

$\frac{2}{3}$ of the sound and punctured fruits to the training set, while the rest $\frac{1}{3}$ used for external validation. We calculated the image-level iPLS-DA models considering different interval sizes, and we performed an image reconstruction by evaluating the most frequently selected variables.

Finally, we applied the automated annotation procedure developed considering year images from 2022 to the hyperspectral images acquired in 2023 as an additional external validation. The proposed approach allowed to correctly select the pixels ascribable to BMSB related damages on 212 out of 322 images of punctured cv. Abate Fétel pears (65%) and on 273 out of 352 images of punctured cv. Williams pears (77%). Concerning the detection of different kind of damages, such as bruises, Lee et al. [53] reached 92% accuracy while Li et al. [54] reached 95% accuracy using near-infrared hyperspectral imaging on pear fruits. A similar annotation procedure was proposed on apples in Ferrari et al. [22], in which 92% and 94% efficiency values were obtained for “Golden Delicious” and “Pink Lady” apple varieties, respectively.

Starting from the ROIs of the annotated punctured areas, it will be possible to build a dataset of representative spectra belonging to both punctured and sound regions, which represents a crucial step for the development of more effective pixel-level classification models and the selection of relevant spectral regions ascribable to BMSB punctures. Indeed, the selection of spectral variables able to identify BMSB punctures is a key step in the implementation of MSI systems, which are more suitable for postharvest sorting lines in terms of computational time and lower costs of optical components.

VIII. CONCLUSION

In this article, we highlighted the main steps taken in the HALY.ID project to implement a system aimed at automating the monitoring of BMSB pests in orchards. Specifically, we detailed computer vision techniques for effectively detecting the BMSB, primarily on RGB images captured by UAVs, as well as utilizing spectral imaging as a complementary strategy. We also proposed an edge-based smart IoT sticky trap with integrated cameras and running resource efficient algorithms to be used in conjunction with the entire monitoring system to estimate population of specific invasive insect species. Finally, we successfully applied computer vision algorithms to spectral imaging to detect punctures on harvested pears, which can be integrated into a fruit sorting system to optimize food quality on the shelves of supply to customers. In addition, we developed a client-server application to enrich the dataset and enhance the trained models within this system.

As next steps, it will be necessary to effectively counteract BMSB by leveraging the aforementioned techniques to monitor and control their population. A comprehensive monitoring system, coupled with a decision-process model to actively combat this pest, is essential for successful pest management.

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