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CADAT 2024 Editors

Sandra Sendra, Universitat Politècnica de València, Spain

CADAT 2024

Forward

The First International Conference on Accessible Digital Agriculture Technologies (CADAT 2024), held between November 17th, 2024, and November 21st, 2024, in Valencia, Spain, aimed at integrating cutting-edge Artificial Intelligence (AI) and Internet of Things (IoT) technologies into the agricultural sector. This conference focused on harnessing the power of AI and IoT to revolutionize farming practices, enhance productivity, and ensure sustainable food production for a growing global population. CADAT offered a comprehensive platform for researchers, practitioners, industry experts, and policymakers to exchange ideas, showcase innovations, and collaborate towards shaping the future of smart agriculture. Through interdisciplinary discussions and knowledge sharing, CADAT 2024 aimed at driving the transformative change in the agricultural sector towards sustainability, efficiency, and resilience.

We take here the opportunity to warmly thank all the members of the CADAT 2024 technical program committee, as well as all the reviewers. The creation of such a high-quality conference program would not have been possible without their involvement. We also kindly thank all the authors who dedicated much of their time and effort to contribute to CADAT 2024. We truly believe that, thanks to all these efforts, the final conference program consisted of top-quality contributions. We also thank the members of the CADAT 2024 organizing committee for their help in handling the logistics of this event.

We hope that CADAT 2024 was a successful international forum for the exchange of ideas and results between academia and industry for the promotion of progress related to accessible digital agriculture technologies.

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Variety Classification by Image Recognition of Grape Leaf and Berry

Ryo Sugiura, Mitsunori Ishihara, Jihyun Lim,
Chisa Iwasaki, Yu Oishi
Research Center for Agricultural Information Technology
National Agriculture and Food Research Organization
(NARO)
Tsukuba, Ibaraki, Japan
e-mail: rsugiura@naro.affrc.go.jp,
ishihara.mitsunori@naro.affrc.go.jp, j_lim@naro.affrc.go.jp,
i.chisa@naro.affrc.go.jp, oishi.yu@naro.affrc.go.jp

Hiroshi Yakushiji, Yoshihiko Kuwana,
Toshiya Yamamoto
Department of Intellectual Property
National Agriculture and Food Research Organization
(NARO)
Tsukuba, Ibaraki, Japan
e-mail: aoe@naro.affrc.go.jp, kuwana@naro.affrc.go.jp,
toshiya@naro.affrc.go.jp

***Abstract*— Protection of the rights of plant breeders is essential to preserve the value of new varieties. However, table grapes, for instance, are easy to propagate vegetatively by grafting or cutting, and once they become popular and the cultivation area increases, they face a high risk of unauthorized cultivation and propagation, leading to overseas outflow. To prevent such infringements, effective methods for promptly identifying protected varieties have been desired, and deep learning-based image recognition can be one of the key techniques. The objective of this study is to verify the possibility of identifying grape varieties using images of leaves and berries. The images of leaves, young berries, and mature berries of Shine Muscat and two similar varieties were captured using smartphone cameras, and an image dataset was created to train and test classification models. Image classification models named VGG16, ResNet50, and Vision Transformer (ViT) were applied and redesigned to classify three categories. After training, these models were tested on 51 images of leaves, 174 images of young berries, and 171 images of mature berries. The models achieved classification accuracies of more than 96.1% for leaves, over 99.4% for young berries, and 100% for mature berries. Although additional testing at different sites or in different years will be needed, these results indicate that image recognition techniques can help identify plant varieties toward infringement detection.**

Keywords-image recognition; variety classification; grape leaf; grape berry.

I. INTRODUCTION

Measures to prevent superior crop varieties from being grown and propagated without permission are necessary, and breeders must receive profits from licensing the varieties. Furthermore, the protection of the rights of plant breeders is essential for preserving the value of new varieties. However, table grapes, for instance, can easily propagate vegetatively by grafting or cutting; once they become popular and their cultivation area increases, they face a high risk of unauthorized cultivation and propagation, leading to overseas outflow.

Several cases of infringements have been observed worldwide. A private company with a breeder's right of a blueberry variety filed a lawsuit in the Federal Court of Australia, alleging that some farmers were growing and selling the variety without any license [1]. Another US company that has several patented grape and cherry varieties launched administrative complaints against the illegal sale of propagation and harvested material of their varieties [2]. An Italian Court admitted the infringement of a breeder's right and stopped an alleged grape producer from harvesting and selling the infringed variety [3]. In Japan, young, high-quality grape vines have been cultivated outside the country [4]. These infringements were often confirmed using DeoxyriboNucleic Acid (DNA) profiling or comparison tests. Although DNA analysis and comparison tests are currently among the most reliable ways to identify varieties [5][6][7], they usually take time to obtain results and are sometimes tedious. It might be difficult to develop a method that completely replaces conventional methods at present. However, a simple and prompt complementary method is desired, and Deep Learning (DL)-based image recognition [8][9][10][11][12] can be one of the key techniques. This study proposes an image-based method to identify crop varieties using Deep Neural Networks (DNNs). DNNs are often used for numerous tasks, including image classification, and DL is the easiest and best way to generate classification models.

The objective of this study is to verify the possibility of identifying crop varieties using images. Grapes of the three varieties were selected, and images of their leaves and berries were captured to create the training dataset. Three classification models were trained using this dataset, and their classification accuracies were compared.

The plan of the paper is as follows. In Section II, we mainly describe the details of the image dataset and the DNN-based classification models. Section III shows the classification accuracies obtained by the trained models and discusses the results of visualizing the regions focused by the model for classification. Section IV addresses the concluding remarks.

II. MATERIALS AND METHODS

A. Image Dataset

The grape varieties used in this study were Shine Muscat [13] and its similar varieties, Muscat of Alexandria and Rosario Bianco. Images of the leaves and berries of these

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varieties were captured using three smartphone cameras (SONY Xperia 10IV, Google Pixel 7, Apple iPhone 13 Mini). A single leaf was laid face up on a black plate immediately after sampling off the trees, and an image was captured using one of the cameras. The cameras were held by hands facing down at a distance of approximately 35 cm from the leaves. All leaves were sampled from trees in the experimental field of National Agriculture and Food Research Organization (NARO) in Akitsu (34.33°N, 132.82°E), Hiroshima, Japan, from July 3rd to July 20th in 2023. Similarly, images of young berries sampled from June 20th to June 28th and mature berries sampled from September 21st to September 28th were captured at a distance of approximately 20 cm from the berries.

The image sizes in pixels were 4000 × 3000 (Xperia), 4080 × 3072 (Pixel 7), and 4032 × 3023 (iPhone). The spatial resolutions of leaf and berry images were approximately 0.11 and 0.07 mm, respectively. Image data were created by cropping a square region of 2500 × 2500 pixels with a leaf at the center and 800 × 800 pixels for berries. Consequently, 186 image data of leaves, 665 image data of young berries, and 673 image data of mature berries were obtained. Fig. 1 shows examples of image data for the three varieties.

B. Training and Evaluation of Classification Models

The image classification models VGG16 [14], ResNet50 [15], and Vision Transformer (ViT) [16] were applied and redesigned to classify the three categories. VGG16 is one of the simplest and most classical Convolutional Neural Networks (CNNs). It stacks 13 convolutional layers and three fully connected layers. ResNet50 is the most commonly used classifier. It has residual connections across layers in the network, which improve network performance in training process. This model is characterized by fast convergence of the trainable weight despite the large number of layers. ViT is an image classifier based on Transformer architecture, which has been the de facto standard for natural language processing. It divides an input image into a sequence of patches and examines their contextual relationships with each other using Self-Attention, which contributes to model robustness [17].

The Python programs of these three models and the corresponding pre-trained weights were obtained from TorchVision [18], which is part of the DL framework of the PyTorch project [19]. The output layer of each model was modified to match the classification of the three varieties.

To train and test the models, the dataset mentioned in the previous section was randomly divided into those for training, validation and test as summarized in Table I. The models were trained by fine-tuning the pre-trained weights as the initial values. The weights of each model were updated repeatedly using the training data such that the loss (cross entropy) decreased. The loss on the validation data was also calculated for each update. After 100 iterations (epochs), the weights with the lowest validation loss were selected as the best. During training, accuracy was calculated as the percentage ratio of the number of correct predictions to the total number of samples in each epoch.

After the training process, the best models were tested on 51 images of leaves, 174 images of young berries, and 171 images of mature berries to obtain the final accuracies.

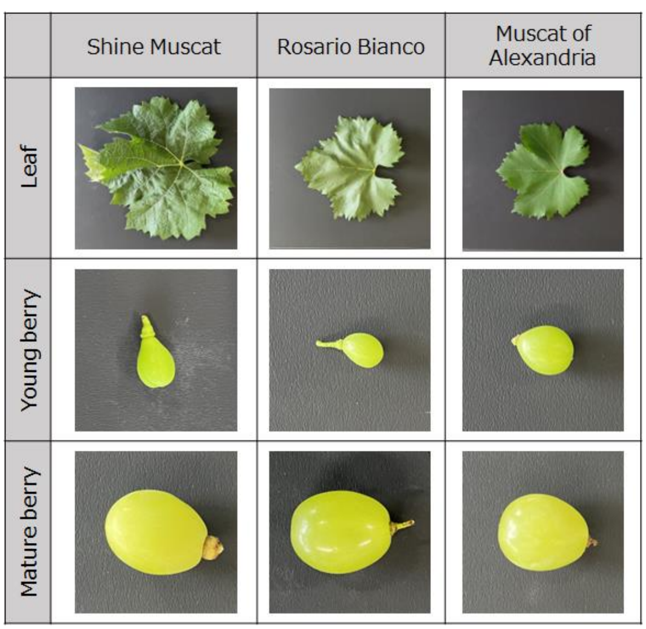


Figure 1. Image data examples of three varieties.

C. Visualization of Interest Area

For the VGG models, Gradient-Weighted Class Activation Mapping (Grad-CAM) was applied to show the important portions of an input image for making predictions. Grad-CAM uses the gradient information flowing into the last convolutional layer of a CNN to assign importance values to each neuron for a particular decision of interest [20]. The magnitude of influence on the prediction results can be obtained as a heat map overlaying the input image. This helps us understand where the models focus on the leaf or berry to predict variety. The Grad-CAM program was obtained from the website of [21].

III. RESULTS AND DISCUSSION

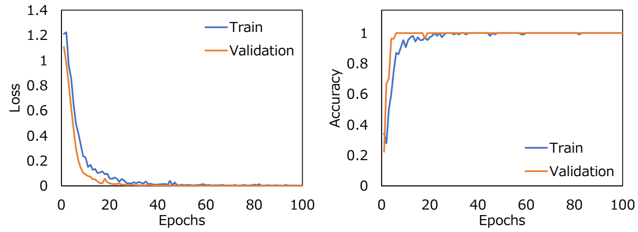
A. Loss and Accuracy Variations in Training Proccess

As an example, Fig. 2 shows the variations in loss and accuracy with an increase in the number of epochs for the training process of VGG16 for leaves. The curves of the training and validation losses gradually converged, and those of the training and validation accuracies quickly reached 1.0

TABLE I. NUMBER OF IMAGE DATA

	Train			Validation			Test		
Leaf	108			27			51		
	37	36	35	9	9	9	17	17	17
Young berry	401			90			174		
	135	141	125	30	30	30	58	58	58
Mature berry	409			93			171		
	147	129	133	31	31	31	57	57	57

The three numbers in the bottom row of each cell are of image data of Shine Muscat, Rosario Biance, and Muscat of Alexandria.



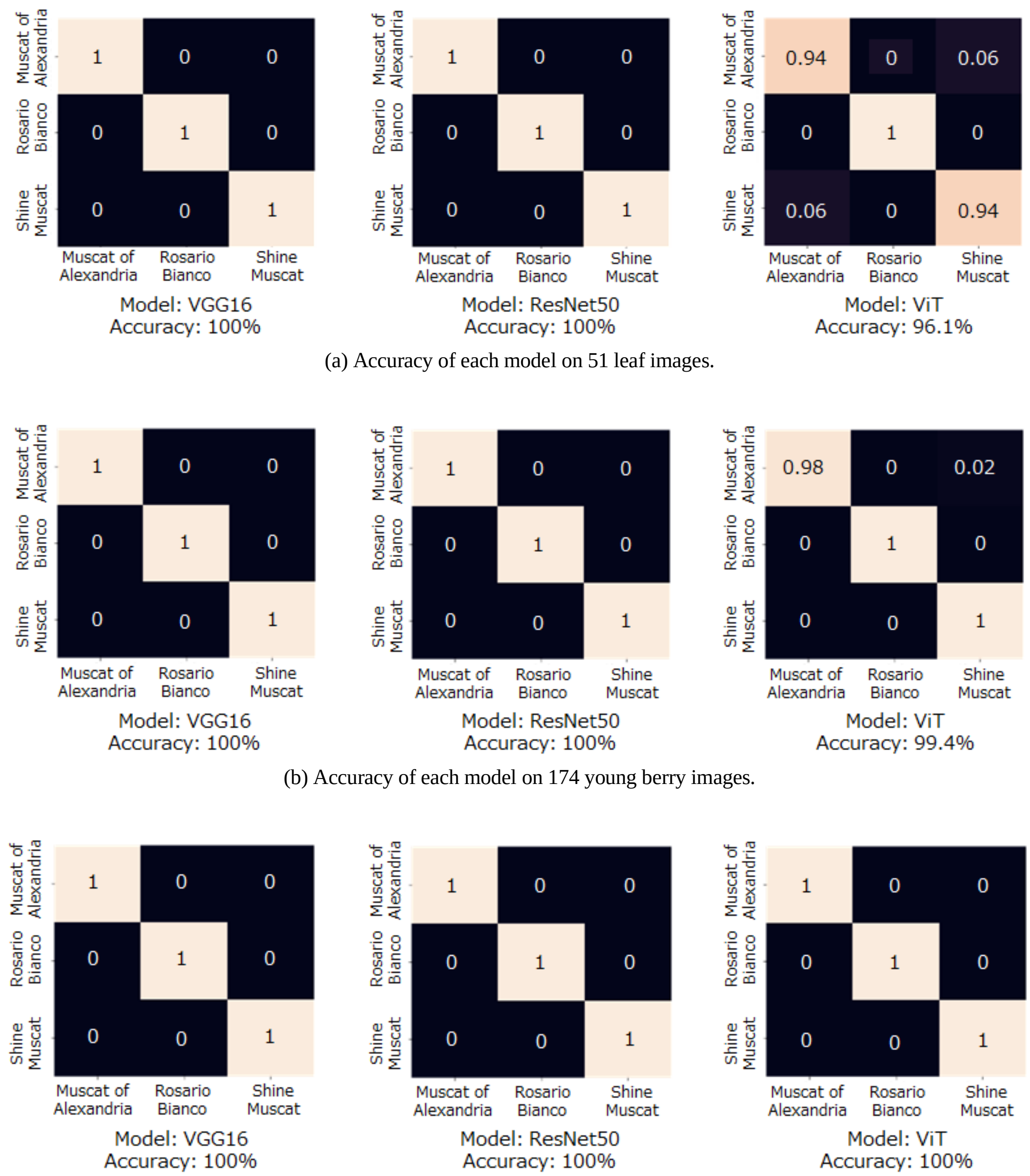
(a) Training loss (b) Training accuracy

Figure 2. Variation in loss and accuracy in the training process of VGG16 with leaf images.

within the early epochs. This implies that the training process was successfully performed, and a model was created to classify an image into three varieties. As the variations in loss and accuracy for both young and mature berries on the other models were similar, their figures were omitted from this report.

B. *Accuracies on Test Data*

The test accuracies of the trained models for leaf classification were obtained and are summarized as confusion matrices, as shown in Fig. 3(a). VGG16 and ResNet50 correctly classified all varieties on the 51 test images with 100% accuracy. However, ViT had some misclassifications and its accuracy across the three varieties was 96.1%. One of the 17 images of Muscat of Alexandria was misclassified as Shine Muscat, resulting in a recall of



(a) Accuracy of each model on 51 leaf images.

(b) Accuracy of each model on 174 young berry images.

(c) Accuracy of each model on 171 mature berry images.

Figure 3. Confusion matrices of test accuracies of variety classification. The vertical and horizontal axes are true and predicted labels, respectively.

94.1%, and one of the 17 image of Shine Muscat was misclassified as Muscat of Alexandria, whereas the images of Rosario Bianco were classified correctly.

