HyperNut: Hyper Spectral Dataset of Nuts for Unsupervised Defect Detection and Segmentation

Afshin Dini[a], Farnaz Delirie,[b] and Esa Rahtu[c]
Unit of Computing Sciences, Tampere University, Finland

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Abstract: Hyperspectral Imaging (HSI), providing detailed information from various spectrums, is a suitable candidate for detecting defects in real-world applications, which is a hot topic in the field of computer vision nowadays. We introduce the HyperNut dataset, containing hyperspectral images of almonds and pistachios in the visible and near-infrared (VIS-NIR) ranges (400nm-1000nm). This dataset contains non-anomalous samples that can be used for training unsupervised approaches and defective samples for testing purposes. To our best knowledge, our dataset is the only one in the literature that (a) allows a thorough analysis of nuts quality by providing different types of defective samples, (b) provides real-world samples containing multiple objects and considering noise and variable environmental conditions while sampling, and (c) allows defect segmentation by providing masks presenting exact locations of defects in samples. Moreover, we have tested basic and simple anomaly detection methods on the hyperspectral data and the related RGB images and compared the results to show that hyperspectral images are suitable candidates for defect detection problems.

1 INTRODUCTION

Generally, anomalies refer to patterns in the data that differ significantly from the typical behavior of normal patterns (Cao et al., 2024; Dini and Rahtu, 2025). Similarly, defect detection and segmentation are the processes of finding and locating abnormal patterns, respectively (Rippel and Merhof, 2023). Defect detection plays a vital role in many real-world applications, such as manufacturing quality control (Dini et al., 2024), industrial inspections (Dini and Rahtu, 2024; Dini and Rahtu, 2023; Dini and Rahtu, 2022), and autonomous driving (Bogdoll et al., 2022), where identifying defects properly enhances efficiency and effectiveness.

Many anomaly detection methods (Rippel and Merhof, 2023) have been developed for different applications, mainly based on the datasets containing RGB images (Bergmann et al., 2019; Zou et al., 2022; Mishra et al., 2021) or 3D images (Bergmann et al., 2021; Bogdoll et al., 2024; Liu et al., 2024a). However, they cannot detect all types of defects due to some intrinsic limitations of RGB images. First, RGB images struggle to recognize subtle defects, specifically if they appear in the same color or pattern as the main object. Moreover, they face some difficulties in representing defects that are related to the material of the object rather than only the patterns (Xu et al., 2022).

To deal with these challenges, we believe that utilizing other types of data, such as hyperspectral images, is a better solution to anomaly detection problems (Udayanga et al., 2024). While RGB images capture only three spectral bands, as red, green, and blue, hyperspectral images capture hundreds of contiguous narrow bands across a wide range of spectra, providing unique and rich spectral fingerprints for each material (Bhargava et al., 2024). Hyperspectral imaging enhances the defect detection performance by capturing spectral data beyond the visible range, allowing the precise differentiation between normal and anomalous patterns (Zhang et al., 2022). Moreover, it is better suited to detect small anomalies that may be overlooked in RGB images, such as contamination, minor defects, or subtle material differences (Ozdemir and Polat, 2020).

We notice the lack of such a hyperspectral dataset in the field of anomaly detection, as a result of which,

[a] https://orcid.org/0000-0001-6234-3322
[b] https://orcid.org/0009-0007-5790-2215
[c] https://orcid.org/0000-0001-8767-0864

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we gather a dataset named HyperNut, containing hyperspectral images from nuts, such as almond and pistachio, in 400nm-1000nm spectra. Due to intrinsic complexities of anomalies such as rareness, unknown-ness, and diversity (Liu et al., 2024b), collecting labeled datasets for training supervised approaches would be difficult as defects occur rarely and are unknown before happening in real-world applications, in addition to the fact that they can appear in different shapes, sizes, and types. So, our dataset contains only normal samples for training purposes, while containing different types of anomalous samples alongside normal ones for testing purposes.

To our best knowledge, HyperNut is a unique dataset that (1) provides VIS-NIR data for almonds and pistachios containing different types of defects such as scratches, holes, insects, broken parts, external materials, etc., (2) contains real samples considering the effects of noise and change in environmental conditions, which is neglected in previous works, (3) contains multiple objects data samples that not only simulates the real-world conditions better than the previous similar works, but also have difficulties of the non-alignment objects which does not exist in previous works, (4) includes defect masks that can be used in developing defect detection and segmentation methods simultaneously. It is also good to mention that we collected hyperspectral images in the visible near-infrared range that can be used not only for material defects detection but also for detecting anomalies in colors, shapes, etc. Not only have we demonstrated that hyperspectral images represent anomalies better than RGB ones, but we also evaluated our dataset with basic methods, providing the baseline results for anomaly detection in hyperspectral images.

