task. There are plenty of methods that can be used to re-purpose sensors [28, 41]. Different sensors could be considered to achieve the same by slightly applying different re-purposing method. For instance, produce quality estimation can be achieved by re-purposing light-sensors [47], wireless sensors [24] and thermal imaging [11].

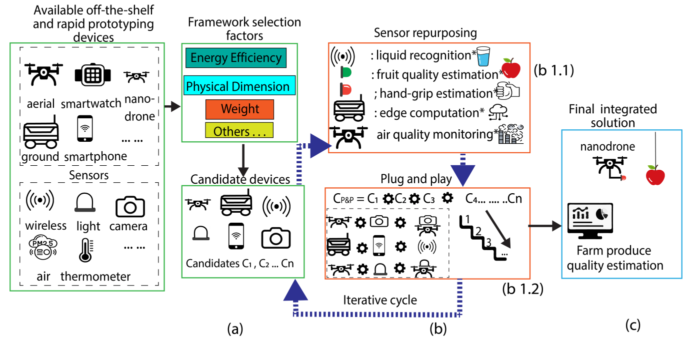


Figure 2: Framework to re-purpose [25, 38, 47] and integrate [45] off-the-shelf components. (a) Off-the-shelf component selection (b) Re-purposing approach requiring 2 steps (c) Performance analysis of integrated solution

Similarly, to this, the re-purposing of autonomous drones also has been investigated by analyzing the impact of augmenting the vehicles with sensors and computing power on demand [25]. In this re-purposing phase, the performance of each off-the-shelf component is also evaluated. This is key to derive an initial insight into the design dimensions of the integrated prototype to be constructed. Our framework defines an iterative down-to-top design approach [45], meaning that after off-the-shelf components are re-purposed (step 1), those are stacked incrementally in a plug and play fashion to achieve augmented functionality in each iteration (step 2). This iteration integration loop is finalized once the integrated prototype, either is equipped with all the functionality or an off-the-shelf component cannot be integrated nor re-purposed, requiring to restart the overall framework from the scratch.

Off-the-shelf benchmark and deployment: Lastly, in this phase, rigorous benchmarks are conducted to analyze the performance of the integrated solution prior to its deployment in the wild. Key metrics under scrutiny include accuracy, energy efficiency, and reliability, all crucial in real-world deployment scenarios. Based on benchmark results, calibration and optimization efforts may warrant fine-tuning the integrated solution. This process aims to rectify performance gaps, ensuring alignment with our objectives. Additionally, the feasibility of introducing supplementary infrastructure to enhance the integrated solution's overall performance can be explored. For example, this may involve deploying edge servers or establishing battery charging stations.

4 THE EXPERIMENTS

4.1 Light re-purposing for produce quality estimation

Re-purposing: Existing work has re-purposed light sensors (in the green spectrum) to estimate quality of produce [8]. We take this idea further by replicating and re-purposing additional light spectrum sources. In particular, we focus on RGB (Red, Green, Blue) light sources as those can be commonly found in off-the-shelf devices and rapid prototyping IoT devices. The key idea of using light sensors is to measure changes in the surface of the producing using the principle of light reflectivity [47]. As the wavelength of each sources influences these reflectivity patterns, it may be the some light sources are more suited for specific conditions and situations. We next describe the design of the experiments used to evaluate our framework. We conduct experiments to first characterize the performance of individual off-the-shelf technologies, and subsequently, we conduct experiments to evaluate the performance of the overall integrated solution. Since a number of differences exist between fruits and vegetables, e.g., latitude and superficial thickness [26], our experiments analyze each separately, demonstrating that the usage of light sensors can be generalized.

Apparatus: Cathode RGB (Red/Green/Blue) LED sensors along with a photo-resistor are used as light sources. The photo-resistor measures (5MΩ) intensity of reflected light. Light measurements are collected by attaching these sensors to a *M5StickC PLUS* , powered by ESP32 with Bluetooth 4.0 and WiFi. The board obtains obtained measurements at a sampling frequency (5Hz), and send the recorded light values to a server with the timestamp for each record. Each light sensor+photoresistor combination has has cost of around 5 EUR, and the *M5StickC PLUS* costs around 20 EUR, altogether making it low-cost for rapid prototyping.