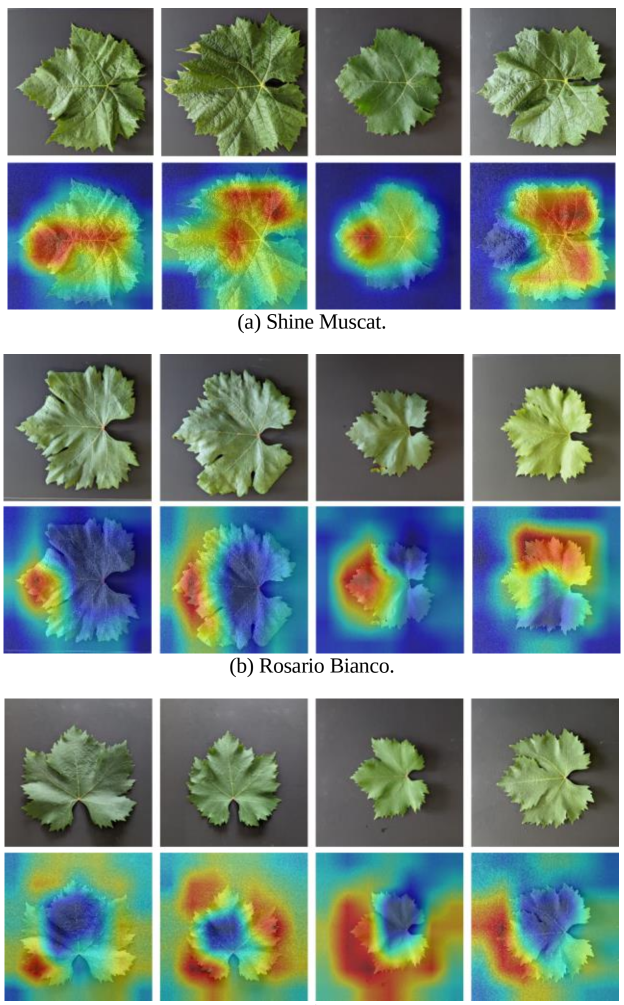
The confusion matrices for the young berries are shown in Fig. 3(b). The accuracies of VGG16 and ResNet50 were 100% similar to the leaf classifications, whereas that of ViT was 99.4% on the 174 images. One of the 58 images of Muscat of Alexandria was misclassified as Shine Muscat and its recall was 98.2%. In the case of mature berries, the accuracies were 100% across all varieties for the 171 test images, as shown in Fig. 3(c). The accuracy of ViT for young berries was 99.4%, whereas that for mature berries was 100%. This implies that the growth of berries might make the features of the variety on its shape and texture more distinct. The accuracies of ViT for leaves and young berries were not 100%. A large amount of data is required for the ViT to achieve optimal performance. However, ViT still achieved good results across leaves and berries.

VGG16 and ResNet50 provided perfect classification of the test data. The method of capturing images contributes to obtaining such good results, even with these basic models. Using a black background and capturing images immediately above the subjects made it easy to capture morphological characteristics and might lead to perfect classifications. Assuming that the images of leaves and berries on trees had been captured at several angles or distances in the outside environment and the background was not uniform, as in [22][23], it would have been difficult to obtain such good accuracies.

Although additional testing at different sites or in different years may be required, these results indicate that image recognition techniques can help identify plant varieties for infringement detection.

C. Visualization by Grad-CAM

Four heat maps generated from leaf images using the Grad-CAM program were used as examples, as shown in Fig. 4. VGG16 is assumed to have classified the images into Shine Muscat by focusing on the leaf surface (Fig. 4(a)), whereas it seems to observe some leaf tips to classify the

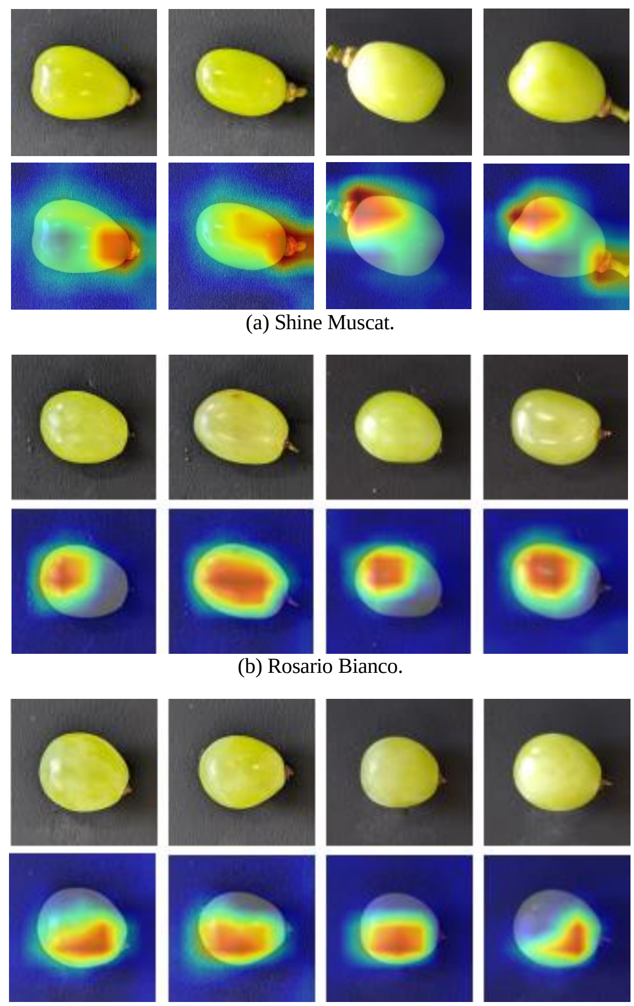


(a) Shine Muscat.

(b) Rosario Bianco.

(c) Muscat of Alexandria.

Figure 4. Heat maps of leaf images of each variety using VGG16 and Grad-CAM.



(a) Shine Muscat.

(b) Rosario Bianco.

(c) Muscat of Alexandria.

Figure 5. Heat maps of mature berry images of each variety using VGG16 and Grad-CAM.

images of Rosario Bianco (Fig. 4(b)). For the images of Muscat of Alexandria, the outline of a leaf appeared to be the focus of attention (Fig. 4(c)). The model for mature berry images may observe the surface of the berries in Rosario Bianco and Muscat of Alexandria (Fig. 5(b) and (c)). However, it possibly focused on the pedicel to recognize the Shine Muscat (Fig. 5(a)).

IV. CONCLUSIONS

To examine whether image recognition can be used to distinguish crop varieties, images of the three grape varieties were collected, and classification models were generated. The test results demonstrated that all models were highly accurate. VGG16 and ResNet50 attained test accuracies of 100% for the leaf and berry images. The accuracies of ViT were 96.1% and 99.8% for leaves and young berries, respectively. Grad-CAM clarified that VGG16 focused on different parts of an image depending on the variety. Based on these results, any other DNN-based classification model is most likely to provide high accuracy. In other words, these three types of classification issues may be comparatively easy to handle in DNN-based image recognition. This study showed that the three grape varieties could be classified based on images of both leaves and berries. However, a model that can classify only three varieties is not sufficiently practical for making infringement decisions, and the number of varieties to be recognized should increase. Additional training data must be collected to update and verify the models.

In general, image recognition models that maintain 100% classification accuracy for any unseen image are rare, even though they are trained on a large amount of training data. The models trained in this study are not expected to maintain high accuracy and may produce some misclassifications in unseen images, such as those captured at different sites and in different years. Therefore, distinguishing variety infringements based on images alone is unreliable, and DNA analysis or other conventional methods are still required to obtain a correct judgement. Image recognition techniques should be utilized to screen for suspicious varieties prior to DNA analysis, which may provide an effective method for infringement detection.

In conclusion, this study represents a stepping stone for future development of infringement prevention technology. By increasing the number of cultivars that can be identified with image recognition while maintaining the accuracy, this image-based approach will become more practical, contributing to prompt detection of illegal cultivation and overseas outflow of registered varieties.

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A Feature-Based Correlation Approach for Analyzing Price Trends of Citrus in Valencia Province (Spain)

R. Arnau, J. M. Calabuig, N. Ortigosa and L. Petrosyan
Instituto Universitario de Matemática Pura y Aplicada,
Universitat Politècnica de València, Camino de Vera s/n, 46022,
Valencia, Spain
e-mail: ararnnot@posgrado.upv.es, jmcalabu@mat.upv.es, nuorar@upvnet.upv.es, luipet@inf.upv.es

Abstract—**In this paper, we are going to present some work in progress results to study and analyze the price variation among different citric varieties in Valencia province from Comunitat Valenciana region (Spain). A data-driven approach is used to represent each citrus variety and season using 5 features for comparing its prices trends using a correlation analysis. Those findings provide the foundation for implementing clustering algorithms, such as k-Medoids, to classify citrus varieties and seasons based on profitability and market behavior.**

Keywords-Citrus; price trends; feature extraction; correlation analysis.

I. INTRODUCTION

The agriculture sector plays an important role in achieving multiple Sustainable Development Goals (SDGs). Its impact ranges from eradicating hunger (SDG2) and poverty (SDG1), to protecting the environment (SDG12) and promoting health (SDG3). Thus, the transformation towards sustainable agriculture is essential to achieve these goals [1], [2]. In this sense, the citrus fruit sector is of great importance both in the Valencia Region (Comunitat Valenciana) and in Spain. Indeed, the Comunitat Valenciana is the main citrus fruit producing region in Spain. In 2022/2023, the production was around 67% of Spain's citrus (the main varieties grown being oranges, mandarins, and lemons) with a production of around 2.8 million tonnes. In this period, 1.8 million tonnes were exported (out of 4.3 million tonnes in Spain) with an economic value of around 2 million euros (out of 3.4 million euros in Spain) [3], [4].

On the other hand, data science and Artificial Intelligence are tools that, as in other areas, are already being used in the agriculture sector [5], [6]. In this sense, it is important to highlight that the interpretability of Artificial Intelligence (AI) algorithms in general, and of machine learning algorithms in particular, is crucial when models are to be used for decision-making. Thus, interpretability not only increases confidence in the models (and their results) but also their validation. One of the most common and easy-to-interpret clustering algorithms is k-Means. In these algorithms, it is common to use the Euclidean distance because it is easy to understand the proximity of the vectors for the formation of the clusters. However, other distances (such as that associated with the correlation between vectors) and similar algorithms (such as k-Medoids) can be used.

Citrus prices can experiment changes across seasons and between seasons, depending on factors such as weather conditions, supply and demand, and production costs, among others, see for instance [7]. In this work, we study the price trends of the citrus fruits in the Valencia province over the period 2015-2022. For this purpose, we identify different varieties of these citrus fruits by means of a vector consisting of 5 features. A correlation analysis of these vectors then allows us to study the trends, which allows us to classify citrus fruits according to their profitability.

In a future work, this first trend analysis will allow us to implement clustering algorithms (such as the aforementioned k-Medoids) based on correlations. This analysis could be a valuable tool for planning, decision-making, risk mitigation and revenue optimization in the agricultural sector. It provides key information that can be used by producers, traders, policy makers, investors and other market actors to improve the efficiency and economic stability of the sector and, as mentioned above, a tool to achieve some of the SDGs.

The rest of the paper is structured as follows. Section II presents the database and the methodology used for this analysis. Obtained results are presented in Section III, while the analysis limitations, discussion and conclusions are drawn in Section IV. Finally, the stages of upcoming research are presented in Section V.

II. MATERIALS AND METHODS

The starting point (and usually critical point) in all data science projects is the collection of data. In our case, we use the "Reports of the Valencian Agricultural Sector" (Informes del Sector Agrario Valenciano, in Spanish), which contain temporary information (with annual breakdown) on the agri-food situation in the Comunitat Valenciana since 2015 (actually since 1998). These reports are divided into different chapters containing both meteorological data (Chapter III) and agricultural (Chapter IV) and livestock (Chapter V) statistics, as well as agricultural prices (Chapter VI). We would like to point out here that these reports consist of 20 documents in Excel format for each of the available years, which means that they are not easy to use [8]. Fortunately, a file (in `csv` format) containing much of the necessary information can be found in [9]. This file contains weekly prices of agricultural products (not only citrus fruits) since 2017. Together with the files downloaded in [8] the data have been completed to have information since 2015 (from earlier dates there was missing data). Hence, we have filtered the data (to have only citrus fruits), as well as transformed the dates. So, at the end, we have a database containing 6745 rows corresponding to the weekly price of 9 citrus products (different kinds of Oranges such as, for instance, Navel, Blancas, etc., but also Lemons and Clementines). The 9 products have 43 different varieties. Unfortunately, there were some varieties that were not priced for many weeks (even years) so we decided not to use them and only use the data of 27.

After data curation, several features were extracted in order to form a vector that will characterize each year, so that annual trends are analysed to facilitate subsequent decisions taken by producers.

In this work, we have focused on 5 data features extracted for each analysed year. Even so, we are currently analysing and working on some additional ones so that we can obtain a more custom-made characterization. Since citrus products' season in Valencia region generally starts in September and ends in July, we are not focusing on natural years. From now on, we will refer to the year of the month when the product season started as year indicator.

As each citrus product has a different season length, and we have the data information of prices sampled by weeks, the first feature to be considered is the duration d (in number of weeks) that each specific product season lasted each year. The second and the third features were the minimum (m) and the maximum (M) prices paid each season per kilo of product. Another feature to be considered was the variance, calculated as

$$\sigma^2 = \frac{\sum_{i=1}^{N} (x_i - \mu)^2}{N}, \tag{1}$$

where x_i is the price paid for the product on the i-th week of the season and N is the number of weeks that we have data information per season. Finally, we consider the coefficient

$$Q = \frac{M - m}{d}, \tag{2}$$

calculated per season, so that a measure of the distribution of the data is also considered.

With the purpose of comparing the tendencies and behaviours of the product prices during each season, we study the correlation of the vectors formed by the extracted features. That is, if $X = (x_1, x_2, \ldots, x_5)$ and $Y = (y_1, y_2, \ldots, y_5)$ represent a fixed variety and a season each, we compute

$$\mathrm{corr}(X,Y) = \frac{\mathrm{cov}(X,Y)}{\sigma_X \cdot \sigma_Y} = \frac{\sum_{i=1}^{5} (x_i - \bar{x}) \cdot (y_i - \bar{y})}{\sqrt{\sum_{i=1}^{5} (x_i - \bar{x})^2 \sum_{i=1}^{5} (y_i - \bar{y})^2}}. \tag{3}$$

A correlation value close to 1 indicates a strong linear correlation between observations, while a value close to -1 signifies a linear correlation, but in opposite directions. A value near 0 suggests that the observations are not linearly correlated. This measure, related to the so called cosine similarity, allows us to identify the relation between price tendencies.

III. Results

When computing the previous features, the 1513 prices observations from [8] and [9] result in a dataframe consisting of 27 varieties of citrus, with its correspondent features for each seasons from 2015-2016 to 2020-2021, since the 2021-2022 data is uncompleted and not used. After removing the observations for which a variety in a concrete season has less than 5 prices recorded, only 19 varieties from Valencia province are considered, each one corresponding to Oranges, Mandarins, and Clementines varieties in a season, and the 5 features extracted. As an example, the first 10 rows can be seen in Table I, where the duration is computed as a portion of a year instead of number of weeks, for convenience.

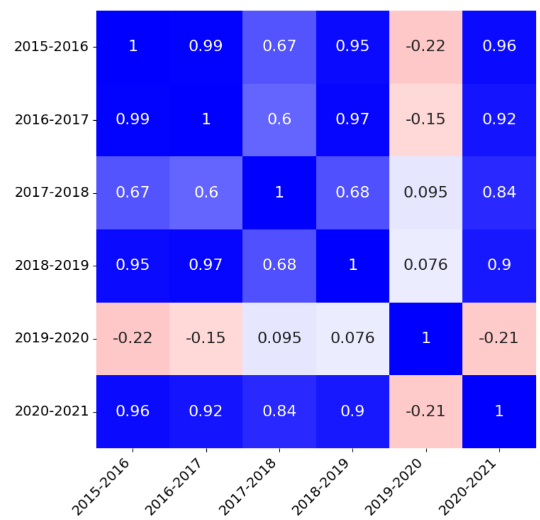

Figure 1. Autocorrelation of features corresponding to "Clausellina/Okitsu" across seasons.

Some correlation results can be seen in Figures 1 and 2. In Figure 1 we show the correlation of "Clausellina/Okitsu" variety, for which the season 2019/2020 is totally uncorrelated with the other 5 studied, probably due to the COVID-19 pandemic, which altered the prices at the end of the season. Also, 2017-2018 season has a tendency of its own, while the other four seasons are fully correlated with each other. In Figure 2, the relation between different varieties is shown. For example, it could be thought that oranges and clementines would present similar trends among them, but one can see that clementine "Clementina Clemenules" variety has a more similar price tendency to oranges than other clementines varieties, which would be the beforehand expected behaviour.

IV. Discussion and Conclusions

In this paper, we have presented some work in progress results that show how weekly prices can be analyzed in order to find significant patterns and correlations. This is done across different varieties of citrus in Valencia province in seasons from 2015 to 2021. We have found that each variety can be identified with a numeric vector of 5 features, which allows for the comparison of varieties with different numbers of recorded prices. This vector can be used as a tool to reveal the behavior of several citrus varieties along different seasons and two comparisons of its prices trends are shown.

However, it is necessary to recognize some limitations. Seasonal variations influenced by external factors, such as the COVID-19 pandemic, have affected the consistency of correlations for certain varieties, as exemplified by the 2019/2020 season of the “Clausellina/Okitsu" variety. While this effect is shown in the study, those external disruptions may make it necessary to integrate additional methods, such as time series forecasting, to adapt the study to irregular market conditions. Moreover, correlation-based similarity, while effective in capturing relative trends, may lack the intuitive clarity of Euclidean-based clustering, resulting in a less interpretable methodology.

To our knowledge, there are no similar studies in the context of agricultural price analysis, although clustering studies (comparing the aforementioned k-Medoids) do exist in the field of identification of management zones in precision agriculture [10]

V. Future Work

The vector identification found will be first step to find an AI-based model that can help to classify products in terms of profitability. More specifically, with the feature vector that identifies each product and the correlation metric (actually 1 minus the correlation to make it a dissimilarity function), we can apply clustering techniques such as k-Medoids, which is part of the on-going work. While it is true that this may produce some loss of interpretability, this technique may be useful: (1) for being less sensitive to differences in absolute magnitudes between features and, (2) to obtain a pattern of relationships between variables, rather than in absolute distances (as seems to be our case).