2 RELATED WORK

2.1 Hyperspectral Imaging in Computer Vision

Hyperspectral imaging (HSI) has emerged as a powerful non-destructive analytical technique in the quality and safety assessment in many applications (Mohammadi Moghaddam et al., 2013). By capturing spatial and spectral information across a wide range of wavelengths, HSI enables a detailed analysis of the chemical and physical properties of objects.

Hyperspectral images can be taken in three main ranges as visible (400nm-700nm), near-infrared (700-1100nm), and short-wave (1100nm-2500nm) ranges. It is shown in (Chandrasekaran et al., 2019) that hyperspectral data in the visible range are suitable for detecting surface defects mainly related to colors, patterns, and sizes, while near-infrared data are suitable for detecting contents of the objects.

Recent research has explored hyperspectral imaging (HSI) for various applications. (Aktaş et al., 2022) demonstrates HSI's effectiveness in assessing nut quality and safety, including classification, composition prediction, and texture analysis. Similarly, (Mohammadi-Moghaddam et al., 2018) shows that neural network models can use HSI data to predict moisture content and texture in roasted pistachio kernels, improving processing control. Other studies have used VIS–NIR HSI to detect fungal infection (Kheiralipour et al., 2016) and aflatoxin contamination in nuts (Wu and Xu, 2019). However, these studies focus on detecting specific nutrients and have notable limitations. Their datasets are not generalizable, are not publicly shared, and are unsuitable for anomaly detection. They are collected in controlled environments that remove real-world noise, and each sample contains only a single object, unlike real applications, where multiple objects and more complex conditions must be handled.

2.2 Anomaly Detection Methods

Many deep learning methods have been proposed for defect detection using RGB image datasets (Liu et al., 2024b). Based on the availability of normal and abnormal samples, these approaches are typically classified as supervised, semi-supervised, or unsupervised (Mohammadi et al., 2021). Supervised methods rely on labeled normal and anomalous data, which are difficult to obtain due to the rarity and unpredictability of defects (Palakurti, 2024). Unsupervised methods (Aytekin et al., 2018) require no training samples and generally detect outliers through clustering, but they often struggle with subtle defects. Semi-supervised methods (Liu et al., 2024b) are more practical for real-world RGB applications, as they learn patterns from normal data and identify anomalies by measuring deviations, requiring only a small number of normal samples for training.

Although detecting defects in RGB images is a well-known problem in the field of computer vision, there is not much effort to detect chemical and physical defects in hyperspectral images. As hyperspectral cameras become more affordable and provide detailed information, they can also be used for anomaly detection purposes, which increases demand for hyperspectral datasets across various applications.

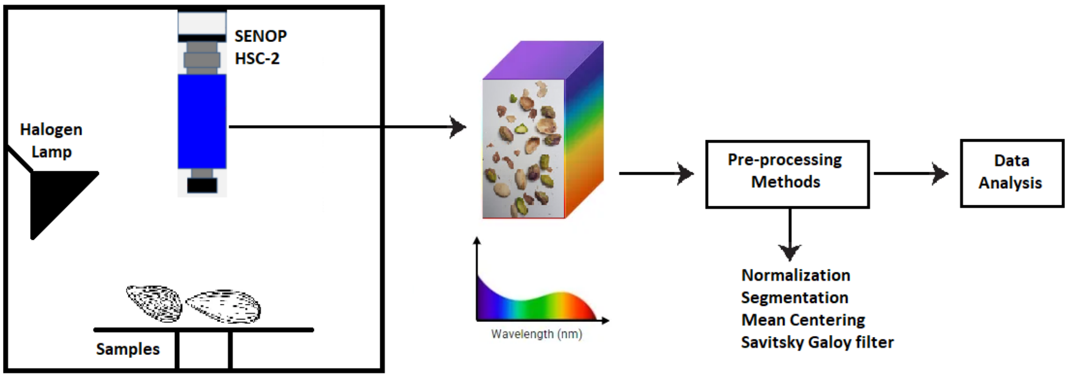


Figure 1: Dataset collection setup and pipeline overview.