4.1.1 Fruits.

Produce: We consider five different fresh produce that are commonly available in a supermarket and that cover all 5 main categories of produce identified in the literature: pepo (melon), pome (pear), berry (banana), drupe (mango) and hesperidium (lemon). Since it has been demonstrated that light reflectivity can capture decomposition of produce over time [47], one unit per fruits is considered, and we first focus on replicating the reported results with green light. After that, we focus on analyzing the performance of blue and red light under the same conditions. Measurements with the three sensors (RBG) are taken during 8 consecutive days.

Testbed: A controlled testbed is setup for obtaining the measurements with the sensors. The testbed design is shown in Figure 3 and consists in a black surface with strategically placed markers for positioning the test samples consistently across the experiments. This arrangement guarantees uniform assessment across all samples, eliminating variability stemming from location discrepancies. Additionally, the use of a dark background mitigates potential interference from background reflections, thus enhancing the accuracy of the measurements. Each sampled fruit is then placed 1 centimeter away from the light sensor. We also measure the ambient light of the environment where the experiment is conducted. The light intensity is measured using a LUX light meter application running in a smartphone device. Notice also that the ambient light source is located right on top of the testbed, such that it is possible to resemble daytime scenarios.

Procedure: Each sample is located in a basket and then selected randomly in each day. The fruit is located in the testbed in the position indicated by the markers. One minute measurements are taken with each sensor. The angle of the sensor and the surface of the fruit is perpendicular and fixed for all measurements. Once the fruit has been positioned according to the marked position, the light sensor collects light intensity data from various locations on the fruit's surface. First, measurements are taken with red light, then the same procedure is repeated with green and finally with blue light. The researcher achieves this by rotating the fruit to 8 different positions, ensuring randomness in the selection of spots. Additionally, the lux application meter, is used to record the surrounding light conditions during each measurement. This collected data is then logged for each individual sample over the course of the experiment, for continuous period of 8 days.

4.1.2 Vegetables.

We also conduct experiments to measure the performance of light sensors to capture decomposition in vegetables. A key difference between fruits and vegetables is that vegetables are edible from different parts of the plant, e.g., leaves and roots, while fruits are edible just from the flowering part [15]. This then suggests that vegetables may present more deformities on their surfaces, e.g., leaves, making it difficult to characterize the decomposition process.

Produce: A set of fresh vegetables commonly available at retail stores is considered for the experiment. Our selection covers the following five categories of vegetables: leaves (cabbage and spinach), stem (celery), fruits (tomato), pods (bean) and flowers (cauliflower). Since the performance of light sensors on vegetables have not been analyze previously, we selected multiple units of produce per each category. Thus, for each category of vegetable we had 2 samples, (Sample-1 and Sample-2), these two samples are selected to reduce the impact of outliers or random variations, making the findings more reliable and generalizable. The experiment was conducted for a period of 12 days.

Testbed: We rely on the same testbed design used for our previous fruit experiment. In addition to this, to measure a reference baseline for decomposition for vegetables, we also took measurements with a durometer, which measures firmness of the vegetables over time. We also measure temperature of the ambient as temperature can affect the rate of the decomposition [22].

Procedure: We employed the same procedure from the fruit experiments for the vegetable produce also the baseline durometer readings was after each measurement to quantify the firmness. However data was collected for this experiment for the definitive 12 days with ambient temperature values recorded for each day.

4.2 Nano-drone re-purposing for produce quality estimation

To analyze the integration of different off-the-shelf components using our framework, We then analyze the performance of light sensors as they are integrated into autonomous (nano) vehicles.

Re-purposing: We next proceed to re-purpose the nano-drone, such that it can be equipped with the light sensors and its respective computing units. To re-purpose the nano-drone, we analyze two payload conditions, the first condition focus on characterizing the off-the-shelf operations of the nano-drone without embedding any sensor (no-payload). After that, light sensors are embedded, and a second condition is then evaluated. In this condition, the performance of the nano-drone is measured as light sensors are embedded on it (with-payload). Besides measuring the overhead introduced to the nano-drone, we also benchmark the optimal location in the nano-drone for embedding the sensor. Indeed, the sensor cannot be attached in any random position as it can cause the nano-drone

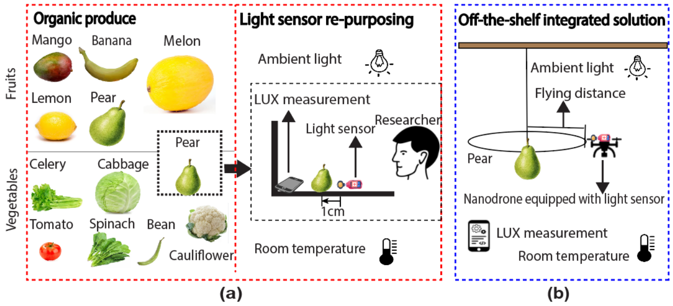


Figure 3: Testbeds design; a) Re-purposing of light sensors; b) Re-purposing of nano-drone

to lose its stability, causing operational collapse and inability to navigate correctly.