In this future work, other metrics added to the correlation as well as time-series analysis will be considered, including an extension of the database to include more features and products, which would be one limitation of the current study.

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TABLE I. FEATURES FROM THE 10 FIRST OBSERVATIONS OF THE DATAFRAME (DETAILS IN SECTION II).

Variety	Season	Duration	m	M	Q	σ^2
Clausellina/Okitsu	2015-2016	0.12	0.20	0.27	0.61	0.00089
Clausellina/Okitsu	2016-2017	0.15	0.16	0.26	0.65	0.00123
Clausellina/Okitsu	2017-2018	0.13	0.23	0.26	0.22	0.00019
Clausellina/Okitsu	2018-2019	0.21	0.15	0.25	0.47	0.00138
Clausellina/Okitsu	2019-2020	0.87	0.20	0.29	0.10	0.00093
Clausellina/Okitsu	2020-2021	0.10	0.23	0.27	0.42	0.00023
Clementina Arrufatina	2015-2016	0.12	0.27	0.34	0.61	0.00079
Clementina Arrufatina	2016-2017	0.15	0.22	0.38	1.04	0.00189
Clementina Arrufatina	2017-2018	0.21	0.29	0.36	0.33	0.00045
Clementina Arrufatina	2018-2019	0.12	0.23	0.30	0.61	0.00054

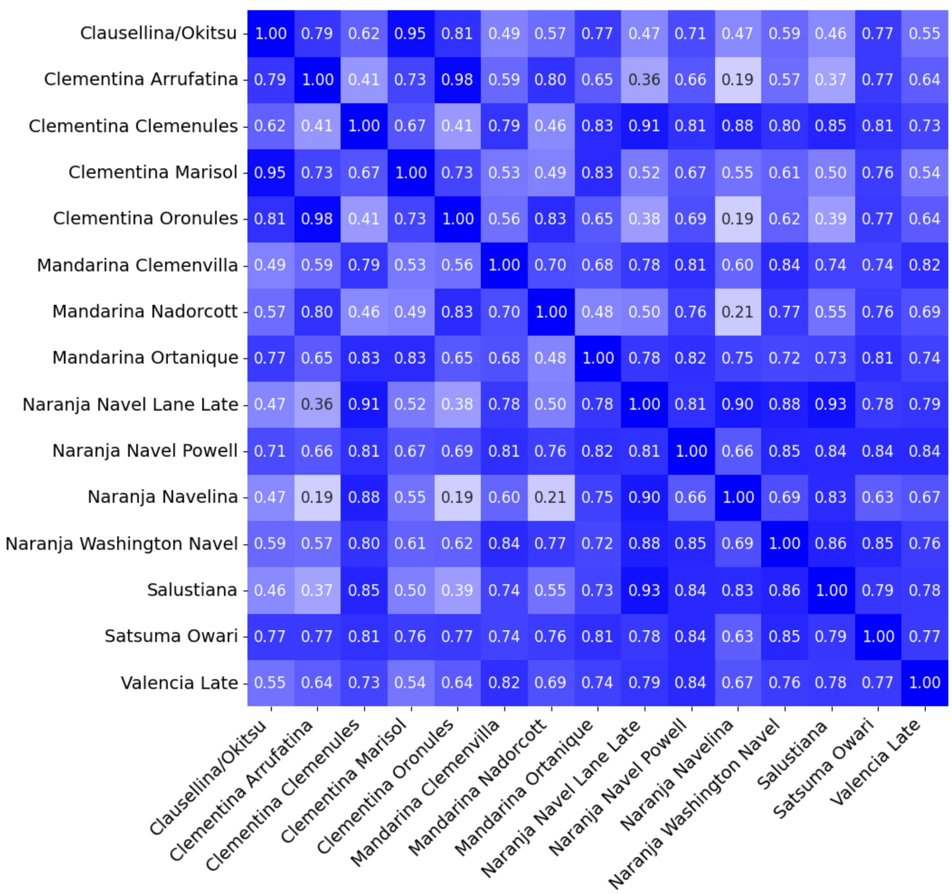

Figure 2. Mean correlation of Orange (“Naranja"), Clementines (“Clementina") and Mandarins (“Mandarina") varieties on the different seasons.

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Shore Identification and Navigation Route Modification Function for Autonomous Boats Used to Measure the Depth of Irrigation Ponds

Sho Nobumoto
Graduate School of Engineering and Science Master's
Shibaura Institute of Technology
Tokyo, Japan
email:al20109@shibaura-it.ac.jp

Tsuyosi Nakajima
College of Engineering
Shibaura Institute of Technology
Tokyo, Japan
email:tsnaka@shibaura-it.ac.jp

Kota Oshima
Graduate School of Engineering and Science Master's
Shibaura Institute of Technology
Tokyo, Japan
email:ma23039@shibaura-it.ac.jp

Yutaka Kaizu
Graduate School of Agricultural and Life Sciences
The University of Tokyo
Tokyo, Japan
email:kaizu@g.ecc.u-tokyo.ac.jp

***Abstract*—Many irrigation ponds are at high risk of collapse due to issues such as aging caused by insufficient management and sediment accumulation. The use of autonomous boats to measure water depth and estimate water storage capacity in these ponds has proven to be effective. However, there were some problems, such as discrepancies between the navigational map and actual conditions, which resulted in insufficient depth data collection near the water's edge or the boats running aground. In this study, we developed an autonomous boat system by improving the technology to utilize image recognition for identifying shoreline positions, allowing the boat to safely and adequately approach the water's edge. To achieve this, the boat's structure was modified by flattening the hull to reduce the risk of grounding. More importantly, three essential functions were also implemented: shoreline recognition, distance measurement from the boat, and route modification based on the collected data. These functions were evaluated in an actual irrigation pond, and it was verified that the distance estimation was accurate enough for the boat to safely navigate near the shoreline. However, several issues were identified, including the impact of boat sway and lighting conditions on recognition accuracy, as well as the need for improved recognition of obstacles along the route that are not part of the shoreline.**

Keywords-Irrigation ponds; Semantic segmentation; Distance measurement; Autonomous navigation.

I. Introduction

Irrigation ponds, known as "Tameike" in Japan, are artificially constructed reservoirs designed to store water for agricultural purposes. However, due to increasing labor shortages, the maintenance of many of these ponds has become insufficient, leading to their deterioration or, in some cases, complete abandonment. As these ponds age, the associated risks of disasters, including flooding and sediment outflow due to structural failure, have escalated. To mitigate these risks caused by aging irrigation ponds and to ensure adequate management in the face of labor shortages, large-scale interventions such as dredging or decommissioning may be required. However, informed decision-making on such measures necessitates regular monitoring of the ponds' water storage capacity, along with the accumulation of sediment and its temporal variations.

To address this need, a method for managing water storage by using autonomous boats to comprehensively measure water depth in irrigation ponds was proposed. However, because the route planning was based on map data, accurate depth measurement at the water's edge could not be achieved, resulting in significant estimation errors in the water storage capacity [1].

In this study, we propose a system that builds upon existing technology by modifying the route of the autonomous boat to enable accurate shoreline recognition. This enhancement allows for the collection of sufficient depth data and reducing estimation errors in water storage capacity. To achieve this, the boat's structure was modified by flattening the hull to reduce the risk of grounding. More importantly, three essential functions were also implemented: shoreline recognition, distance measurement from the boat, and route modification based on the collected data. The shoreline recognition function utilizes a semantic segmentation method to determine the shoreline position in camera images, and the distance measurement function employs a stereo matching method to calculate the distance to that position. The route modification function adjusts the boat's route based on the shoreline recognition results to ensure it can approach the shoreline safely and closely. These improvements not only address the issue of insufficient data collection near the water's edge but also mitigate the risk of grounding, ensuring safe and reliable data acquisition.

In this paper, Section 2 discusses previous research and its challenges, Section 3 presents the proposed system, Section 4 details the experiments and results, and Section 5 provides the conclusions.

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II. Previous Research and Its Challenges

To conduct high-accuracy depth measurements of irrigation ponds at low cost and within a short period of time, Kaizu et al. [1] developed a small autonomous boat equipped with navigation control and Global Navigation Satellite System (GNSS) sonar. The navigation control system utilizes open-source autopilot software originally designed for drones. With this navigation control, the boat autonomously follows along a route so as not to deviate from the planned navigation route based on the Global Positioning System (GPS) position information.

The boat autonomously navigates along a route set using the Mission Planner software. During navigation, the depth data from the sonar and time data are stored in the flight controller's internal memory. Upon completion of autonomous navigation, the depth data are correlated with GPS information to determine the depth at specific pond locations. Spline interpolation is then applied to all depth measurements along the route to generate a map of the pond bed, enabling the estimation of the pond's capacity.

However, in this study, the navigation route was designed using Mission Planner on a map of the pond obtained from Google Maps. Due to inaccuracies in the map and variations in water levels, significant errors often occurred in the shoreline positions. This led to issues, such as insufficient collection of depth data near the water's edge or the boat running aground.

Figure 1 illustrates the distribution of estimation errors. The black line indicates the route taken by the autonomous boat, while the red, blue, and yellow areas on the water surface represent varying degrees of error. As shown in the figure, the central region allows for relatively accurate depth estimation, whereas the water's edge exhibits significantly larger errors. This discrepancy is due to insufficient depth data collection, which causes deviations from the estimated values due to irregular depth changes in the lakebed near the shoreline.

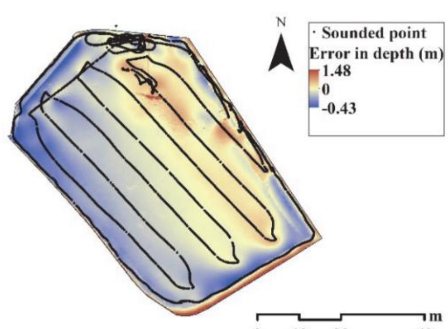

Figure 1. Distribution of Estimation Errors (reproduced from [1]).

To address this issue, it is essential to accurately determine the shoreline position during the boat's navigation and to adjust the route based on this data. This approach enables the boat to safely approach the shoreline while avoiding the risk of grounding.

III. Proposed System

A. Research Objective

The objective of this study is to address the challenges identified in the previous research and propose and evaluate a system that utilizes sensor data to recognize the shoreline and measure the distance to it. This system dynamically adjusts the navigation route to ensure safe and effective autonomous operation of the pond depth measurement boat.

B. Structure of the Prototype Boat

To conduct this research, we developed a new prototype boat. Figure 2 shows an image of the prototype boat.

Figure 2. Developed Experimental Boat.

In Figure 2, a bodyboard was used as the hull to facilitate navigation in shallow waters and minimize the risk of grounding. For shoreline recognition, two types of cameras were mounted at the front of the hull. One of these is a dual-lens 3D stereo synchronized USB camera module (ELP Co., Ltd.), which is used for autonomous navigation and shoreline detection. The other camera serves as a "visual aid" for manual remote control, with its video feed displayed in real-time on the controller's screen via telemetry.

Inside a waterproof case positioned at the center of the hull, the flight controller Pixhawk 6C (Holybro) and the Jetson Nano 2GB (NVIDIA), a development board equipped with a Graphics Processing Unit (GPU) for image processing, are installed. Four ducted fans were mounted on top of the waterproof case. These fans are controlled by the flight controller to manage the boat's movement. Additionally, a sonar system is attached to the rear of the hull to measure the depth of the pond.

The prototype boat performs autonomous navigation based on a route planned using Mission Planner and programmed into the Pixhawk 6C flight controller.

C. Functional Configuration

Figure 3 illustrates the functional configuration of the proposed system. The existing system configuration has been enhanced with three additional functions: shoreline recognition, distance measurement, and route modification.

In Figure 3, the camera mounted at the front of the boat periodically captures images. The shoreline recognition function uses the image data to estimate the position of the shoreline and outputs the coordinates of the shoreline within the image. Based on this shoreline position, the distance measurement function uses triangulation to calculate and output the distance to the shoreline. Then, the route modification function dynamically adjusts the navigation route using the measured distance.

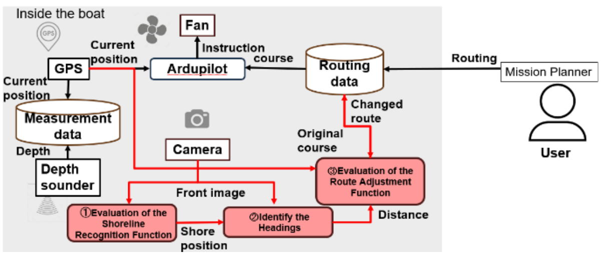

Figure 3. Functional Configuration of the Proposed System.

This series of functions is executed by the Jetson Nano 2GB installed on the boat. The Jetson Nano 2GB is connected to the dual-lens 3D stereo synchronized USB camera module, which manages the timing of the image capture and performs the necessary computational processing for each function. The route modification function communicates with the flight controller Pixhawk 6C via a wired connection, enabling real-time navigation commands and control.

IV. Experiment and Results

The performance of each added function was evaluated through a series of experiments. The purpose, method, and results of these experiments are outlined below.

A. *Shoreline Recognition Function*

(1) Purpose and Method

This function represents the initial step of the proposed system, and it is crucial that it can recognize the shoreline in captured images with accuracy comparable to that of a human determining the shoreline through a camera.

To evaluate this accuracy, we tested the inference performance of semantic segmentation[2]. In this experiment, images of shorelines taken from various distances were input into the shoreline recognition function, and performance was assessed. Multiple models with different training parameters, such as the number of epochs and batch sizes, were developed for semantic segmentation, and a comparison was made to select the optimal model.

(2) Results

The system successfully recognized both the water surface and the shoreline with a visually identifiable level of accuracy across various distances.

Figure 4 provides an example of the output from the shoreline recognition function. In this figure, the shoreline is distinctly identified. The image on the right shows how the system classifies the white areas as water (navigable) and the black areas as land (non-navigable).

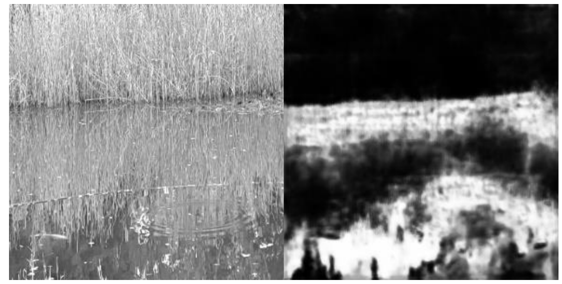

Figure 4. Example of Output from the Shoreline Recognition Function.

The shoreline recognition function utilizes semantic segmentation. The performance of the trained model was evaluated using a confusion matrix, and metrics including the accuracy, precision, recall, and F1 score [3]. The evaluation results for the trained model are shown in Figure 5. As indicated in Figure 5, accuracy exceeded 90%, suggesting that the data volume and number of training epochs were adequate. Although there were a few cases of misdetection in localized areas, such as reflections, the system successfully classified the water and land and recognize the shoreline in most areas.

Accuracy	0.95415149
Precision	0.92114224
Recall	0.91336736
Specificity	0.969868
F1score	0.91723832

Figure 5. Evaluation Scores.

Additionally, for performance comparison, several models were created with varying combinations of batch size (4, 8) and number of epochs (100, 200). Table 1 presents the accuracy metrics for these different hyperparameter settings.

TABLE I. ACCURACY BY HYPERPARAMETER.

epochs	batch size	accuracy
100	4	0.956
	8	0.946
200	4	0.972
	8	0.964

From Table 1, it can be observed that, even with the same data volume, models with more epochs achieved higher accuracy, while smaller batch sizes resulted in slightly better accuracy.

However, a challenge of the shoreline recognition function is the presence of obstacles other than the shoreline. Obstacles such as fences, plants, and rocks can hinder the boat's movement, and thus must be detected and avoided during autonomous navigation. Since the method in this study focuses specifically on shoreline recognition, it is unable to detect such obstacles. To address this issue, it is necessary to develop a function to detect obstacles separately from the shoreline and relay this information to the route modification function.

B. Distance measurement function

(1) Purpose and Method

The distance measurement function calculates the distance from the boat's current position to the coordinates of the shoreline identified by the shoreline recognition function using the stereo matching method [4]. For the boat to adjust its route effectively while navigating, not only is measurement accuracy important, but real-time computation is also required. Additionally, since the boat needs time to alter its course, it is necessary to measure the distance from a point far enough to allow for this adjustment. Therefore, it is important to understand how the distance to the shoreline affects the accuracy of the distance estimation.

To evaluate this, the accuracy of the distance measurement function is assessed by calculating the difference between the measured distance and the actual distance as an error, and then dividing this error by the actual distance.

(2) Results

Figure 6 presents the results of the experiment. The data demonstrate that the distance measurement function accurately measured distances up to 10 meters with an error margin of less than 5% when the boat was stationary. Given that the distance to the shoreline when the boat initiates deceleration is 5 meters, and the error at this distance was less than 0.1 meters (within 1%), the function is confirmed to be sufficiently accurate for practical applications.