3 DATASET

Hyperspectral imaging is well-suited for anomaly detection because it captures rich spectral information that reveals material-specific characteristics not visible in RGB images. Each hyperspectral band provides unique information, making the technique effective for tasks such as defect detection. Surface abnormalities in shape, color, and pattern are best detected in the visible range (400–700 nm), while near-infrared wavelengths (700–1000 nm) highlight chemical differences within samples. Short-wave infrared ranges (1000–2500 nm) are particularly useful for identifying specific materials, such as oils.

According to the properties of different hyperspectral ranges, visible and near-infrared cameras could simultaneously detect physical and material abnormalities. For this reason, we collected data in the VIS-NIR range. Moreover, our dataset, HyperNut, contains images of nuts, such as pistachios and almonds, as analyzing nuts is an interesting topic among researchers. In the next sections, the data collection procedure and setup are introduced, data samples are described, and the pre-processing useful for further analysis is listed, which allows everyone to use them for anomaly detection and segmentation problems.

3.1 Data Collection Setup and Process

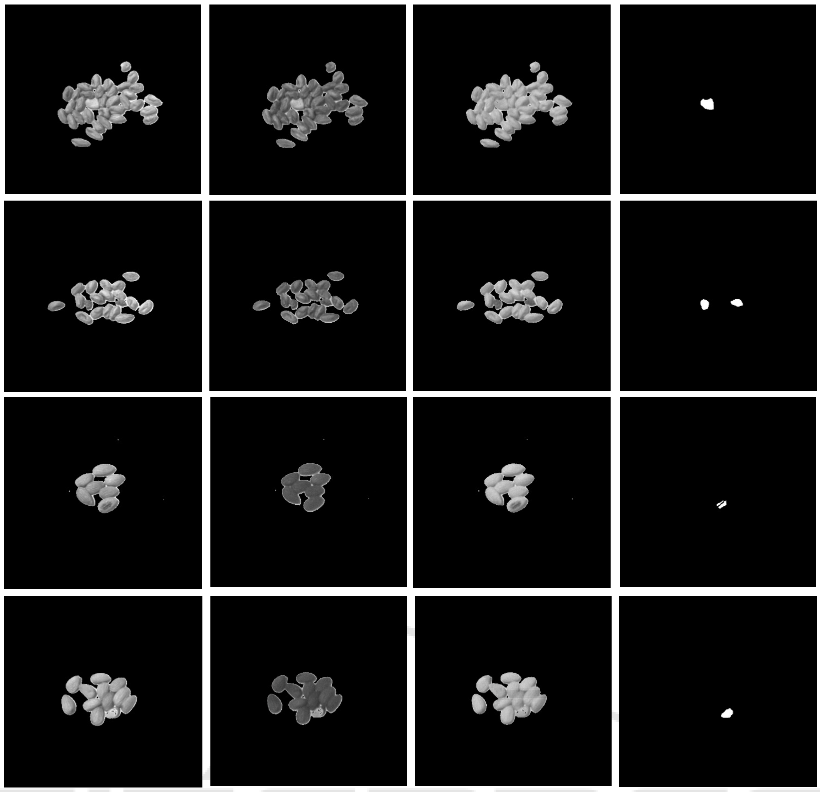
The setup overview with which we collect the data is shown in Fig. 1. Hyperspectral images are taken with a SENOP HSC-2 camera that can capture images with spectral precision of 1nm in the VIS-NIR range. To collect a generalized dataset that can be used for different purposes, such as anomaly detection and segmentation, the images are collected in 600 spectra bands between 400nm-1000nm and also 1024×1024 spatial resolution. The hyperspectral images are saved into two files. An HDR file contains metadata such as wavelength bands, and a DAT file contains the hyperspectral data in 12-bit resolution.

It is important to emphasize that hyperspectral imaging relies directly on proper lighting conditions to ensure accurate data capture and analysis. Lighting significantly affects the quality of hyperspectral images by influencing factors such as reflectance, signal-to-noise ratio, and spectral consistency. Moreover, as the hyperspectral camera measures the reflectance of lights in different bands from the sample, the light should contain all the required wavelength bands. To collect the proper data, we utilized halogen lamps with 45-degree angles compared to the camera, which provides the appropriate wavelength bands for VIS-NIR imaging.