Apparatus: A commercial off-the-shelf nano-drone Loolinn U61 FPV is used for the prototype. The nano-drone is equipped with the apparatus described previously for produce quality estimation of fruits and vegetables. Nano-drone device has a cost of around 20 EUR. The overall cost of the integrated solution is less than 50 EUR.

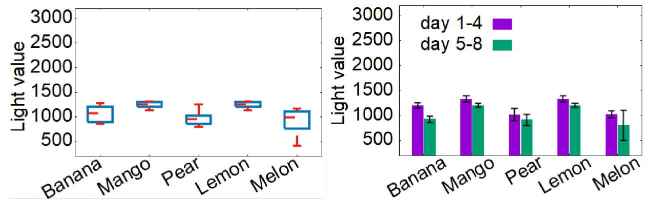
Produce: We opt to rely on an identical set of fruit samples that we previously used for investigating the light sensors. This decision was made to ensure consistency and to facilitate the potential comparison of our results with those obtained previously.

Testbed: We set up a controlled design for obtaining results from our prototype design. We marked a spot where we can hang the fruit samples with the aid of cellophane transparent tapes. The testbed area was well illuminated with light while we strategically made sure each fruit sample is always at an elevation of 2 meters above the ground level to simulate natural growth environment of the fruits that is typically challenging for human access. We also took measurements of the ambient light and temperatures of the environment ascertain if they affect the rate of decomposition of the fruits. Figure 3(b) shows the typical testbed design.

Procedure: We conduct flights with our nano-drone, equipped with the light sensor (red light because of its longer wavelength), flying in close proximity to the fruit. The researcher/operator managed the distance between the nano-drone and the fruit sample to prevent any collisions with the fruit samples. This was carried out using the testbed area with each flight lasting approximately 30 seconds. The experimental prototype underwent a total of 10 flight trials, around the different fruit samples. During each flight, data on light intensity, ambient light and temperatures were collected in a similar manner to the method used when using the light sensor in isolation.

5 RESULTS

Light performance on fruits: Figure 4(a) shows the result of using green light, which matches the results reported from the literature. In addition to this, Figure 5(a) and (c) shows the re-purposing of red and blue lights for produce quality monitoring. From the results, we can observe that any light source can capture the decomposition of produce. Statistical analysis, including Kruskal-Wallis tests, indicated significant differences among various fruit groups for blue, green, and red light colors. Specifically, red and green lights sensing



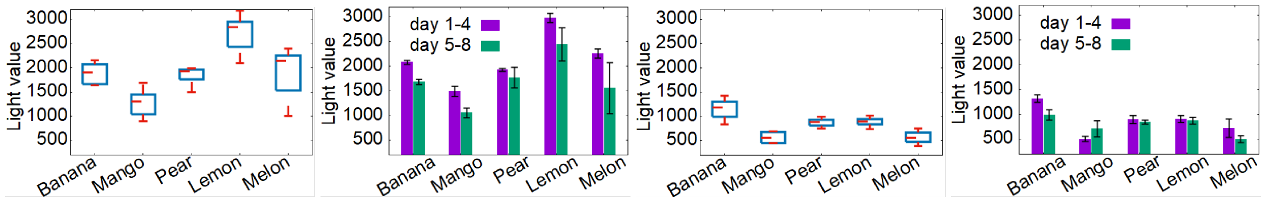
(a) **(b)**

Figure 4: Green light characterization ;(a) Light values across decomposition period (b) Light variation across two periods