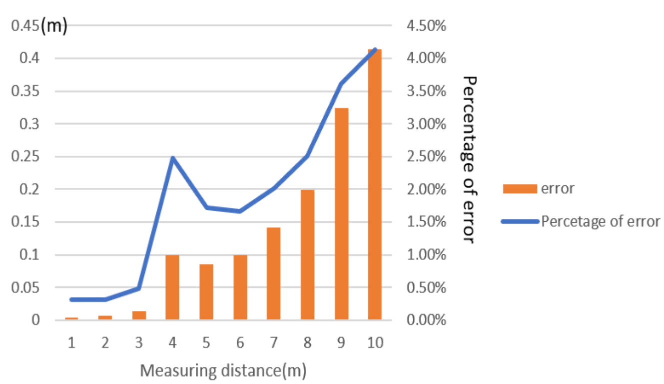

Figure 6. Experiment Results.

However, the camera used in this study had issues when the boat was shaking, causing the captured images to blur and making it impossible to detect distances in some cases. Therefore, for the distance measurement function to operate properly, it is necessary to use a camera capable of capturing clearer images in cases of significant shaking caused by wind, for example.

C. Route Adjustment Function

(1) Purpose and Method

The route modification function prioritizes collision avoidance and the prevention of grounding to ensure safety before making any changes to the navigation route. In this experiment, we evaluated the boat's ability to halt its movement upon approaching the shoreline and to successfully modify its course afterward.

To achieve this, we tested whether the boat could safely navigate while modifying its course.

(2) Results

Figure 7 illustrates the pre-configured route (yellow line) set in Mission Planner, as well as the actual route followed by the boat (red line).

Figure 7. Pre-configured route and the actual route followed by the boat.

The results are as follows:

The boat successfully altered its course to navigate safely before reaching the shoreline. During the experiment, the boat approached the shoreline 25 times along the pre-configured route, but in 8 instances, the route modification function did not perform adequately. The details are as follows:

- At points 2 and 5, the boat ran aground and became inoperable.
- At points 3, 7, 11, 15, 19, and 23, the boat collided with obstacles, requiring manual operation.

The causes of these route adjustment failures are as follows:

- Unclear images due to boat shaking: 4 incidents.
- Unclear images in shaded areas: 3 incidents.
- Collision with obstacles such as fences: 1 incident, where the shoreline recognition function detected these as shorelines.

To address these issues, the following improvements to the shoreline recognition and distance measurement functions are recommended:

- Shoreline recognition function: Enhance the ability to detect obstacles in addition to the shoreline.
- Distance measurement function: Use of higher-resolution cameras to estimate distances with consistent accuracy, regardless of lighting conditions or boat movement.

V. Conclusion

To address the issue of depth measurement errors due to insufficient data in the waterfront areas, we developed a new prototype boat and incorporated three functions to it: shoreline recognition, distance measurement, and route modification. Through experiments, we verified the effectiveness of these functions. The shoreline recognition function achieved over 90% accuracy in its evaluation metrics, the distance measurement function maintained an error of less than 4.5% at a distance of 10 meters, and the route modification function successfully avoided collisions in two-thirds of the cases.

Moving forward, it is crucial to enhance the functionality and accuracy of each component to ensure the system's practicality and facilitate its application to real-world pond depth measurements.

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Real-Time Egg Detection Using Edge Computer Vision

Nicholas Hadjisavvas
Algolysis Ltd
Nicosia, Cyprus
nicholas.hadjisavvas@algolysis.com

Nicolas Nicolaou
Algolysis Ltd
Nicosia, Cyprus
nicolas@algolysis.com

Efstathios Stavrakis
Algolysis Ltd
Nicosia, Cyprus
stathis@algolysis.com

***Abstract*—The adoption of Artificial Intelligence (AI) in agriculture and animal husbandry has accelerated in recent years, driven by the versatility and relatively low costs for development and deployment of smart systems. However, many farms still rely on aging equipment and manual labour rendering these innovations inapplicable. In turn, the inability to harness AI and modernise operations may pose an existential risk. To address this challenge, we advocate for retrofitting existing machinery with AI-based modules as a practical alternative. In this paper, we demonstrate how a poultry egg grading machine can be enhanced with smart capabilities through the integration of deep learning and low-cost commodity edge hardware to enable precise egg counting. We present the methodology and algorithms behind this system that enables real-time processing while maintaining high accuracy. In a limited set of experiments, we demonstrated that the Raspberry Pi 5 (RPi5) running the EfficientDet-lite0 model performed just as well as a desktop with an NVIDIA GPU (graphics processing unit), accurately counting all the eggs it was presented with.**

Keywords-egg counting; smart retrofitting; deep learning.

I. Introduction

Egg production remains to this day as one of the most important farming enterprises providing a steady supply of a highly nutritious and affordable food source. Poultry egg producers are required to follow specific processes for egg handling, processing, labeling, and marketing to ensure the safety and quality of eggs reaching consumers. These are labour-intensive processes that are assisted by purpose-built equipment, such as egg grading and sorting machines, packaging, storage, etc. However, replacing existing equipment and processes can be costly, time consuming and may cause operational disruption. To reduce the cost of modernising existing poultry egg production facilities with little to no interruption the idea of retrofitting can bring about significant gains [1], [2]. Instead of replacing the equipment farmers have learned to rely on, add-on digital devices can be introduced that provide new advanced capabilities.

This work explores the feasibility of ”smart retrofitting” for animal farm equipment. We design, implement, and deploy a low-cost, AI-based edge computing system that integrates with a traditional egg grading and sorting machine. The system automatically counts eggs using computer vision and classifies them based on the configuration of the egg sorting machine. This low-cost solution primarily benefits farms seeking to digitally transform on a limited budget (i.e., the proposed Raspberry Pi 5 system costs approximately one hundred euros).

AI-powered computer vision systems have been widely adopted in animal and food production industries, improving efficiency, product quality, and distribution speed [3], [4]. AI is expected to continue playing a key role in the agri-food industry's transformation [5], [6]. This success is largely due to the availability of pre-trained computer vision models. However, these models usually perform poorly for specialized field applications, such as egg detection, and require to be retrained or fine tuned. Furthermore, most AI models still require substantial computational resources to run in real-time, making them difficult to implement on low-end devices and deploy them in the field.

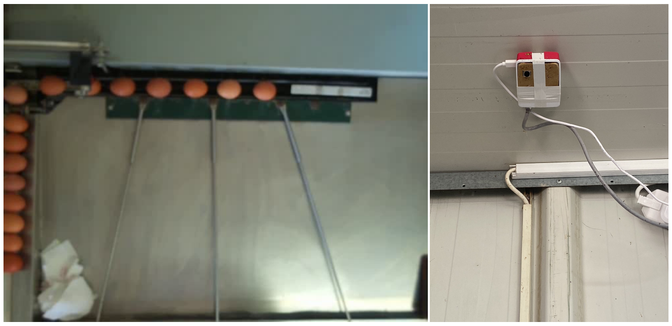
The system presented in this work demonstrates that with very limited computational resources, widely available AI models can be employed to improve operations in animal farms. Our system provides extremely accurate egg counts through a robust object detection algorithm enabling low-end single-board computers (e.g., the Raspberry Pi) to perform object detection and tracking in real time. The system's hardware is inexpensive (i.e., Raspberry Pi and the Pi Camera) and it can be trivially deployed in the field without expert knowledge.

The remainder of this paper is structured as follows: Section II provides information regarding the setup of the system in the environment that it is intended to be used. Section III provides a brief overview of related research that informed our approach. In Section IV, we outline our methodology and present our solution for egg counting at the edge. Section V details the experiments conducted to evaluate the system and discusses the results. Finally, Section VI provides a summary of the paper and highlights key conclusions.

II. Environment

The system developed in this work is based on a Raspberry Pi 5 single-board computer with a Pi Camera V2 module. It was deployed to a chicken farm with a Riva-Selegg Grader, configured to sort eggs into four weight classes (Extra Large, Large, Medium, and Small) with a single feeding lane, shown in Figure 1(a). As eggs move along the horizontal feeding lane, they drop into preconfigured collection areas when their weight exceeds the machine's preset value. These areas are slightly inclined, causing the eggs to roll towards the operator, following random paths, until collected by hand. The machine itself is purely mechanical, without digital features for counting or recording data, so egg counting is done manually by the operators.

The vision-based egg counting edge device was placed



(a) **(b)**

Figure 1: (a) A snapshot of the images obtained by our system. Egg weighting positions are below the eggs running horizontally and located above the egg grading zones separated with metal rods aligned vertically. (b) Ceiling-mounted egg counting Raspberry Pi 5 deployed above a Riva Selegg egg grading machine.

directly above and almost perpendicular to the egg grading machine at a distance of around 2m, as shown in Figure 1(b), in order to provide a top view of the feeding lane and the weighting positions of the eggs.

The system is composed of two subsystems running as independent services: (a) a back-end developed in Python and providing for image acquisition, object detection and tracking, egg counting, and (b) a front-end implemented in ReactJS providing a web interface for controlling the system and its parameters (e.g., calibration, start/stop egg detection, view/edit/confirm egg counts, etc.)

Once deployed, the system requires a simple calibration procedure (detailed in Section IV-E) and is then ready for use. Re-calibration is needed if either the egg detector or grading machine are adjusted.

III. Related work

In the past decade, the application of computer vision and AI in agriculture and animal husbandry has seen a significant increase. In poultry egg production, deep learning has been used to address egg grading [7], identify egg defects [8], [9] or assess freshness [10]. Egg counting, alongside detection, has also been a popular use case for deep learning based applications in the industry [11]–[14].

Automated egg counting using deep learning entails the training of a convolutional neural network to detect eggs first and then the development of a tracking and a counting algorithm to maintain eggs detected through time. Thus, we review some relevent work in object detection, tracking, alongside their application in edge computing.

A. Object detection Models

Ulaszewski et al. [12] conducted experiments comparing MobileNet-SSD (Single Shot Detector) v2, YOLOv3 (You Only Look Once), and Faster-RCNN (Region-based Convolutional Neural Network) for egg detection and counting on various hardware platforms. Using inference speed (fps) and counting accuracy as the primary performance metrics, their results demonstrated that MobileNet-SSD was the fastest and most reliable model under the specific conditions of their experiments.

Yang et al. [8] employed four different versions of RTMDet (Real-Time Models for object Detection) [15] models to perform egg detection for automated defect observation and sorting. While the focus was on a different egg-related task, all models still conducted pure egg detection. Among these, RTMDet-x demonstrated the highest accuracy, outperforming the other versions.

Subedi et al. [13] tested various YOLO (You Only Look Once) model versions for detecting floor eggs, while Luo et al. [16] enhanced a YOLOv5 model for detecting leaky eggs on a production line, achieving superior performance over YOLOv4 and F-RCNN models. Similarly, Vinod et al. [11] utilized a YOLO model for implementing an egg counting system.

B. Tracking

Tracking is a fundamental prerequisite for effective object counting. Tracking algorithms range from simple geometric approaches to more advanced deep learning-based methods, though the latter often come with increased computational demands.

Ulaszewski et al. [12] and Vinod et al. [11] used simple, yet effective, center-based tracking to pair with their detections. Shen et al. [17] also used a similar center location tracking approach to count people in elevators. Other algorithms like SORT [18] and DeepSort [19] are also used for object tracking (e.g Dinh et al. [20] used it for traffic counting). While algorithms such as SORT and DeepSORT are optimized for more robust tracking, it is crucial to account for their increased computational cost, particularly when designing edge applications where processing resources are limited.

C. Edge Applications

Maximizing efficiency and performance in real-time object detection and counting remains an open challenge. Chen et al. [21] reviewed the use of Deep Learning with edge computing, highlighting key issues such as latency, scalability, and privacy. They also focused on the challenges of deploying deep learning models on resource-constrained devices, such as the Raspberry Pi.

Tsu-Chuan et al. [17] have worked on a similar task of edge-based people counting in elevators using a MobileNet-SSD object detector and a line of interest counting strategy. They deployed their system on NVIDIA Jetson nano boards. Deployment of counting systems on the edge also has relevant applications in traffic management and monitoring. Duc-Liem Dinh et al. [20] have introduced a low-cost edge-based system utilising object detection for vehicle detecting, tracking and counting.

IV. Methodology

Our methodology involves four steps: (a) acquire real-time time images from a camera observing the egg feeding lane of the egg grading machine, (b) perform object detection inference using a single-shot model, (c) compare detected objects with those of the previous image to track the objects, (d) use a set of predefined zones to count eggs of different grades, that are either defined interactively or automatically via a calibration step.

A. Image Acquisition

A simple camera module is used to obtain images in real-time. A standard resolution of 640 x 480 pixels is chosen to provide sufficient image quality for processing.

B. Object detection

Single-shot detection models [22]–[24] are regarded as state-of-the-art solutions for real-time object detection. However, achieving real-time performance on edge devices is challenging due to processing power limitations, which render many otherwise effective algorithms impractical for such environments.

The YOLO architecture, depending on the model size chosen, contains a number of parameters in the range of 3.2 to 68.2 million and require 8.7 to 257.8 billion floating point operations (GFLOPs) for a single network forward pass to detect objects in a single image. For reference, the Raspberry Pi 5 can reach around 34 GFLOPS [25], while the Raspberry Pi 4 is rated around 10 GFLOPS. An NVIDIA RTX 3070 Ti discreet GPU can reach 21.75 TFLOPS. It is therefore reasonable to expect that while object detection models can be run on all three hardware configurations, the lower-end Raspberry Pi 4 may have difficulties keeping up with real-time processing. On the other hand, a modern discrete GPU can easily handle larger detection models. This allows for verifying the performance of egg counting algorithms without the risk of reaching a processing power limit.

Since we are only interested in egg detection and counting, it is also necessary to consider the ability of these general purpose detectors to reliably detect eggs. In our tests, we noticed that these models either do not recognize eggs, or they need to be specifically trained with egg samples to be able to perform well.

These limitations highlighted the need for an object detection model with a lighter architecture. Such a model should deliver satisfactory results when trained with an appropriate dataset, without being as computationally intensive as the YOLO models. Lightweight object detection models designed for on-mobile or edge device inference are well-supported within the open-source community. Examples of these models include MobileNet-SSD [23], TinyYOLO, and EfficientDet [22]. Google's autoML provides a family of object detection models which include some light, mobile-sized versions. Probably the smallest model is EfficientDet-Lite0, which offers a good balance between performance and computational efficiency.

Although it has the lowest performance among all the EfficientDet models on the COCO dataset [26], EfficientDet-Lite0 is likely the best fit for our needs due to its lightweight and efficient design. Its documented Mean Average Precision (mAP) 26.41% [27] reflects its ability to generalize across a dataset with various object classes, many of which are irrelevant to our goal of recognizing just one class of objects (i.e., eggs). Therefore, the model was further trained and fine-tuned using a curated, custom egg dataset, as described in Section V.

C. Object tracking and counting

Efficient object tracking is essential for accurate counting across frames, requiring an algorithm with minimal computational demand and reliable results. Distance-based centroid trackers meet these needs by matching detected objects between frames using simple Euclidean distance calculations. The accuracy of the counting relies on correct tracking, as each detected object is assigned a unique ID to ensure it is only counted once.

Distance-based object tracking methods, such as the centroid tracker, have notable limitations, with their performance heavily influenced by factors like inference frequency (i.e., the number of frames processed per second by the detection model).

Low inference frequency poses a major challenge when running deep learning models on edge devices in real-time. This limitation can negatively affect centroid tracking algorithms, which rely on comparing an object's position between consecutive frames. Processing only a few frames per second while skipping others can degrade the algorithm's performance, as objects may be too far apart in time, leading to unmatched or mismatched objects.

D. Counting using Region Of Interest (ROI)

Detection and counting is performed at the feeding lane of the machine. This compartment of the egg grader is responsible for weighing each incoming egg (using weight springs placed along a mechanical conveyor belt at predefined different positions).

First, the feeding lane is divided into four zones, corresponding to extra large (XL), large (L), medium (M) and small (S). Zones are defined as polygonal areas by four points on the image plane, as shown in Figure 2. To count eggs in these zones we adopted a binning approach. We utilise the centroid tracker's results (which include the ID and the centre coordinates of each detected object for each frame) to execute the counting logic. A detected egg is added or removed from the count in any of the bins (zones) based on the location of its center. We use a simple point-in-polygon test to determine if an egg's centroid falls within the region of any given zone. As the eggs move along the feeding lane, eggs are reassigned to zones. As eggs drop from the feeding lane into the collection area of the machine they remain assigned to the last bin they have been detected in.

The pseudocode for the ROI egg counting process is provided in the algorithm shown in Figure 3.

E. Calibration: Automatic Zone Computation

The ROI-based counting algorithm relies on the definition of several detection zones. Although this process is a one-off

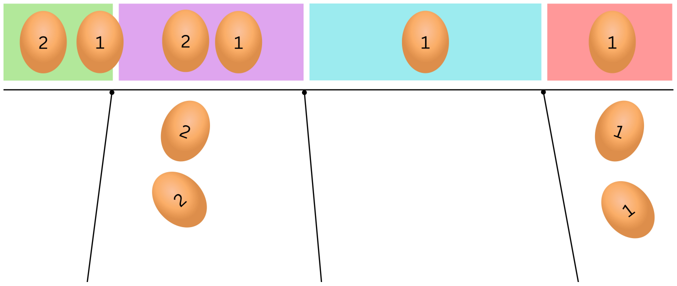


Figure 2: Schematic of the bin counting process using zones. Both eggs with IDs 1 and 2 are assigned to green zone (XL). As they move on the feeding lane (left to right), the eggs are reassigned from the previous bin to the current bin. Therefore, the egg with ID=1 is finally assigned to red bin (S), while the egg with ID=2 is assigned to purple bin (L).

```
  // order by which egg grader sorts eggs
Require: zones = [XL,L,M,S]
Require: bins = dict()
  while isStreaming do
    frame = camera.getFrame()
    detections = model.detectEggs(frame)
    ids = assignIds(detections)
    for id, centroid in ids do
      for zone in zones do
        if pointInPolygon(centroid, zone.polygon) then
          bins[zone].append(id)
        end if
      end for
    end for
  end while
```

Figure 3: Pseudocode of the ROI-based egg counting algorithm.

procedure once the equipment has been deployed in the field, it is still necessary to provide the system with at least four points per zone. In our system the operator can connect to the edge device with a smartphone or tablet and configure the zones via a web interface interactively. However, this can be time consuming and tedious to perform in an animal farm and therefore we devised an effective automatic identification of the counting zones.

