An AI-based Platform for Hazelnut Variety Classification

Alfredo Massa[†], Alfredo Ambrosone[‡], Giuseppe Celano[‡], Marcella Di Marino[*], Rosario Frontino[*], Elena Grobler[‡], Alfredo Troiano[*], Enrico Landolfi[*]
[*]NetCom Group S.p.A., [†]QuantumNet S.r.l., [‡]University of Salerno, Department of Pharmacy

***Abstract*—This work presents a platform for AI-assisted hazelnut variety classification from mobile images. The system integrates a mobile application, a web portal, and server-side AI microservices based on YOLOv8l. Experimental results show strong classification performance and suggest that the proposed technology could serve as a valuable tool for future smart-agriculture applications.**

***Index Terms*—Artificial intelligence, computer vision, hazelnut classification, smart agriculture, YOLO, mobile application**

I. Introduction

Hazelnuts are in strong demand from the food industry, where they are used in the production of a wide range of products. Commercial interest in hazelnut cultivation has increased over recent decades, leading to the expansion of both production and harvested area in many regions worldwide. Turkey is the first hazelnut producing country, followed by Italy. The request for efficient traceability protocols to identify hazelnut cultivars has become a critical issue. The large difference in quality between cultivars and production from different areas of the world can lead to significant price differences, which in turn may lead to frauds and safety risks for consumers [1]. Artificial Intelligence (AI) has shown significant potential for improving efficiency and sustainability in agriculture [2]–[4]. Advanced image processing techniques, such as Convolutional Neural Networks (CNNs) [5], have proven to be effective solutions for tasks such as crop monitoring, early disease detection, and plant variety classification. In this context, the *Artificial Intelligence for Hazelnut (AI-NUT)* project aims to develop an AI-based decision support system for hazelnut cultivation and related industrial processes. The core task of the support system is to process images acquired through a dedicated mobile application and to perform cloud-based AI inference to automatically enable varietal recognition. The remainder of this paper describes the AI-NUT platform and its experimental validation.

II. System Architecture

The architecture of the AI-NUT system is depicted in Fig. 1. It is composed of three interconnected building blocks: a set of AI microservices hosted on a dedicated server, a mobile application and a web portal. This separation between acquisition, inference, and visualization improves modularity and makes the system easier to maintain and extend. The individual components are described in the following.

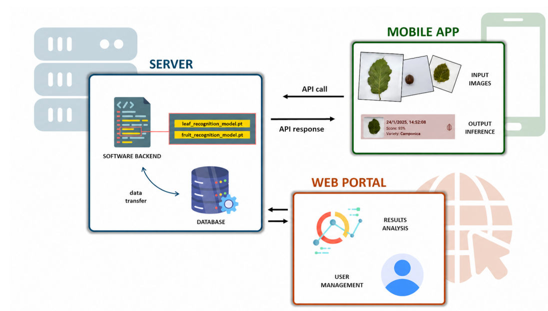


Fig. 1. AI-NUT system architecture.

A. AI Microservices

The AI microservices are deep classification models trained for hazelnut variety identification. To decouple the inference process from the rest of the project infrastructure, the microservices run on a local server and are invoked by dedicated software responsible for processing input images and returning the results.

B. Mobile Application

The mobile application allows the user to acquire a new image through their smartphone camera or to upload an image already stored on the device. The mobile client sends the image to the backend, where the inference process is executed, and the predicted hazelnut variety, together with the associated confidence score, are returned to the user.

C. Web Portal

The web portal provides access to the results generated by the platform and is intended for result visualization and management.

III. AI Model Development and Experimental Results

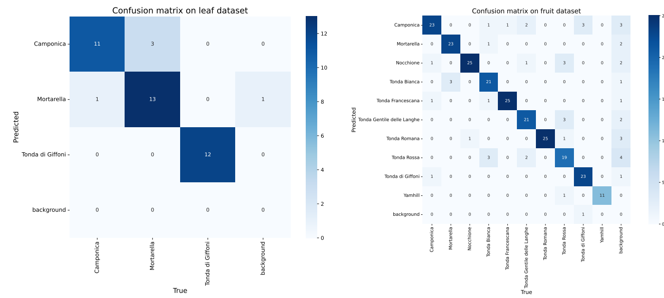
AI-NUT's AI component (i.e., the microservices described in II-A) was designed to perform hazelnut variety recognition from images acquired through mobile cameras. Two independent deep learning models were developed: one for classifying hazelnut varieties from leaf images and the other for classifying hazelnut varieties from fruit images. In both cases, the employed model was *You Only Look Once (YOLO)*. YOLO is a family of CNN architectures which gained high traction in latest years due to their high compatibility with

TABLE I
DATASETS USED FOR HAZELNUT VARIETY RECOGNITION.

Dataset	Type	Classes	Instances
Dataset-1	Leaves	3	871
Dataset-2	Fruits	10	6741

TABLE II
PERFORMANCE METRICS OF BOTH LEAF AND FRUIT CLASSIFICATION MODELS ON VALIDATION AND TEST SETS. METRICS ARE AVERAGED OVER CLASSES.