yielded good results (Blue: $\chi^2 = 45.72$, $\eta^2 = 0.61$, $p < .05$, Green: $\chi^2 = 38.30$, $\eta^2 = 0.52$, $p < .05$, and Red: $\chi^2 = 46.29$, $\eta^2 = 0.63$, $p < .05$). Pairwise post-hoc comparisons (Dunn-Bonferroni) further confirmed distinctions, while acknowledging specific cases with limitations. In parallel to this, Figure 5(b) and (d) show the Mean Absolute Deviation (MAD) of light values, highlighted differences under same ambient conditions. Wilcoxon-signed rank tests between two periods (days 1-4 and days 5-8) revealed statistically significant differences in light values for most fruits, except for blue light sensing. This potentially suggests that blue light sensing can characterize types of fruits, but not very reliable to capture their decomposition. At the same time, Figure 5(a) shows better performance of red light when compared with green light (Red: $Z = 739, r = 0.69, p < .05$; Green: $Z = 687, r = 0.69, p < .05$), indicating that red light is more suitable for both, fruit characterization and monitoring of fruit decomposition.

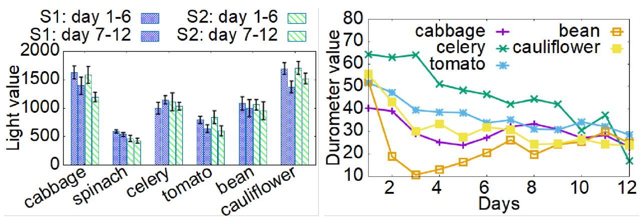
Light performance on vegetables: We next demonstrate the performance of different light sources for characterizing vegetables and monitoring their decay. As noted before, there are drastic superficial differences between fruits and vegetables. Thus, the generalization of the method for any type of produce is critical for having a robust solution. Figure 6 displays the median and standard deviation (SD) of ripe (days 1-6) and decay (days 7-12) stages for each vegetable item in two different day intervals, distinguishing between sample-1 and sample-2 for blue light. This result further supports the effectiveness of using different light colors' reflectivity values to accurately estimate the quality of vegetables. Kruskal-Wallis test confirms the differences to be significant between various vegetables (Blue: $\chi^2 = 73306$, $\eta^2 = 0.82$, $p < .05$, Green: $\chi^2 = 76754$, $\eta^2 = 0.85$, $p < .05$, and Red: $\chi^2 = 67493$, $\eta^2 = 0.75$, $p < .05$). These variations constitute unique fingerprints that allow to determine the vegetable type irrespective of samples. Given the observations of vegetable items from red, green and blue light sensors for both sample groups, light reflectivity pattern and 12-day long time span, it appears that blue light is most appropriate for conducting individual analysis. In addition, Figure 7 demonstrates the blue light median values with a 95% confidence interval (CI) of sample-1 and sample-2 for each day over the 12-day decomposition period. The ability of blue light reflectivity to capture produce quality is then assessed independently for the vegetable items.

Payload performance of nano-drone: We start by observing the overall operational behavior of the nano-drone. Without any extra payload, it was observed that the nano-drone was able to remain stable for a period of time, but as the battery was drained (aka low energy available), landing policies were triggered and the



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

Figure 5: Red and Blue light characterizations; (a) Red light values (b) Red light variation across two periods (c) Blue light values (d) Blue light variation across two periods



(a) Blue light **(b) Durometer**

Figure 6: Light characterization for vegetable; (a)Two-stage median + SD light values (b) Average durometer readings