3.2 Data Description

Our dataset, HyperNut, contains images of two types of nuts, pistachios and almonds. The reason for selecting these nuts is that the food industry is interested in removing defective objects from almonds and pistachios before sorting them. Although few researchers have attempted to deal with this topic from a specific point of view (Panda et al., 2022; Mohammadi-Moghaddam et al., 2018; Kheiralipour et al., 2016; Wu and Xu, 2019; Mishra et al., 2024), they are not generalized enough to tackle the problem from different points of view, and the datasets are also not public for further analysis.

The HyperNut dataset is collected in such a way that it contains many types of defects that can be used for real-world applications, such as nut defect detection and sorting. Our dataset contains only normal samples for training semi-supervised anomaly detection methods, while it contains normal and anomalous samples for testing purposes. Defects in the test dataset may appear in the data samples themselves,



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

Figure 2: Samples overview of nuts. The first 2 rows are from the pistachio sub-dataset, and the next 2 rows are from the almond sub-dataset. Images are from wavelength (a) 406nm, (b) 520nm, (c) 850nm. (d) is segmentation mask that shows the location of anomalies.

Table 1: Overview of the HyperNut dataset, its categories and descriptions.

Category	Training Dataset	Testing Dataset			
	No. Normal Samples	No. Normal Samples	No. Abnormal Samples	Defect Groups	Abnormalities Types
Almond	100	26	35	6	scratch, broken, rotten, insect, external material, mix
Pistachio	118	36	35	6	branch, shell, stone, insect, external material, mix

such as scratches, broken parts, and insect effects on the almond dataset, or even as other objects in the pistachio dataset, such as branches, stones, and shells. Due to the unknown-ness property of the defects, our dataset also contains defects as external materials, which refer to all other types of unexpected objects that may exist in the data samples. It is also good to note that the defective samples in the test dataset are manually labeled by experts.

The dataset overview is presented in Tab. 1. Moreover, as is shown in Fig. 2, hyperspectral images provide detailed information that can be used to detect defects. It is clear that various types of defects can appear better in specific wavelengths than others. For example, in pistachio samples, stones can be detected in the 850nm band, while shells are more visible in the 520nm wavelength. On the other hand, in almond samples, rotten defects are visible in 406nm band better than in other bands, while broken parts are better visible in the 520nm band. In addition, as shown in Fig. 2(d), ground truth masks, which specify the exact location of the defects, are also provided for anomaly segmentation purposes. The HyperNut is available in https://huggingface.co/datasets/industoai/HyperNut.

3.3 Pre-Processing Methods

Before using hyperspectral images to develop different methods, a few pre-processing techniques should be applied to the data, as shown in Fig. 1. Normalizing data is the first important one. The data should be normalized based on the maximum and minimum values, which represent the completely white and dark areas, respectively.

Because environmental noise and background reflections affect the samples, isolating the Region of Interest (RoI) is essential. We use Otsu thresholding (Otsu et al., 1975) and find that the 600 nm band yields the best segmentation, outperforming other wavelengths and RGB images since it is less affected by noise. This illustrates a key advantage of hyperspectral imaging: different wavelengths reveal different information, enabling even simple tasks like RoI extraction to be more robust. Besides normalization and segmentation, the noises on the spectral data are filtered by the Savitzky-Golay filter (Schafer, 2011), which itself increases the performance of defect detection significantly. Moreover, it is important to remove the offset that may appear in different samples due to changes in the lightning or other environmental conditions. A mean centering filter is utilized for each spectrum to remove the offset between the samples.

4 EXPERIMENT

In this section, we not only attempt to show that hyperspectral data presents detailed information compared to RGB ones, but we also provide a baseline result for defect detection on our dataset, allowing further development in the future. To reach this goal, two methods such as PaDiM (Defard et al., 2021) and PacthCore (Roth et al., 2022) are tested on different wavelengths of the HyperNut dataset, and the results are compared with RGB ones extracted from specific bands of the same dataset. The main goal is to show that defects appear in different bands better than RGB, as is already shown in Fig. 2.