The calibration procedure shown in Figure 4 is as follows:

- At least 12 small eggs are passed through the egg grading machine. The choice of “small” eggs allows eggs to travel across the entire feeding lane.
- For each image, the centroid of each detected egg is extracted using the trained object detector.
- Locations of all centroids on the image plane are accumulated over the entire duration of the calibration procedure, as shown in Figure 4(a).
- During calibration, the grading machine sequentially moves each egg along the top horizontal feeding lane on the weighing springs. Based on the egg’s weight, the springs may release it into the appropriate collection area. Eggs spend more time stationary on the weighing springs than in other positions or while rolling into the gathering area, leading to the formation of dense point clusters at these locations. To identify potential counting zones, we apply DBSCAN [28], [29], a density-based clustering algorithm, to group these closely packed points (see Figure 4(b)). The center of each cluster is then calculated by averaging the positions of the points and stored for further use.
- The computed centers of the clustered points are fitted to straight lines to identify the actual weighing locations of the egg sorting machines. First, a grayscale filter (Figure 4(c)) is applied to the image plotting all raw object centers, followed by a thresholding operation (Figure 4(d)) that converts the image to binary. This process removes areas with few or no detections. Subsequently, the Hough transform is used on the remaining centroids to extract a set of straight lines.
- These straight lines are then used in conjunction with the previously extracted cluster centers. The centers are fitted to each line. Lines with cluster centers matching the number of weighting positions of the machine are preserved, while the rest are discarded (see Figure 4(f)).
- For the specific egg grader used in this work, there are two weight springs for large and medium eggs each, and one spring for extra large and small eggs. A bounding box for each of the weight spring locations is computed and then the ones which are responsible for the same egg size are merged. The result of this is visualised in Figure 5.
- Masking Optimization: Once the counting zones are computed, a region that encompasses all zones is estimated. That region is a convex hull computed using the corners of all counting zones. Any pixel outside that region act as a mask (i.e., set to 0). This masking is a significant optimization for the egg detector, because no masked pixels are used when egg detecting, significantly improving accuracy and reducing processing.

V. System Evaluation & Results

A. Experimental Setup

Experiments were conducted to assess the performance of the counting system on three different hardware configurations: (i) a Desktop PC (OS: Windows 10 Pro, CPU: Intel Core i7-4790K, RAM: 32GB, GPU: NVIDIA GeForce RTX 3070 Ti), (ii) a Raspberry Pi 4 (OS: Raspbian, Model: 4B Rev 1.5, SoC: Broadcom BCM2711, Quad core Cortex-A72 (ARM v8) @ 1.8GHz, RAM: 8GB), and (iii) a Raspberry Pi 5 (OS: Raspbian, Model: 5, SoC: Broadcom BCM2712, Quad core Cortex-A76 @ 2.4GHz, RAM: 8GB).

All devices were tested over two different object detection model architectures: (i) the EfficientDet-Lite0 [22], and (ii) the YOLOv8n [24]. Both models were trained with a custom dataset of 2,226 egg image samples (2065 training and 161 validation images). The dataset contains a variety of egg images covering different lighting conditions and angles, as well as different heights between the camera and the eggs. No augmentation was carried out. While the EfficientDet-Lite0 architecture is lightweight enough to run on all three devices, the YOLOv8n model was converted to the NCNN [30] high-performance neural network inference framework optimized

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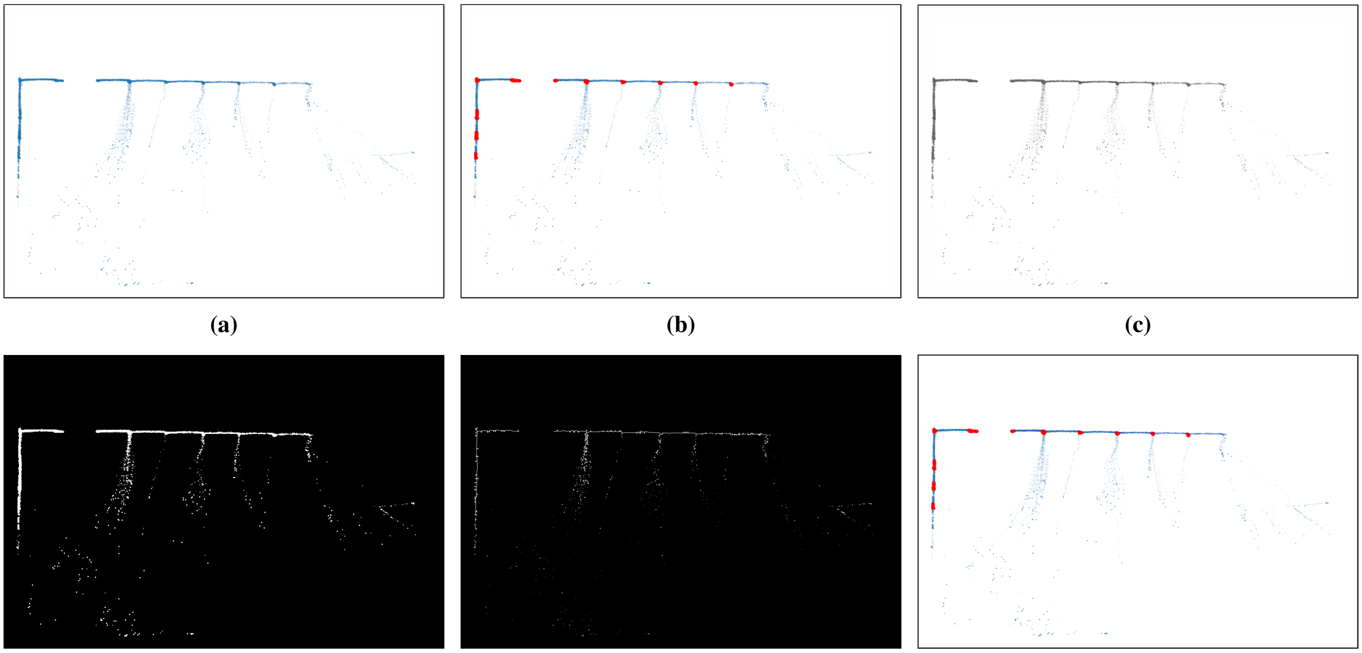

Figure 4: (a) Detection centroids plotted on the XY plane, (b) post application of DBSCAN to the centroid data, with dense locations plotted in red, (c) result after applying grayscale to the plot image, (d, e) result after applying thresholding (add params) and thinning (add params) operations to the image, (f) the final extracted line matching the cluster centers.

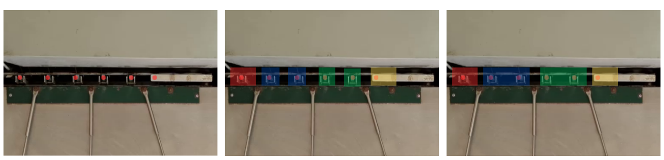

Figure 5: (a) Left: After step 7 of the calibration algorithm. The locations (red points) of the weighting springs along the conveyor belt are acquired. (b) Middle: During step 8 of the calibration algorithm where each point is enclosed into a polygon. (c) Right: Towards the end of step 8, where the polygons of weight springs that are responsible for the same egg size are merged and the zones are finally formed.

for mobile and embedded platforms.

The methodology was tested over 3 video recordings of the single-lane egg sorting machine in operation, each capturing a counting session of a mixture of 30 to 110 eggs of 4 different egg grades: small (S), medium (M), large (L), and extra large (XL).

B. Evaluation Results

For each test case, the system was evaluated for its counting accuracy. Figure 6 presents the results from our experiments. Each row in the figure corresponds to a different video feed, while each plot in a column corresponds to the counts produced by a different device. The blue bar corresponds to the ground truth (i.e., a count obtained by manually counting the eggs), while the orange and green bars correspond to the counts achieved using the EfficientDet-Lite0, and YOLO algorithms respectively.

The results justify our initial hypotheses: the Desktop Personal Computer (PC) managed to count flawlessly in all scenarios. In particular, on the workstation, arguably the most powerful device in terms of computation capability among all others, the system manages to produce perfectly accurate counts for all videos with the EfficientDet-Lite0 model. On the same device, inference with the YOLO model manages to achieve similar results, only missing the count of a couple of extra large (XL) eggs in Video 1.

The Raspberry Pi 4 counting accuracy suffered from its low compute power, producing the worst results across all devices. The slow processing and thus long inference times, prevented RPi 4 to catch up with the speed of the counting machine and resulted in under-counts in almost all scenarios. In particular, EfficientDet-Lite0 performed inference in ≈ 0.159 seconds per frame on RPi 4, while YOLO inference took ≈ 0.515 seconds per frame. Worth noting is the fact that our methodology seems to have a positive impact on the egg-counting, since in almost all scenarios the device appears to under- and not over-count the eggs.

Last but not least, the Raspberry Pi 5 appears to draw the processing boundary at least for the performance of EfficientDet-Lite0. Using the EfficientDet-Lite0 model, we managed to achieve perfect counting accuracy for all egg sizes across all three test recordings (see table I) with an inference time of ≈ 0.046 seconds per frame. On the other hand, Raspberry Pi 5 with YOLO produces sub-optimal results by missing the count of a considerable amount of eggs, especially those in large (L) and medium (M) groups. With YOLO on Raspberry Pi 5, inference time per frame reached

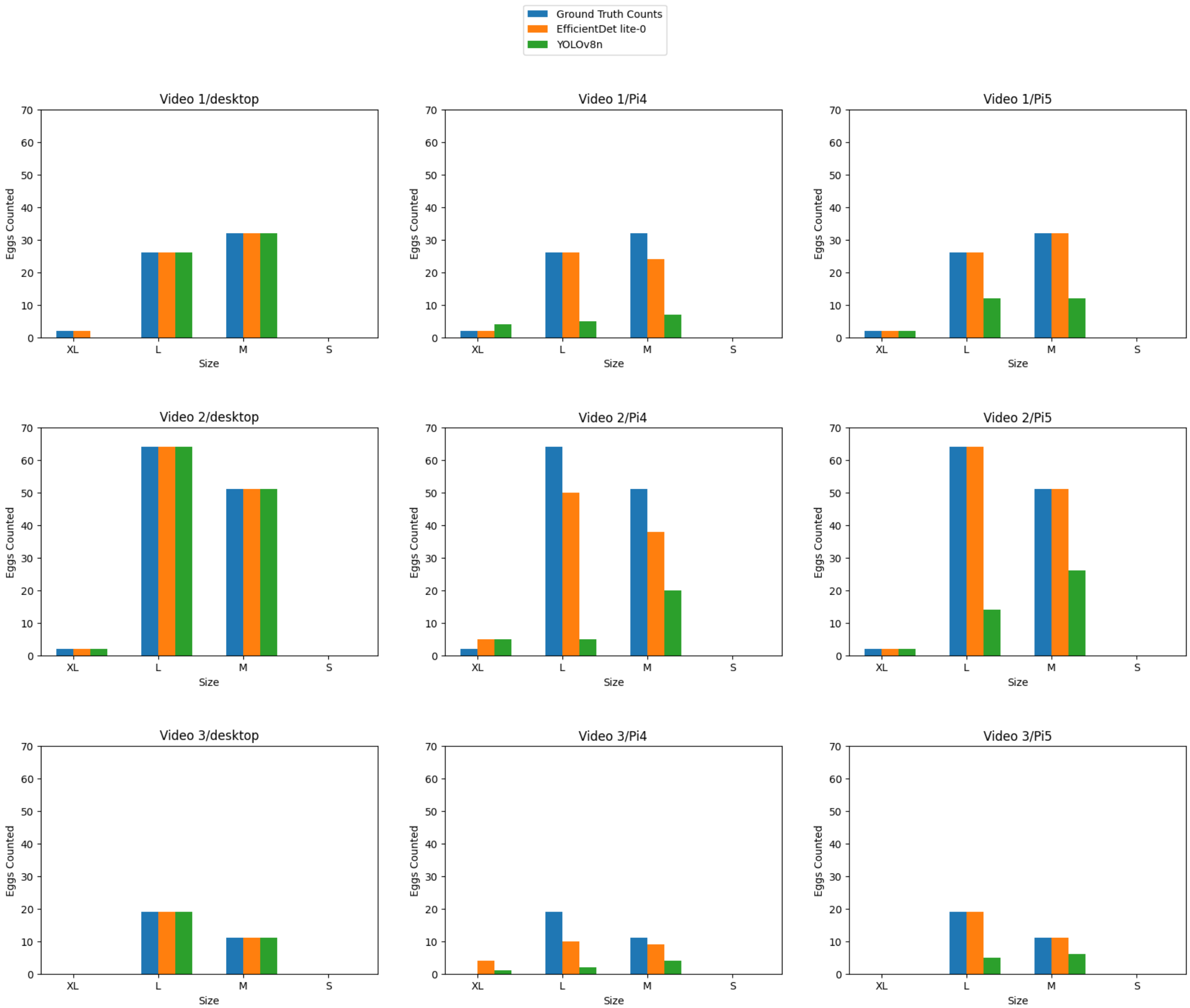

Figure 6: Produced results for all three devices and models over three different test videos. Each row represents processing of a different video. The first column displays the results achieved on the Desktop PC, the second column the counting performance of the Raspberry Pi 4 and the last column that of Raspberry Pi 5.

$\approx$ 0.256 seconds, 5.6 times greater than the time required by EfficientDet-Lite0 for the processing of an individual frame. In light of the preceding observations and analysis, it is apparent that egg-counting accuracy of our system is influenced by variations in inference frames per second. Additionally, the adaptability of the system to diverse egg grading machines poses a challenge, as modifications to certain components would be required for compatibility across other machine layouts. Future work could focus on transforming the system into a more generalized solution capable of operating on a wider range of equipment configurations. Moreover, extending the evaluation to environments with diverse conditions, such as varied lighting, would provide valuable insights into the system's robustness. Expanding testing to a larger, more comprehensive dataset would also help assess the system's accuracy on a broader scale, thus enhancing its reliability in practical applications.

TABLE I: ACCURACY OF THE RASPBERRY PI 5 BASED SYSTEM UTILIZING THE EFFICIENTDET-LITE0 MODEL.

Pi5 / EfficientDet-lite0			
	Counted Eggs	Ground truth	Accuracy(%)
Video 1	60	60	**100**
Video 2	117	117	**100**
Video 3	30	30	**100**

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VI. Conclusion

In this work, we have demonstrated the usage of low-cost, resource-strapped, edge device capable of detection, tracking and counting of eggs. In an attempt to apply the idea of smart retrofitting, we have enhanced existing egg sorting equipment with a small footprint device, a Raspberry Pi 5. Following our methodology, we managed to count a set of graded eggs using visual inspection, in *real time*, and with *very high accuracy*. In fact, in the experiments we conducted, the accuracy of our counting was identical of that of a GPU equipped Desktop PC, and matched the ground truth in all cases. This showcases the advantage of our system compared to the rest in the relevant literature, which is the full capability of our system to operate on edge devices without the availability of computing intensive hardware like GPUs, something that other works in the area relied on.

VII. Acknowledgment

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Beehive Monitoring Based on IoT Technologies and AI

Benahmed Khelifa[1], Merbouh Abdeldjalil[1], Tab Mohamed Abdeessamd[1], Lorena Parra[2, 3], Jaime Lloret[3*], Bourouis Amina[1]

[1] Department of Mathematics and Computer Science, Faculty of Exact Sciences, Tahri Mohamed University, Bechar, Algeria

[2] Departamento de Producción Agrícola, Escuela Técnica Superior de Ingeniería Agronómica, Alimentaria y de Biosistemas, Universidad Politécnica de Madrid, 28040, Madrid, Spain

[3] Instituto de Investigación para la Gestión Integrada de Zonas Costeras, Universitat Politècnica de València, 46730 Grau de Gandia, Spain

Emails: benahmed_khelifa@yahoo.fr, jalilbns08@gmail.com, tab.mr@yahoo.com, lorena.parra@upm.es, jlloret@dcom.upv.es, amina.bourouis@univ-bechar.dz

***Abstract*— The bee is the best pollinator of plants, essential to the balance of ecosystems and our food. Beekeeping and honey collection in their traditional forms have existed for decades in southern Algeria. Currently, beekeeping faces many problems: climate change, chemical pesticides, diseases, theft, predators, and pollutants. The aim of this work is to propose a system to monitor the state of a hive from inside and outside to remedy the problems raised. In this article, we propose an automated hive system based on the Internet of things (IoT) and Artificial Intelligence (AI). This system will collect the internal and external climatic parameters of the hive using different wireless sensors and transfer these values to the beekeeper's smartphone. Actuators placed in the hive will regulate the hive climate and perform other actions. The results of the experiment indicate that the proposed system is effective for monitoring and securing a beehive. An accuracy value of 0.9022 indicates that the decision tree model used for monitoring achieves a high level of accuracy.**

Keywords- Beehive; Smart beehive; IoT; sensor network; Artificial Intelligence; decision trees.