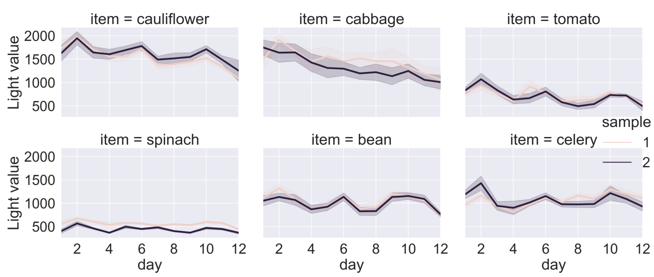


Figure 7: Blue light Day-wise median + 95% CI light values

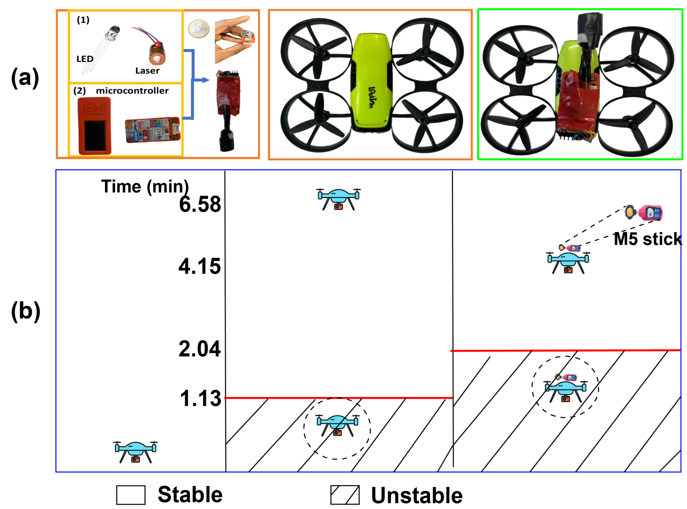


Figure 8: Nano-drone re-purposing; a) Nano-drone and light sensor prototype; b) Nano-drone operational flight time.

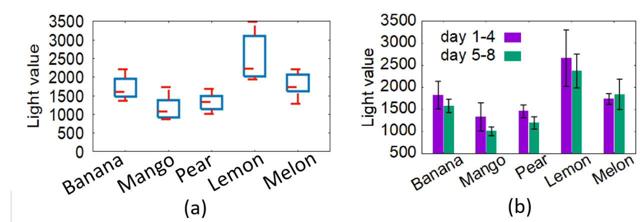


Figure 9: Nano-drone repurposed prototype (a) Light values from nanodrone (b) Light variation across periods.

nano-drone tend to collapse spontaneously. Figure 8 shows further results of our experiment with and without payload. The nano-drone and the light sensor were found to have weights of 62 g and 24 g, respectively. The total operational time of the nano-drone without the light sensor was recorded as 6.58 minutes, and it could be controlled at different altitudes; however, when the time ran down to 1.13 minutes, the nano-drone was unable to remain stable flying in the air. Similarly, when the light sensor was mounted on the nano-drone, the total operational time dropped to 4.15 minutes. This means that the extra payload reduced the usage of the nano-drone by 2 minutes. At the same time, when the time ran down to 2.04 minutes, the nano-drone loss its stability. This indicates that the extra weight not only reduce the operational time, but it also influenced the overall landing policies by accelerating them. The overall process is depicted in Figure 8(b).

Light performance during flying motion: Next, we evaluate the performance of light as the sensors are integrated into nano-drones. Figure 9 show the results. From the figure, it is possible to observe significant variations when employing the light sensor coupled with the nano-drone prototype. Indeed, light measurements tend to have more variations due to the flying motion of the nano-drone. However, it is still possible to observe accuracy characterization and identification of decay when using red light as a source. Kruskal-Wallis test indicate significant differences ($\chi^2 = 27.87$, $\eta^2 = 0.53$, $p < .05$) for the whole analysis period. This indicates that by re-purposing individual off-the-shelf components and integrating them into a single combined solution, it is still possible to monitor produce quality. All in all, while our integrated nano-drone with light sensors can be used for both, fruits and vegetables, our results indicate that the solution may be more suitable for fruits.

6 RELATED WORK

Produce quality estimation: Produce quality estimation has predominantly been a manual human task. This approach is inefficient, laborious, and not suitable for large-scale quality estimation. Besides, it is also subjective and highly susceptible to error, causing inconsistencies in quality evaluation [32]. In recent times, other methods have been explored. For instance, the spectral imaging method; While this method reveals the innermost attribute of produce for estimating quality, it relies on specialized equipment and high-level data analysis know-how[44]. Similarly, the computer vision-based approach employs visual data to estimate quality, but it remains vulnerable to changes in environmental conditions like light variations and adverse weather conditions (such as rain and fog) [7]. Other methods like thermal imaging, wireless signals [13], and NIR spectroscopy [18] are non-invasive, but they need specialized tools and technical expertise and can be limited by calibration. Our work relies on the simple principle of light absorption and reflection for estimating produce quality. We combine the off-the-shelf red, green, and blue light of the light spectrum for collecting light values of produce, which is then used to characterize the quality of produce.