4.1 Method

To highlight the advantages of hyperspectral data over RGB images, two state-of-the-art anomaly detection methods as PaDiM (Defard et al., 2021) and PacthCore (Roth et al., 2022) are tested on our dataset. The overview of both models is shown in Fig. 3. It is good to mention that in both methods, a model is trained only based on normal samples, as a result of which it can detect the normal pattern of the data, while anomalies can be distinguished based on how far they are from the normal patterns. In both methods, the features of hyperspectral images, on specific wavelengths and also RGB bands, are first extracted with the help of a pre-trained feature extractor, which is ResNet18 (He et al., 2016). Then, different approaches are used to learn the normal patterns from the features of normal samples and to separate anomalies from normal samples. PaDiM finds the Gaussian distribution of the normal features in each pixel and then, in the testing phase, detects the anomalous pixels of the test sample by finding the distance of the test features to their related normal features. On the other hand, PatchCore collects a memory bank of patches from the normal features and then makes clusters from similar feature patches. In the testing phase, the closest distances of the feature patches of the test samples are calculated from the normal clusters in the memory bank, and the anomalies are recognized on the basis of their distances. We applied both methods on RGB bands, 406nm, 520nm, and 850nm separately and compared the results in Section 4.3.

4.2 Metric

Although the performance of deep models can be evaluated with different metrics, the Area Under the Receiver Operating Characteristic Curve (AUROC) is the most suitable metric in the assessment of anomaly detection methods. Since defect detection methods output anomaly scores, AUROC evaluates performance across all thresholds without requiring a predefined one. It also captures the trade-off between true and false positive rates, providing a single, comprehensive measure of model performance. For these reasons, we use AUROC to compare the proposed methods.

4.3 Results

The qualitative results of applying the anomaly detection and segmentation methods on HyperNut are shown in Fig. 4. As irregularities appear in specific wavelengths better than others, applying a detection method, even on a single band, allows one to detect defects and locate them. The quantitative results are also presented in Tab. 2. It is clear that the anomalies appear on the 406, 520, and 850-nanometer wavelengths of Pistachio better than the RGB ones, and the PatchCore method is able to detect and locate them. On the other hand, almond defects are more visible in the 520nm band than in the RGB ones. One can conclude that hyperspectral data contains more detailed information for defect detection than RGB ones, al-

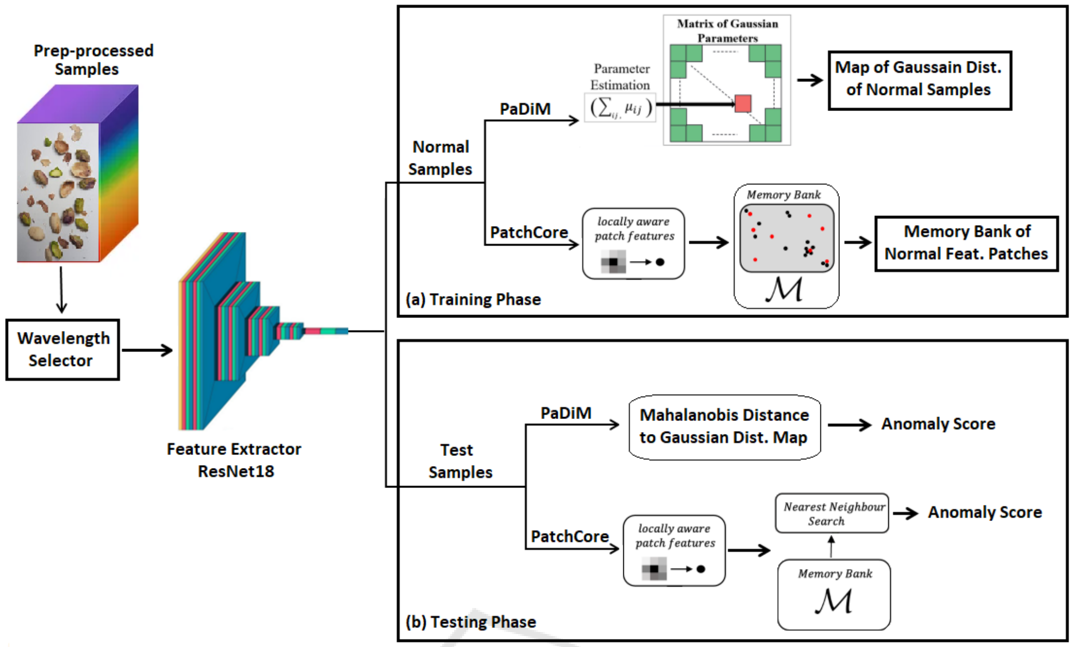


Figure 3: Overview of PaDiM (Defard et al., 2021) and PatchCore (Roth et al., 2022) methods, applied to HyperNut as baseline methods.