I. INTRODUCTION

Apiculture involves the keeping of honeybees for the purpose of collecting honey and its derivatives. It is an important practice that has many benefits: honey is an essential nutrient which is used in many industries, bees are natural pollinators that heavily influence the biodiversity of our planet and greatly enhance agricultural yield, and investing in this sector represents an opportunity to reduce poverty in rural areas [1][2]. Honey is commonly used as food and medicine, making its protection from contamination crucial to reducing health issues [3].

Bees and their keepers are facing great challenges due to climate change, the use of chemicals in agriculture, pollution, the urbanization of our planet, water scarcity, and overexploitation of plants. For these reasons, several scientists are concerned about the possibility of bee extinction and how it could affect human life in general. Among the issues of apiculture is the sudden hive collapse syndrome where a beehive dies unexpectedly. Another is overheating in the hive due to unprecedented planet-wide temperature increase leading the bees to less food collection and more focus on temperature regulation resulting in less honey production. In addition, sabotage and theft result in incredible loss for beekeepers. Furthermore, natural predators like certain types of birds and insects destroy entire colonies especially when beekeepers keep their hives in distant and rural areas where plant life is more abundant, and pollution is less apparent [4].

To face these problems, beekeepers need to keep constant watch on their hives making sure their temperature is stable, that they receive additional water and food during drought periods, and that they are active and safe from both human and animal enemies. As such, we can say that beekeeper challenges range from hive and bee health, climate, and status monitoring, to controlling their hives for optimal environmental metrics for bee survival and increased yield. Recently, smart IoT and AI technologies are used everywhere in precision agriculture management [5]-[7], including the monitoring and control of environmental metrics.

Considering the needs of beekeepers and the available IoT technologies, we aim in this work to propose a new beehive monitoring system based on both IoT and AI technologies. Our proposed system consists of two subsystems: the first one for monitoring the microclimate of the hive using sensors for temperature, humidity, carbon dioxide (CO2), and weight; the second subsystem is designed to secure the hive against predators, diseases, etc. This security system is based on smart cameras and speakers. Both subsystems use AI processing algorithms, Wifi communications and an Android application ensuring the communication of full system data access by the beekeeper.

The rest of this work is organized as follows. In Section 2, we present a literature review as well as the extraction of parameters/tools used in this research area. In Section 3, we describe the architecture and design of our proposed system. Section 4 presents the results of the work and their discussion. Finally, we conclude this work with a summary and some perspectives in Section 5.

II. RELATED WORK

Many approaches have been used throughout the years to leverage technology to assist in collecting data that can be used to study the health and behavior of individual honeybees and their hives.

In [8], the authors proposed an IoT-based beehive monitoring system. This system captures sensor data (temperature, humidity, weight, video and audio) recordings

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at the hives and sends them using the Message Queuing Telemetry Transport (MQTT) protocol to a ThingsBoard dashboard. In [9], the authors describe the recent advances in precision beekeeping as systems and as services. In [10], the article proposes a Self-Powered Smart Beehive Monitoring, Control System (SBMaCS) using IoT, and interconnecting various sensors of temperature, humidity, weight, motion s, and flame. In this article, the authors develop a mobile phone application that interacts with the SBMaCS hardware to monitor and control the various parameters related to the beehives. In [11], the authors proposed a smart beehive monitoring by microservices and a Web platform using the following hardware and software: Raspberry Pi, Android OS and Microsoft SQL Server. In [12], smart sensor systems were developed for real-time and long-term measurement of relevant parameters related to beehive conditions such as the hive weight, sounds emitted by the bees, temperature, humidity, and CO2 inside the beehive, as well as weather conditions outside. In [13], an innovative Edge-based IoT solution is presented for the detection of Varroa disease. The solution relies on Tensor Processing Unit (TPU) acceleration for machine learning-based models pre-trained in the hybrid cloud environment for bee identification and Varroa destructor infection detection. This proposed system can detect the presence of varroosis in beehives in real-time with the use of Edge Artificial Intelligence invoked for the analysis of video streams. In [14], the authors propose an IoT based smart beehive monitoring system integrated with advanced sensors, the system monitors temperature, humidity, hive weight, and diurnal cycle. The system provides real-time data, remote connectivity, and actionable insights for beekeepers. The system enables early disease detection, proactive interventions, and optimized hive management.

Based on this literature review, we conclude the following: Most of the research works in the field of smart hive monitoring have been based on various techniques, algorithms, Artificial Intelligence (AI) and IoT technologies. However, none of these works have addressed the issues of hive security or the challenges associated with the arid climate of a Saharan region. Our study aims to integrate these aspects by taking these specific constraints into account, while using Artificial Intelligence for data classification and decision making. This opens new perspectives for sustainable hive management in harsh environments.

III. PROPOSED SYSTEM

A. System architecture

Figure 1 shows the architecture of our system. The first component is the beehive climate monitoring component. This part is equipped with sensors for temperature, humidity, CO2, pressure, weight and an internal camera. The security component of the beehive includes an external camera, a motion sensor, a proximity sensor, and a GPS. The actuator part contains a fan and a speaker. The software component includes the cloud, databases, and the Web application.

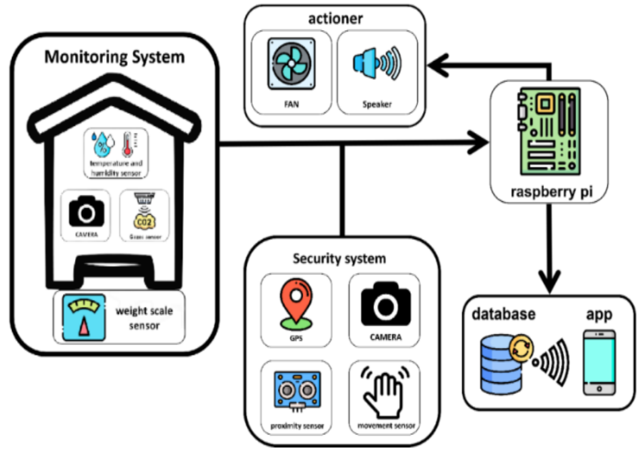

Figure 1. Architecture of the proposed system.

B. Description of the used components

In this section we describe the different components included in the proposed system.

- Raspberry Pi

Raspberry Pi is a Controller using the operating system Raspberry Pi OS (Raspbian). This installation necessitates an SD card. To install Raspberry Pi OS on SD card we used Raspberry Pi Imager.

- BME280

The BME280 sensor typically uses the I2C (Inter-Integrated Circuit) protocol for communication with the Raspberry Pi.

- DHT11

Installing the Adafruit_DHT library is a reliable means to acquire temperature and humidity data from DHT series sensors. Connecting the DHT11 sensor to the Raspberry Pi.

- MQ135

Since the Raspberry Pi 3 B+ lacks analog pins, we utilized an Arduino Uno to read the output of the MQ135 sensor. We established a serial communication between the

- HC-SR04

The RPi.GPIO libraries provide convenient functions to access the GPIO pins to interface with HC-SR04 sensor. Connect HC-SR04 to the Raspberry Pi.

- Raspberry Pi Camera V2

Installing the Pi camera library in Python allows access and control of the Raspberry Pi Camera Module. Connect Raspberry Pi Camera Module to the Raspberry Pi.

- SRD-05VDC-SL-C Relay

The RPi.GPIO libraries provide convenient functions to access the GPIO pins to interface with the SRD-05VDC-SL-C relay. Connect the relay to the Raspberry Pi.

In Figure 2, the experimental components of our monitoring system are identified. Both the pictures of the physical components, (Figure 2 a) to c)), and a scheme of their communication (Figure 2 d)) are displayed.

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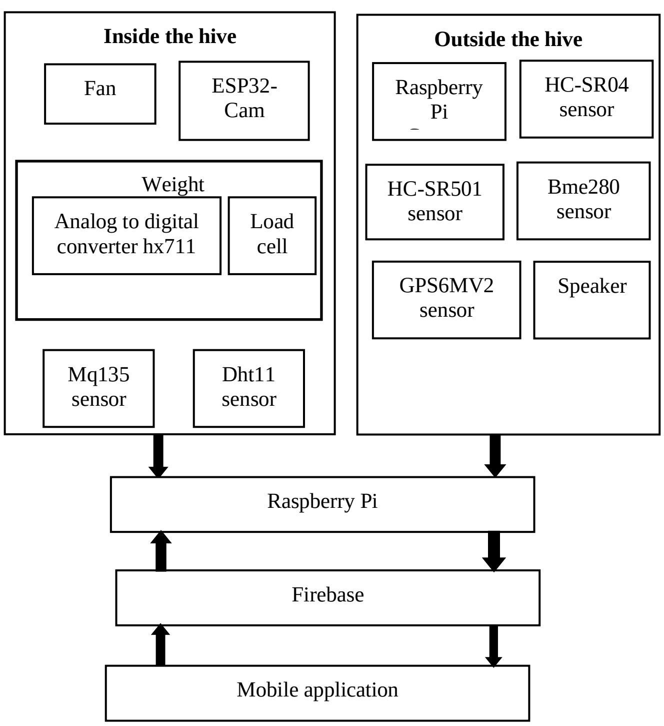
(a) Beehive External and Internal components.

(b) Weight sensor. c) Security sensors.



(d) Components communication.

Figure 2. System description including physical components a) to c) and their communication d).

C. System funcional modules

Our proposed system performs two primary functions. Firstly, it monitors the beehive by collecting and analyzing data (temperature, humidity, weight, etc.) at regular intervals which is then sent to the cloud for storage and can be accessed through our mobile app. Secondly, it secures the beehive by conducting environmental scans to detect potential hazards (predators, thieves, etc.), with alerts sent to the mobile app. Below, Figure 3 shows the two monitoring modules of a beehive.

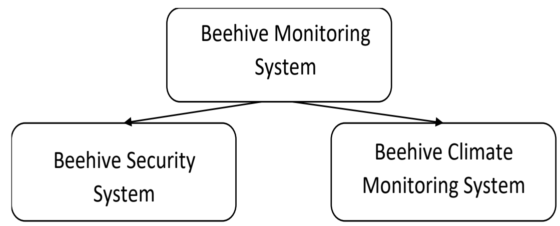


Figure 3. Beehive monitoring modules.

The module of beehive climate monitoring system is presented in Figure 4. This system collects temperature, pressure, humidity, CO2, weight, and photos from sensors and a camera at regular intervals.

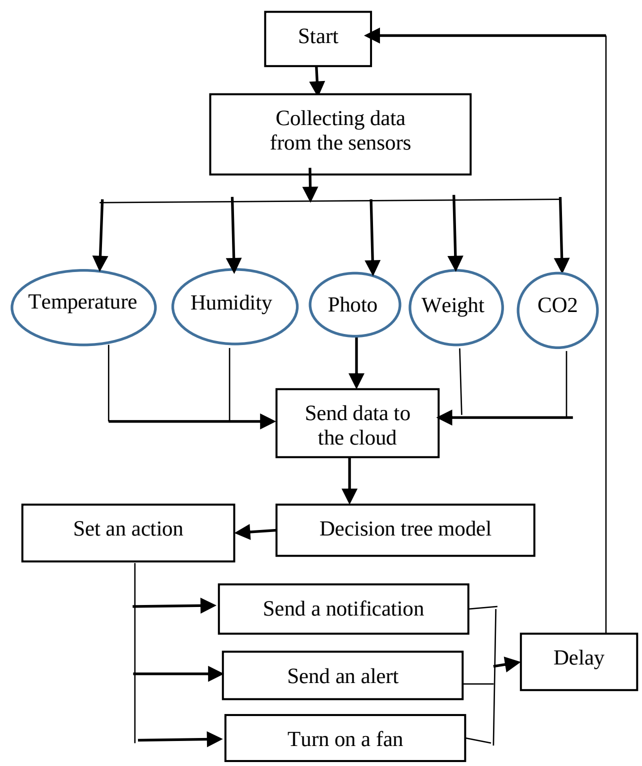


Figure 4. Climate monitoring diagram.

The collected data is then analyzed by the Decision tree (an AI Algorithm) to identify any necessary actions and send results to the cloud for storage. The data can be easily accessed through the mobile app.

To improve the productivity of the bees as well as their safety from the dangers of the surrounding area, the system in Figure 5 is designed to conduct environmental scans on a regular basis. This involves using a combination of proximity sensors, HC SR501 sensors, and a camera to detect potential hazards in the beehive's surroundings. The proximity sensors can detect any objects that are too close to the hive and may pose a threat to bees like predators or humans. The HC SR501 sensors can detect any movement such as intruders. The camera can capture images of the beehive's environment allowing beekeepers to visually inspect the area for any potential hazards.

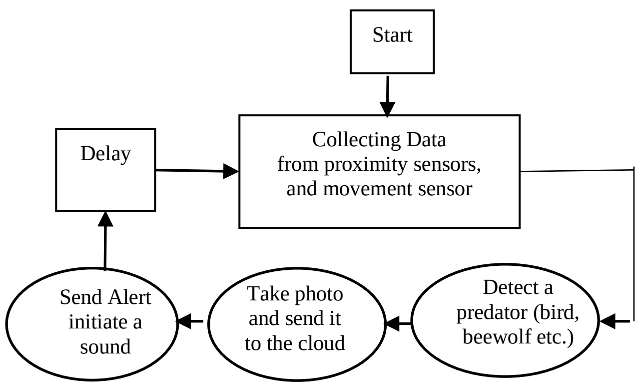


Figure 5. Beehive security system.

These used sensors and cameras can detect potential threats to ensure the security of the hive and take appropriate measures. For example, if the proximity sensors detect a predator (bird, beewolf, thief, etc.), the system can warn the beekeeper and send him a notification and a photo. The system through a speaker can trigger a hawk sound to deter nearby birds which effectively protect the hives. The camera can also be used to monitor activity around the hive as well as the detection of diseases such as varroa.

IV. RESULTS AND DISCUSSIONS

In this section, we will present the implementation of our beehive monitoring system. The experiment took place in the south-west of Algeria, in Bechar city, which is an arid area with a dry Saharan climate. The data from this experiment are derived from the beehive shown in Figure 2 a).

A. Collected data

The data collected in Table 1 are a series of measurements taken at different dates and times, concerning various environmental factors of a beehive. Here is a general description of the data collected from IoT sensors of our proposed system:

1. Date: The dates range from March 8, 2023, to June 10, 2023, capturing a period of several months.
2. Interior Temperature: The temperature recorded inside the location varied between 24.5°C and 37.0°C, with the highest temperature observed on May 29, 2023.
3. Exterior Temperature: The recorded exterior temperature ranged from 27.2°C to 40.4°C, with the highest temperature observed on June 10, 2023.
4. Rainfalls: The data indicates whether rainfall occurred during the measurements.
5. CO2 Levels: The CO2 levels ranged from 465.62 to 538.94 parts per million (ppm), with the highest level observed on May 29, 2023.
6. Humidity: Humidity levels ranged from 32% to 80%, with the highest humidity recorded on April 26, 2023.
7. Weight: The weight measurements indicate a range from 11.38 to 18, representing units specific to the context of the data collection.
8. Pressure: The pressure values ranged from 925.6 Pa to 933.7 Pa.

TABLE I. COLLECTED DATA FORM DIFFERENT SENSORS AND AT DIFFERENT DATES.

Date/Time	Interior temp. (°C)	Exterior temp. (°C)	Rain falls	CO2 (ppm)	Humidity (%)	Wight (Kg)	Pressure (Pa)
08/03/2023 22:38	24.5	27.2	false	490.06	70	15	930.6
26/04/2023 16:53	25.0	28.0	false	498.21	80	18	925.6
27/04/2023 00:55	30.2	31.0	false	506.35	60	12	927.1
29/05/2023 17:07	37.0	38.1	true	538.94	34	11.5	930.1
10/06/2023 15:10	33.0	40.4	false	506.35	32	11.4	933.7

B. Decision tree model

In our monitoring system, hive management is done based on AI and Machine Learning (ML) models to improve the efficiency of beekeeping operations.

The decision tree is a model created and integrated into our monitoring system for decision making and beehive management. Table 2 illustrates the different classes of hive state generated by our decision tree model.

Courtesy of IARIA Board and IARIA Press. Original source: ThinkMind Digital Library https://www.thinkmind.org

TABLE II. GENERATED CLASSES BY THE DECISION TREE MODEL

Example	**Attributes**						**Result**			
	Humidity %RH	Exterior Temp. Cº	Interior Temp. Cº	Weight Kg	Co2 ppm	Rainfall in last 24h	Send Notification	Send Alert	Requires hive visit	**Class**
1	70 -95	9- 47	10- 36	1- 35	440-500	N	N	N	N	Normal
2	70 -95	<8	10- 36	1- 35	440-500	N	Y	N	N	Hibemation
3	>96	9- 47	10- 36	1- 35	440-500	N	Y	N	N	Evaporating Nectar
4	0 -70	9- 35	10- 36	1- 35	440-500	N	Y	N	N	Low humidity hive
5	60-85	9- 35	10- 36	1- 35	440-500	N	N	Y	Y	Colony no longer in hive
6	70 -95	9- 35	10- 36	1-35	400-440	N	N	Y	Y	Diminished population - Reduced C02 production
7	70 -95	9- 47	>38	1-35	440-500	N	N	Y	Y	Hive is too hot
8	>96	2- 47	10- 36	1-35	440-500	Y	N	Y	Y	Hive is too damp
9	0- 100	9- 47	10- 36	>'5	440-500	N	Y	N	N	Hive is too heavy

Table 3 shows the evaluation of the performance of the proposed decision tree model system, including the following metrics: F1-Score, recall, and accuracy.