Model	Split	Accuracy	Precision	Recall	mAP50	mAP50–95
Leaves	Val.	0.920	0.934	0.919	0.979	0.979
Leaves	Test	0.900	0.891	0.907	0.896	0.896
Fruits	Val.	0.898	0.918	0.921	0.959	0.944
Fruits	Test	0.878	0.887	0.908	0.951	0.941



(a) Leaf classification

(b) Fruit classification

Fig. 2. Confusion matrices obtained by the two YOLOv8l networks on the test sets of the considered datasets, namely the leaf image dataset (3 classes) and the fruit image dataset (10 classes).

industrial requirements, such as accuracy, lightweight, and edge-friendly deployment conditions [6]. The specific architecture selected for this project was YOLOv8l, configured for a sequential segmentation and classification pipeline and chosen after a preliminary comparison with alternative configurations.

Two datasets were used in the experiments (cf. Table I). The first, used for training the leaf classification model, consists of images of hazelnut leaves from three cultivars: *Camponica*, *Mortarella*, and *Tonda di Giffoni*. The second, used for training the fruit classification model, consists of images of hazelnut fruits from ten cultivars, including the previous three as well as *Nocchione*, *Tonda Bianca*, *Tonda Francescana*, *Tonda Gentile delle Langhe*, *Tonda Romana*, *Tonda Rossa*, and *Yamhill*. In both cases, image acquisition was performed under controlled conditions using a softbox with white background, LED illumination, and a fixed camera-to-object distance, in accordance with the main methodological trends reported in the literature [7]–[11]. Each image was manually annotated by segmenting the relevant object and assigning the corresponding variety label. The datasets were then pre-processed through a pipeline consisting of auto-orientation, resizing to 640×640 pixels, and data augmentation to improve the generalization capability of the models with respect to slight changes in orientation, acquisition conditions, and image quality. Since the leaf dataset contained both upper and lower sides of the same leaves, paired views of the same physical leaf were kept within the same partition during the split process to avoid a potential source of data leakage. At the end of the training process, the two models were exported as PyTorch files and integrated into the AI-NUT backend as independent microservices. Table II reports the main evaluation metrics computed on both the validation and test partitions of the datasets, while the corresponding confusion matrices are shown in Fig. 2. Both models achieved high performance. After training, the models were further validated by means of app-based tests, in which images from the test sets were loaded onto different smartphones and processed through the AI-NUT mobile interface. The results confirmed that the models retained high performance after integration into the workflow.

IV. CONCLUSION

Experimental results showed high performance for both the leaf and fruit classification models, supporting the employment of the proposed technology in smart agriculture applications. Future developments will focus on improving acquisition consistency through the development of a Smart Acquisition Box (SAB), namely an engineered version of the current softbox equipped with an integrated camera and IoT connectivity to the rest of the platform. Additional work will also address new AI models for the detection of hazelnut diseases and nutritional deficiencies, as well as the extension of the framework to other agricultural products and industrial use cases.

REFERENCES

[1] T. Giulia, G. Vallauri, V. Pavese, N. Valentini, P. Ruffa, R. Botta, and D. Torello Marinoni, "Identification of the hazelnut cultivar in raw kernels and in semi-processed and processed products," *European Food Research and Technology*, vol. 248, no. 9, pp. 2431–2440, 2022.

[2] M. J. Smith, "Getting value from artificial intelligence in agriculture," *Animal Production Science*, vol. 60, no. 1, pp. 46–54, 2019.

[3] N. C. Eli-Chukwu, "Applications of artificial intelligence in agriculture: A review." *Engineering, Technology & Applied Science Research*, vol. 9, no. 4, 2019.

[4] S. Y. Liu, "Artificial intelligence (ai) in agriculture," *IT professional*, vol. 22, no. 3, pp. 14–15, 2020.

[5] Z. Li, F. Liu, W. Yang, S. Peng, and J. Zhou, "A survey of convolutional neural networks: analysis, applications, and prospects," *IEEE transactions on neural networks and learning systems*, vol. 33, no. 12, pp. 6999–7019, 2021.

[6] M. Hussain, "Yolo-v1 to yolo-v8, the rise of yolo and its complementary nature toward digital manufacturing and industrial defect detection," *Machines*, vol. 11, no. 7, p. 677, 2023.

[7] B. Gencturk, S. Arsoy, Y. S. Taspinar, I. Cinar, R. Kursun, E. T. Yasin, and M. Koklu, "Detection of hazelnut varieties and development of mobile application with cnn data fusion feature reduction-based models," *European food research and technology*, vol. 250, no. 1, pp. 97–110, 2024.

[8] E. Dönmez, S. Kılıçarslan, and A. Diker, "Classification of hazelnut varieties based on bigtransfer deep learning model," *European Food Research and Technology*, vol. 250, no. 5, pp. 1433–1442, 2024.

[9] A. Taner, Y. B. Öztekin, and H. Duran, "Performance analysis of deep learning cnn models for variety classification in hazelnut," *Sustainability*, vol. 13, no. 12, p. 6527, 2021.

[10] Ü. Yavuz, "Classification of hazelnut species with pre-trained deep learning models," *intelligence Methods in engineering sciences*, 2023.

[11] E. Gunes, E. E. Ulku, and K. Yildiz, "Classification of hazelnuts with cnn based deep learning system," *Selcuk University Journal of Engineering Sciences*, vol. 21, no. 3, pp. 111–120, 2022.