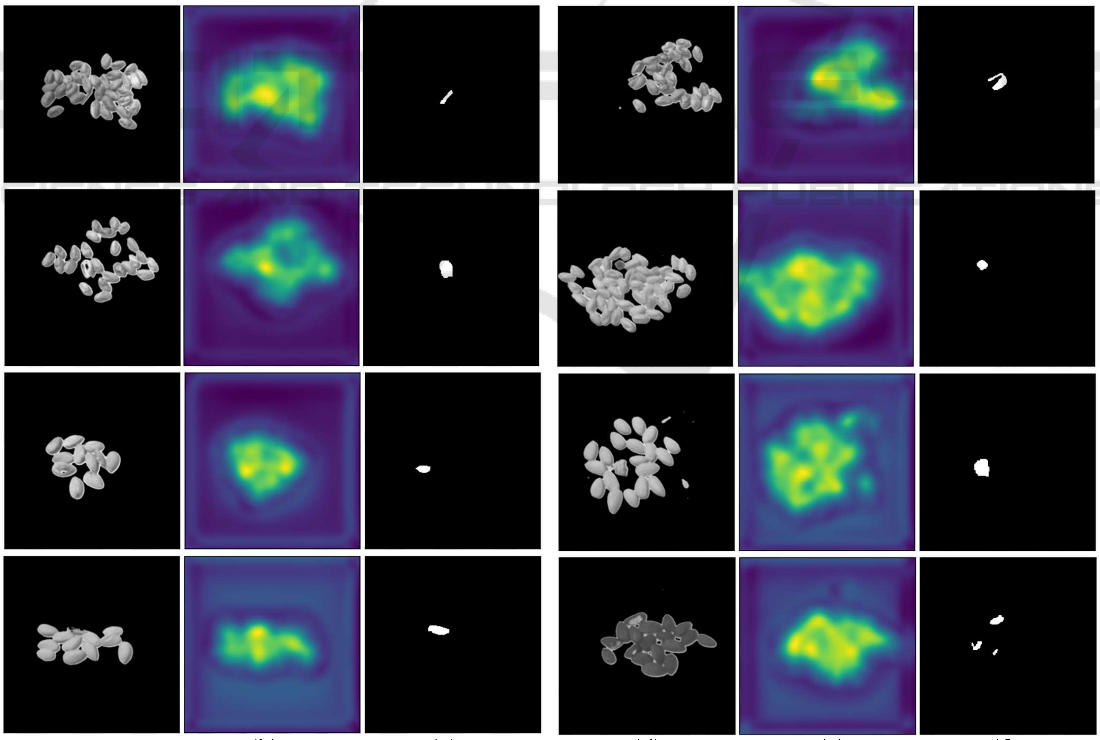


Figure 4: Results of applying the PatchCore (Roth et al., 2022) on different wavelengths of hyperspectral data to detect defects. (a) and (d) are hyperspectral images at a specific wavelength, (b) and (e) are color jet images of the final results which specify the location of anomalies, (c) and (f) are ground truth masks.

Table 2: Results of applying the defect detection methods on HyperNut prsenting in AUROC per sub-dataset.

	PaDiM (Defard et al., 2021)				PatchCore (Roth et al., 2022)			
Category	RGB	406nm	520nm	850nm	RGB	406nm	520nm	850nm
Almond	53.2	51.7	54.7	51.5	55.2	54.6	**59.8**	57.6
Pistachio	67.9	64.5	67.1	68.1	71.9	79.5	81.7	**82.8**
Average	60.5	58.1	60.9	59.8	63.5	67.0	**70.7**	70.2

though finding the correct bands requires a thorough analysis of the data. It is important to emphasize that the above-mentioned results are based on using only one hyperspectral band for defect detection purposes, although other wavelengths contain useful information. The main goal of this work is to show that hyperspectral data contains more data than RGB ones, indicating that they are a better candidate for anomaly detection purposes. Developing a method that utilizes multiple spectral bands of the data requires further research, which the HyperNut dataset makes possible.

5 CONCLUSION

We introduce HyperNut, a new dataset of visible and near-infrared hyperspectral images from pistachios and almonds, collected in real conditions with multiple objects, noise, and varying environments. Because hyperspectral data provide richer information than RGB, they are well suited for nut quality assessment and for developing defect detection and segmentation methods. To demonstrate this, we apply two baseline anomaly-detection methods on selected wavelengths and RGB bands, showing that hyperspectral data better reveal defects across different spectral ranges. HyperNut also enables future research on multi-band defect detection to further improve performance.

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