TABLE III. EVALUATION METRICS VALUES

Metrics	**Metric value (%)**
F1 Score	88.5
Recall	88.3
Accuracy	90.2

These results highlight its excellent performance in classification tasks.

C. Discussion and Graphs

Analysis of these graphs provides an insight into the environmental conditions surrounding the hive which can be valuable to beekeepers in managing and understanding hive health and productivity.

From the observations, it has been found that there is a close relationship between the different environmental parameters of the hive (temperature, humidity, CO2, weight, etc.). The ideal conditions for these parameters can be regulated by the bees themselves or with the help of the proposed intelligent system actuators. For example, fans can be used to improve air circulation if the temperature or CO2 becomes too high; a misting system can be used to control humidity if it is insufficient. Another is heating, which can increase the temperature when needed, mainly during cold seasons.

By combining natural bee regulation and advanced technologies, it is possible to create an optimal environment for colony development which can increase productivity and overall hive health. This represents an opportunity for modern beekeeping to evolve towards more sustainable and efficient practices.

The gathered data is presented in the next paragraphs. First, the results of temperature inside and outside the beehive on March 10, 2023, are presented in Figures 6 and 7.

It is possible to see that inside the hive the temperatures are lower than outside during the day. Regarding the rest of the monitored parameters inside the hive, we can identify in Figure 8 that the humidity is minimum at midday with maximum values during the night. Finally, the CO2 concentration is maximum in the late hours of the day, as shown in Figure 9, since this is the moment in which the bees are inside the hive.

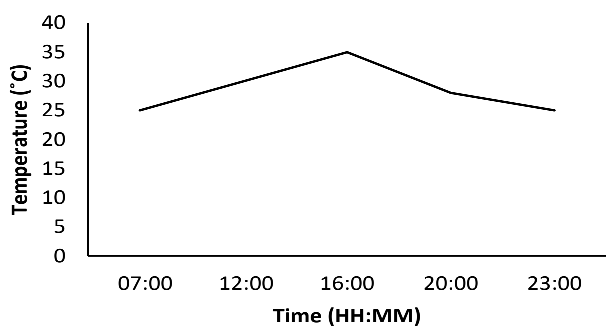


Figure 6. Variation of Temperature Outside the Hive on March 10, 2023.

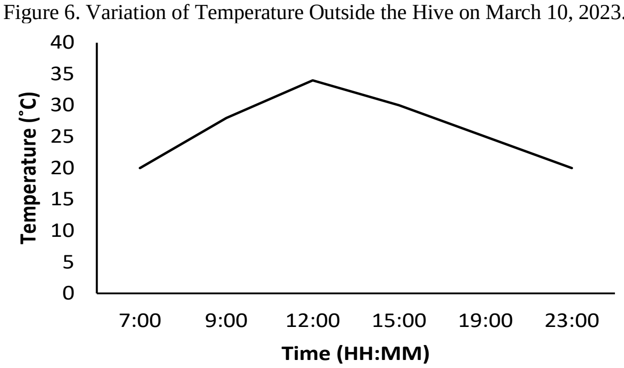


Figure 7. Variation of Temperature Inside the Hive on March 10, 2023.

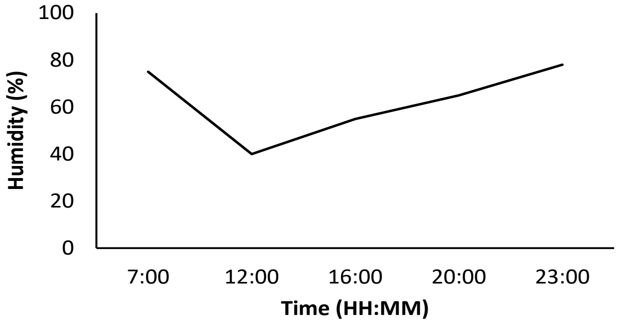


Figure 8. Variation of Relative Humidity Inside the Hive on March 26/27, 2023.

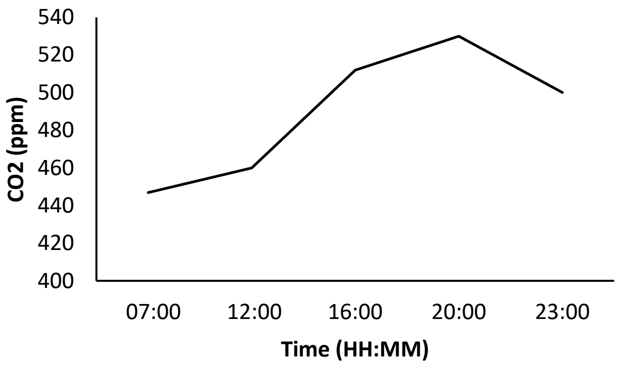


Figure 9. Variation of CO2 Inside the Hive on March 10, 2023.

Moreover, with this gathered data it has been possible to compare the parameters of a beehive on two different dates: March 9/10, 2023, and June 9/10, 2023. This information is presented in the following figures. In Figure 10, we compare the temperature inside the hive. It is possible to see that despite the high difference on date, the temperature inside the hive is very similar. Figure 11 represents the variation on the humidity inside the hive. In this case, there are differences among the dates with high humidity values in March.

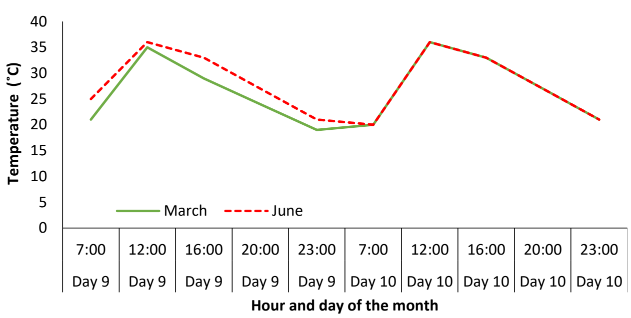


Figure 10. Variation of Temperature Inside the Hive in March and June.

In Figure 12, the variation in the beehive weight is depicted. The weight is slightly higher in June than in March.

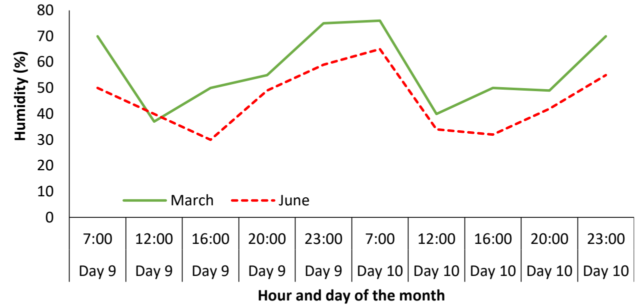


Figure 11. Variation of Relative Humidity Inside the Hive in March and June.

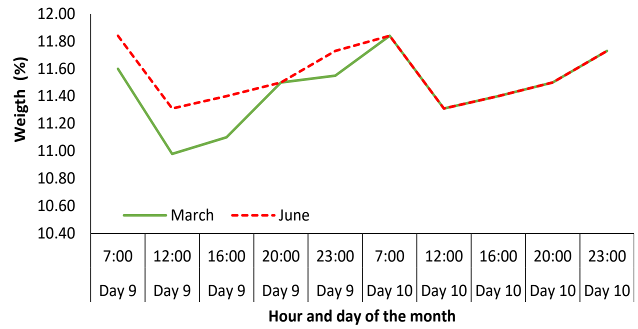


Figure 12. Variation of Weight Inside the Hive in March and June.

V. Conclusion and Perspectives

This work highlights the growing importance of IoT and AI technologies in monitoring beehives in the Sahara region in southwestern Algeria. These technological advances offer innovative solutions to monitor the health status of the hive and protect the bees from predators such as bee-eating birds, diseases like varroa, and theft, therefore, contributing to the preservation of the ecosystem and the sustainability of beekeeping. The experimental part of this work shows that AI algorithms can analyze data from IoT devices which ensures intelligent monitoring of the hive.

Our future work will provide more details on the results of experiments related to hive security, namely the detection of predators and diseases affecting bee colonies, besides the study of other parameters like bee sounds, and bee behavior based on Artificial Intelligence and Internet of Things technologies. We also plan to evaluate the system in varied environments and integrate more data analysis methods and AI models for better, deeper insights.

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A Monitoring System of Crops and Meteorology Parameters by Bringing Together Physical Sensors and Computer Vision Cameras

Francisco Heredia-Blaya, Laura García, Antonio-Javier Garcia-Sanchez, Rafael Asorey-Cacheda,
Joan Garcia-Haro
Deparment of Information and Communications Technologies
Universidad Politécnica de Cartagena (UPCT)
Cartagena, Spain
emails: francisco.heredia@edu.upct.es, {laura.garcia, antoniojavier.garcia, rafael.asorey, joang.haro}@upct.es

***Abstract*—Mediterranean countries have been facing severe droughts in recent years, leading to water restrictions for consumers and farm owners in the most affected areas. This situation has resulted in increased interest for investing in smart systems to monitor crops, aiming to reduce resource usage and improve crop quality. Existing sensor devices typically measure only a limited selection of physical parameters, such as soil moisture, air temperature, and relative humidity, among others. Furthermore, these devices are usually deployed in various parts of the fields and require different power sources. In this paper, we present a system that gathers data not only from physical sensors but also from cameras to implement computer vision models that enable the monitoring of aspects such as insect presence and plant diseases. These tasks are conceived within the AerOS framework. The system consists of a set of electronic devices designed and developed by ourselves, a heterogeneous wireless network for communication among all devices, and a server to manage the network, store the data, process it, and present it to users. All these components are housed in an anti-vandalism case and powered by a single power source, consisting of a solar panel and a battery. This integrated system expands the features of conventional agriculture monitoring systems.**

Keywords-agriculture; IoT; monitoring; heterogeneous network.

I. INTRODUCTION

The use of sensing devices in agriculture has experienced a significant growth in recent years. It has been fueled by severe droughts and other adverse conditions farmers have suffered, with special dificulties in the Mediterarnean area subject to irrigation water restrictions mandated by local governments. These events have led to the development of multiple Internet of Things (IoT) solutions for agriculture, specifically employing low-cost components [1]. This choice of components is primarly motivated by the limited economic resources that farmers may have. However, this also leads to devices that cannot cope with the weather conditions to which they are exposed for long, or sensors that do not provide reliable readings. Thus, it is necessary to invest in quality materials to ensure the correct performance of sensing devices. Furthermore, these devices are often placed in rural areas without access to the power grid, requiring the provision of alternative sources of power such as batteries and solar panels [2]. However, when a set of devices is deployed, the cost of these materials to power each device increases. Therefore, combining some of these devices to be powered by the same set of solar panel and battery may alleviate the higher cost of quality components.

New technological solutions aimed at solving agricultural challenges are including not only sensor data, but also data from images that get analized [3]. But deploying cameras on fields is not done in a straightforward manner [4]. Powering the camera is one of the limitations that need to be faced. However, there are suitable solutions on the market that include solar panel powering. The main challenge cameras face is communication. Pictures and images require higher bandwidth than the numerical values (telemetry) obtained from sensors, resulting in the need for high-bandwidth connectivity. 5G can provide high connectivity to agricultural systems, but the cost of endowing every device with 5G connectivity would be prohibitive, as each will require a SIM card module and a contract with a service provider for each SIM card. Thus, new approaches would benefit from adapting to the different wireless communication needs of each device.

Heterogeneous wireless networks consist of several wireless technologies that are used within the same wireless network [5]. A set of gateways enable the information encapsulated in messages to change their format according to the standards of the required wireless communication protocols. This allows cellular technologies such as 4G and 5G, long-range low-bandwidth technologies, such as LoRa (Long Range), and medium-range high-bandwidth technologies such as WiFi to provide wireless connectivity to agricultural smart devices. These types of solutions adapt to different transmission needs, facilitating the deployment of telemetry sensor devices with low bandwidth requirements at far distances from the gateway using LoRa, and high-bandwidth demanding cameras to transmit pictures and videos using WiFi or 5G/4G communication. The flexibility heterogeneous wireless networks provide can be leveraged by solutions that required seamless connectivity to manage systems that operate in the edge-cloud continuum. Meta operating systems such as AerOS [6] are vouching for developing distributed solutions with cross-domain resource orchestration for different type of use cases, including agriculture. Therefore, considering the aforementioned needs, in this paper, we present a system for crop and meteorology monitoring in agricultural fields that include physical sensors and cameras collecting images intended for computer vision solutions. It comprises a weather-resistant anti-vandalism encapsulation and provides connectivity to heterogeneous wireless devices using a common power source for all devices.

The remainder of the paper is organized as follows. Section 2 reviews the related work. The methodology is detailed in Section 3. Section 4 discusses the results. Lastly, the conclusion and future works are written in Section 5.

II. Related Work

Monitoring soil moisture and other soil parameters has been the main focus of precision agriculture for many years. As a result, there have been many works dealing with this topic. Park et al. presented a system that monitored soil moisture, atmospheric temperature, and relative humidity using low-cost sensors and open-source software [7]. The system also included a water pump to control irrigation. Experiments were conducted at a soybean cultivation. The results showed that the system was able to maintain soil moisture at 40%. Chen et al. introduced a high-density in-situ solution for soil moisture monitoring using the Narrow-Band Internet of Things (NB-IoT) protocol [8]. Thus, the devices required a SIM card to communicate. They used an RS485 soil moisture sensor and tested battery life. The results from one year of tests showed better spatial-temporal accuracy of soil moisture, lower cost, and better energy consumption performance using NB-IoT than other technologies such as ZigBee [9].

Favorable meteorological conditions are also paramount for good crop development. However, optimal weather is rare. Therefore, many works focus on monitoring weather parameters to adopt solutions to adverse climatic events. Khan et al. implemented a low-cost solution for weather monitoring [10]. It was comprised of an Arduino Mega, operating as a control system, and sensors for wind speed, wind direction, rain, solar irradiance, and CO2 concentration monitoring. The gathered data was then transmitted to the cloud. Marwa et al. proposed a system that monitored temperature, humidity, and rain in real time using the S-THB-M008 and S-RGB-M002 sensors [11]. Data were sent to a cloud server that included a MySQL database. Their climatic monitoring system was tested in Tunisia for one year. The results revealed the correct performance of the system. Moreover, Rajapaksha et al. designed a handheld weather station for monitoring barometric pressure, air temperature, air humidity, soil moisture, and carbon monoxide [12]. The device uses an ATMEGA 2560 Microcontroller, a power unit with removable and rechargable batteries, an LCD display, a sensor panel, local storage, a micro-USB charging port, and a common port to connect external sensors. The device also allowed for SMS alerts when temperature thresholds were exceeded.

As soil and meteorological aspects are both indispensable in precision agriculture systems, some works have included sensors intended for these two aspects in their solutions. Placidi et al. proposed a Wireless Sensor Network (WSN) for low-cost soil water content monitoring [13]. Their solution included a photoresistor, a temperature sensor, a low-power microcontroller, and a solenoid valve. Tests were performed in Silty Loam and Loamy Sand, with a non-constant sensitivity for the low-cost volumetric water content sensors. Furthermore, the parameters of the non-linear fitting equation were optimized to correlate the analog voltage output to the reference values for the volumetric water content. Singh et al. designed an irrigation system for precision agriculture in urban environments [14]. The system was based on soil and weather conditions including soil moisture, air temperature, relative humidity, wind speed, and wind direction. The system was tested for two months and the data was displayed using the Thingspeak platform.

Lastly, a growing number of works have begun proposing the use of heterogeneous wireless networks in agriculture. Sanjeevi et al. introduced a scalable WSN using devices comprised of air temperature, air humidity, air pressure, and pH sensors, as well as an Arduino board [15]. Tests were performed to determine the performance of a heterogeneous network with WiMax, WiFi, and LTE wireless technologies, showing that each technology can be advantageous depending on the network requirements of the deployment. Furthermore, Jose Agustín Rodríguez-Mejía et al. proposed a heterogeneous WSN for precision agriculture that combined LoRa, Bluetooth Low Energy, Zigbee, and WiFi using low-cost Heltec Wireless Stick V3 devices [16]. The selection of the wireless technology is based on the content to be transmitted and the Received Signal Strength Indicator (RSSI). The tests concluded that their solution was efficient and reliable.

The solution presented in this paper includes soil and weather monitoring as well as a camera and the use of a heterogeneous communication network to transmit the data from the different devices to the servers. This way, we combine the key aspects necessary for up-to-date precision agriculture solutions, and provide a reliable source of data and images to feed Artificial Intelligence models.

III. Methodology

This section describes the implementation of the hardware of the system and the software development.

The system consists of a base station that houses all the sensing devices, batteries, and the solar panel (see Figure 1.) It features an anti-vandalism enclosure with weather-proof materials and the solar panel on top, shielding the inside. Inside, the Suspended Particulate Matter (SPM) sensor, temperature sensor, humidity sensor, wind speed sensor, solar irradiance sensor, soil moisture sensor, and batteries are placed on the different shelves of the housing. The gateway is installed vertically hanging on one of the walls of the enclosure. The camera is placed on the outside of the enclosure to get a full vision. Furthermore, the camera includes its own solar panel for power supply that is also placed on the outside of the enclosure. The additional powering system was engineered to guarantee the operation of the gateway and sensing devices during nighttime and cloudy days.