Drones and AGV for produce quality: The desire to reduce the risk involved in agricultural process and increase farm productivity and quality are driving the integration of drones and autonomous ground vehicles (AGV) into farming operations [5, 30]. They are leveraged for agricultural field and crop monitoring [31] and other purposes during different phases of agricultural activities. Prior to commencing planting, drones and AGV can be utilized for regular data collection to support pre-farming activities for bolstering high produce quality. For instance, drones and AGV are used for soil sampling (field) for collecting data that can be used to understand soil topography, nutrient level and manage irrigation for optimal planting[35]. Moreover, they can be instrumented for specialized functionality to preserve the quality of produce during planting and harvesting such that they can be utilized for seeds dissemination [46], control of dispensation of fertilizers and nutrients [19], pest and disease management[40], and crop maturity monitoring[4, 31].

Pervasive sensing: Sensor technology and network infrastructure advancements have paved the way for extensive data collection using lightweight devices. In agriculture, a diverse range of sensors, including imaging sensors like cameras, wifi, light, thermometers, accelerometers, magnetometers, and humidity sensors, have been successfully deployed to gather data. These sensors function within the agricultural domain, capturing real-time data that provides valuable insights into resource utilization, field productivity, crop health, and livestock behavior. Image sensors encompass various types of cameras, such as multispectral cameras [27], hyperspectral cameras [26, 42], Near Infra-Red(NIR) [37, 39], thermal cameras [9, 10], and RGB camera[17], in conjunction with other sensors, to collect visual data from agricultural fields. These non-destructive and non-invasive techniques offer a means to acquire data for studying and monitoring produce quality [18, 42], detecting plant diseases[17], monitoring stress levels [6], and soil nutrient and plant health [29]. Wireless technologies provide flexible and cost-effective solutions for monitoring crops and agricultural areas. Sensors like wifi have been utilized for spatial data collection, irrigation planning, application of essential soil nutrients, pest control, influence livestock behavior, and precision planting [2, 12, 20, 43].

7 DISCUSSION

Room for improvement: We demonstrate that by re-purposing different off-the-shelf components, it is possible to build an integrated solution to perform produce quality estimation. While we focus on re-purposing light sensors to identify the decomposition state in fresh produce, other sensors could be selected and re-purposed to achieve the same task. For instance, wireless sensing can be used to characterize different fruits [24]. Ultrasound sensors could also be used to identify continuous changes on surfaces as it has been demonstrated that ultrasound signals characterize different materials [1]. Besides this, we are also interested in investigating further how to assemble and coordinate swarms of off-the-shelf nano-drones for massive monitoring of produce in open fields. Moreover, further investigation into 3D printing could provide valuable insights into mapping integrated off-the-shelf components into a 3D printing encasing.

Autonomy: By using our framework, we demonstrate that it is possible to combine different off-the-shelf technologies into a single monitoring solution. This solution, however, is partially autonomous and currently requires human-in-the-loop operators to control the navigation of the nano-drone. We are interested on investigating further how fully autonomous capabilities can be granted to off-the-shelf solutions consisting of heterogeneous components. Ultimately, fully autonomy may require a central master component controlling and regulating all the augmented off-the-shelf components, following a plug and play approach [45].

Surrounding proximal infrastructure: While in principle, it is possible to execute heavy processing in our current prototype. It is possible to improve the efficient operations of our prototype if external services are available. For instance, object detection services could be deployed and accessed on the edge to avoid the battery drains of constrained devices. In this manner, the nano-drone could preserve its energy and improve its navigation to target behavior, which incidentally will improve the quality of estimation.

Recurring issues: The battery life of autonomous drones is a critical issue for their effective operations. Nano-drones are not exempt from it and present even more constraints for operational usage. Nano-drones can operate for less than an hour. This is a recurring issue that constrained technologies face. Advancements in energy transferred using WiFi can be considered as part of the deployments to make nano-drones even last longer.

8 SUMMARY AND CONCLUSIONS

In this paper, we presented a practical framework that re-purposes off-the-shelf and low-cost components into integrated solutions that can be easily scaled and subsequently deployed in the wild. We demonstrate the potential of our framework by presenting a monitoring solution that can be built for produce quality estimation (with less than 50 EUR cost), fostering further the digital transformation of agricultural practices. Through rigorous experiments and benchmarks that analyze the performance of the re-purposed technologies (three different light sensors and a nano-drone), our results indicate that off-the-shelf light sensors embedded in autonomous (nano) drones can perform produce quality estimation with high accuracy. Our work paves the way towards practical guidelines that can be used to assemble complex off-the-shelf components in a plug and play fashion.

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