A. Hardware implementation

The sensors included in the base station are distributed into several sensing devices. Namely, a meteorology and soil

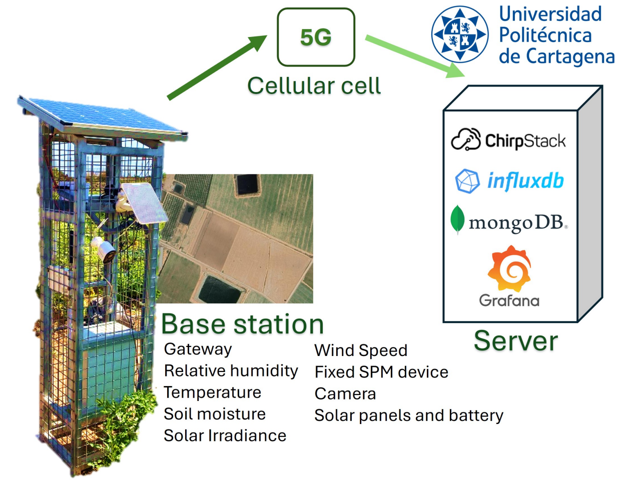

Figure 1. Architecture of the system.

Figure 2. System deployed in anti-vandalism enclosure.

monitoring device that includes the air temperature, humidity, wind speed, solar irradiance, and soil moisture sensors. It is important to highlight that the wind sensor requires a higher voltage power supply than the other sensors. Another device with a case that allows air flow through it includes the SPM sensor. Lastly, the camera is deployed on its own.

Figure 2 shows a detailed view of the inside and outside of the enclosure with the different sensing devices. The meteorology and soil monitoring device is composed of the following elements. The Arduino board itself provides a standard 5V power output, which is shared to power all sensors. However, the wind sensor requires a Direct Current (DC) amplifier to step up the voltage from 5 to 12 volts to ensure its proper functioning. Another consideration is the data output of each sensor. Data obtained from these sensors include parameters such as environmental and soil humidity, temperature, wind speed, radiation, and the battery charge level of the device. To access the sampling values of soil moisture, radiation, and battery voltage, the analog pins on the Arduino board are used. Other sensors, such as the temperature and environmental humidity sensor, operate under the Inter-Integrated Circuit (I2C) communication protocol. Therefore, the SDA and SCL pins were used to facilitate the connection, as their output is not directly connected to an analog pin. Lastly, the wind sensor, poses a particular challenge due to the fact that the Arduino board has an internal Analog-to-Digital Converter (ADC) operating in a 0 to 3.3 volts range, while the wind sensor's proportional output operates in a wider range of 0 to 5 volts. To address this mismatch, we have employed an external analog-to-digital converter capable of processing these inputs and generating a compatible output with the I2C protocol. This converter is powered by the Arduino board and uses a pin of the ADC to send data to the board.

The SPM device is made of a suspended particle sensor with a 0.35 to 40 µm particle range and a data aquisition frequency ranging from 1 to 30 seconds [17]. The SPM sensor is connected to the Arduino board through the Serial Peripheral Interface (SPI) interface. The Arduino board has LoRa connectivity and uses this wireless technology to transmit data to the gateway.

The RAK gateway has LoRa, WiFi, and 5G connectivity. The SPM device and the meteorology and soil monitoring device transmit their data through LoRa to the gateway. Conversely, the camera, requiring higher bandwidth, sends images and video to the gateway through WiFi. The gateway is equipped with a SIM card and uses 5G/4G to send the data to the cellular cell of the service provider. If there is no 5G connectivity in the area, other cellular technologies could be used as long as video traffic can be transmitted.

Regarding the power supply for the devices, two distinct sources are used: a solar panel and a battery. The Arduino boards, the gateway, and the battery are connected through a charge controller. While the solar panel generates power, it ensures that the battery is charged and the Arduino boards and gateway are powered. However, when the solar panel does not provide enough power, the battery takes over as the power source for the system until the solar panel starts generating power again or until the battery is depleted. The battery can last up to 5 days in adverse weather conditions with no sunlight. This is the standard for solar panel infrastructures in the area.

B. *Server implementation*

On the server side, the managmenet and processing of the information generated by the sensors to obtain a meaningful and easily interpretable visual representation of the data is programmed. This step is crucial, as it allows better understanding the performance and behavior of the device under different conditions.

The server at the UPCT receives all the data using the LoRaWAN communication protocol. The network server is the Chirp-Stack open-source LoRaWAN server [18]. When the network server receives the messages from the field devices, the acquired data is stored in a database. Due to the different characteristics of the data, including numerical values and images, two types of databases where used. InfluxDB was the choice for storing and managing time series data [19]. The decision to use InfluxDB is made to its ability to handle large volumes of real-time data and its efficient structure for time series storage, which is well suited for the numerical data gathered from the sensors. Conversely, MongoDB was used to store images, which could not be stored using InfluxDB [20].

Once the databases were configured and running, Grafana [21] was integrated into our system. Grafana allows interactive dashboards with graphs, tables, and other visual elements, making it easier to interpret and analyze the data stored in InfluxDB. Furthermore, Grafana can also embed images and videos retrieved form MongoDB. To achieve the final graphical representation, the necessary queries were made to visualize the extracted data as effectively as possible. Line graphs were chosen to represent the evolution of humidity levels, temperature, wind speed, solar radiation, and soil moisture over time. These line graphs help in identifying trends, seasonal patterns, and significant changes in the sensor data. Additionally, the battery status of the device was presented using pie charts. These charts provide a quick and clear view of the battery charge percentage, which is crucial for evaluating the device's autonomy and energy efficiency. Nevertheless, while line and pie charts were used for our current purposes, Grafana offers a wide range of visualization options. Dashboards can be customized and adapted according to the user specific needs and preferences as well as the requirements of each project.

IV. Results

In this section, we present the results from the base station deployed on the fields. These results show some relevant observations from different time periods.

Figure 3 shows the overview of the Grafana dashboard for our system. The user interface was designed so that one can easily view the current values from the sensors. This includes different sizes of particulate matter (PM01, PM2.5, and PM10), wind, solar radiation, humidity, soil moisture, and temperature. Furthermore, the map with the location of the base station and the real-time video from the camera is also displayed on the dashboard.

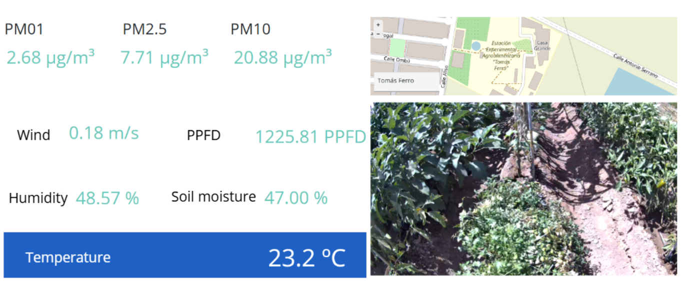

Figure 3. Grafana dashboard of the system.

The graphs plotting the time-series data for each sensor are also available in another Grafana dashboard. Figure 4 illustrates an extract of temperature data for the variation in temperature experienced at different hours of the day. As it can be seen, nights and early mornings are always the periods with the lowest temperatures, whereas it rises in peak sunlight hours.

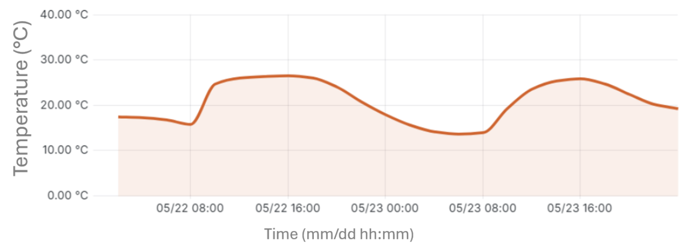

Figure 4. Temperature readings.

Humidity readings are represented in Figure 5. The graph indicates that humidity rises at nightime and decresaes through the day up to mid-afternoon. This can vary depending on the time of year.

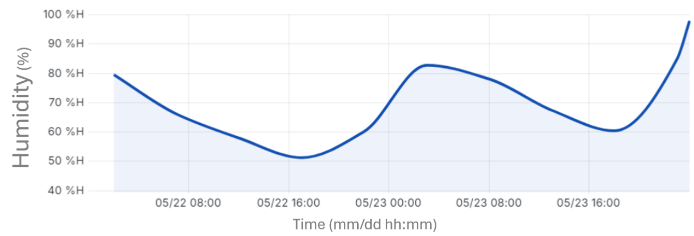

Figure 5. Humidity readings.

Regarding radiation, it can be observed that it is much higher during sunlight hours. The small variations observed in Figure 6 are due to the clouds creating shadows, as they reduce the brightness and radiation captured by the sensor. Then, light is reduced at night. The fields under monitoring are close to a small town and some light might be appreciated at night.

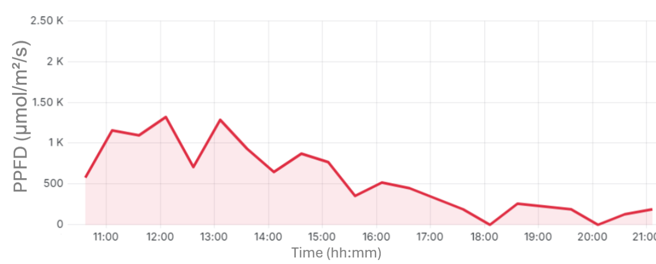

Figure 6. Solar radiation expressed in Photosynthetic Photon Flux Density (PPFD).

As for the wind sensor, the readings in Figure 7 show that wind is strongest in the afternoon on the field. According to the Beaufort scale, this would correspond to grade 3, which indicates a gentle breeze. It can also be seen that wind readings are more abrupt than other parameters.

Figure 8 depicts the readings for the suspended particulate matter. The particles with a bigger size such as PM10 have higher concentrations. Conversely, the particles with lower

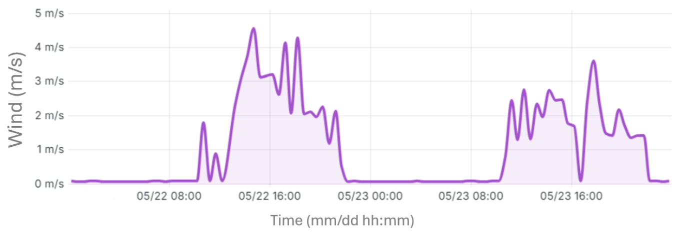

Figure 7. Wind speed readings.

sizes, such as PM2.5 and PM1 have smaller concentrations. Particle concentrations on fields can increase due to several reasons. Strong winds, dust storms, or agricultural machinery working can contribute to higher outcomes.

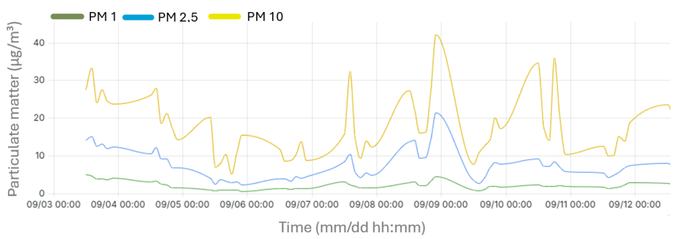

Figure 8. SPM readings.

The readings regarding soil moisture are represented in Figure 9. It can be observed that soil moisture was decreasing during the night but it increases again after the drip irrigation system is turned on in the morning.

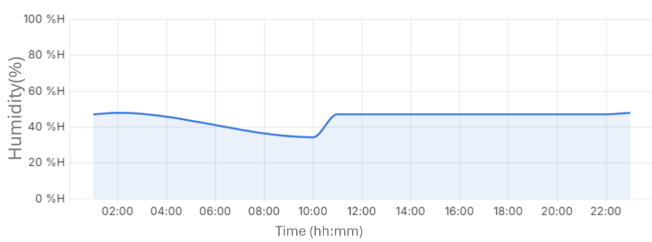

Figure 9. Soil moisture readings.

Lastly, Figure 10 shows the device's battery level and the incoming voltage. These values help users to monitor potential battery issues during periods of low sunlight.

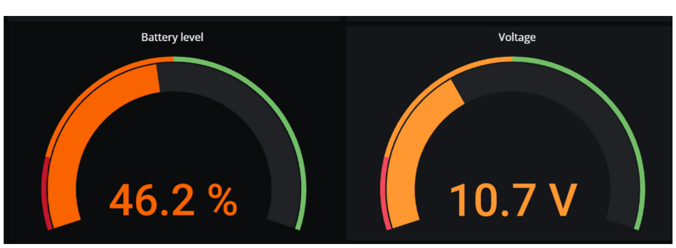

Figure 10. Baterry readings.

The images gathered by the camera of our solution are being used for developing computer vision tools for agriculture. The images collected from the fields can be used to feed Artificial Intelligence (AI) engines and detect different aspects from plants, including plant diseases (see Figure 11) or pests [3].

Figure 11. Output from computer vision plant disease detection feature.

The output from the sensors and computer vision features presented in this section can help farmers improve their irrigation schedules and determine if plants are being affected by a disease, alerting the farmers in case the results are positive. Nonetheless, there are no anomalies in the results presented in this paper.

V. Conclusion and Future Work

The adverse climatic conditions faced by Mediterranean countries have led to the need to implement solutions for monitoring meteorology and soil parameters that affect the crops of these areas. This type of system helps reduce water consumption for irrigation and simultaneously optimize crop growth and production. However, existing approaches typically include only a limited selection of parameters. This paper presents a system for crop and metheorology monitoring intended for precision agriculture. It includes a camera to perform computer vision, increasing the number of features that can be provided to the users. The devices were placed in a custom-made anti-vandalism enclosure. Moreover, a heterogeneous wireless network was deployed to ensure all types of data, with their respective bandwidth requirements, could be transmitted. It included WiFi, LoRa, and 5G connectivity. Finally, the proposed system is powered by renewable energy, so it can be placed anywhere in the field, providing positioning independence.

For future work, this system will be used as part of an agrivoltaic solution to monitor meteorologic and soil parameters, as well as serving as a gateway for other devices deployed to monitor other parts of the fields or greenhouses, and the energy produced by the solar panels of the agrivoltaic system. Furthermore, more computer vision models will be developed to increase the available features and/or detecting options.

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Chatbot Integrated Holographic System for Digital Agriculture and Education

Kübra Kara
Instituto de Investigación para la Gestión Integrada de Zonas Costeras (IGIC)
Universitat Politecnica de Valencia, Valencia, Spain
Email: kkubra@doctor.upv.es

Daniel Matheus Brandão Lent
Electrical Engineering Department
State University of Londrina, Londrina, Brazil
Email: matheus.daniel@uel.br

Alberto Ivars-Palomares
Instituto de Investigación para la Gestión Integrada de Zonas Costeras (IGIC)
Universitat Politecnica de Valencia, Valencia, Spain
Email: aivapal@epsg.upv.es

Jaime Lloret
Instituto de Investigación para la Gestión Integrada de Zonas Costeras (IGIC)
Universitat Politecnica de Valencia, Valencia, Spain
Email: jlloret@dcom.upv.es

***Abstract*— The digitalization of agriculture, known as Agriculture 4.0, is revolutionizing the way agricultural products are produced, managed, and marketed. This transformation is driven by the integration of advanced technologies, such as the Internet of Things (IoT), Artificial Intelligence (AI), big data, and digital twins. Digital twins, virtual replicas of physical systems, enable farmers to simulate and optimize agricultural operations in real-time, enhancing their decision-making process. AI plays a crucial role in analyzing vast amounts of data collected from wireless sensor networks, allowing for precision agriculture and addressing global challenges, such as food security and climate change. The adoption of digital technologies also facilitates traceability and transparency in the agricultural supply chain, ensuring food safety and quality. Among the emerging technologies, holography stands out as a promising tool for intelligent agriculture. Digital holography techniques, such as computational holography, iterative holography, Fourier-based holography, Computer-Generated Holography (CGH), Deep Holography (DH), and tensor holography, offer immersive and realistic experiences for users. The integration of holography with AI and other technologies has the potential to revolutionize digital agriculture by providing real-time monitoring, management, and interaction with crops. However, the development and implementation of these technologies must be inclusive, sustainable, and focused on enhancing the quality of life for all individuals. This study presents a communication algorithm flowchart and a system proposal to elucidate the interaction between a user and a holographic system, demonstrating the potential of holography not only in digital agriculture but also in effective human learning and communication.**

Keywords-Agriculture 4.0; Internet of Things (IoT); Artificial Intelligence (AI); Digital twins; Holography; Large Language Models (LLM).

I. INTRODUCTION

The digitalization of agriculture, also known as Agriculture 4.0, revolutionizes how agricultural products are produced, managed, and marketed. This transformation is based on the integration of advanced technologies, such as the Internet of Things (IoT), Artificial Intelligence (AI), big data, and digital twins to improve the efficiency, sustainability, and profitability of the agricultural sector [1].

Digital twins, virtual replicas of physical systems, are instrumental in agriculture. They enable farmers to simulate and optimize agricultural operations in real-time, a feature that significantly enhances their decision-making process [2]. These digital replicas collect data from Wireless Sensors Networks (WSN) distributed in fields and agricultural machinery, providing detailed information on soil conditions, weather, plant growth, and crop health [3]. By analyzing these data, farmers can make informed decisions about irrigation, fertilization, and pest control, resulting in more efficient resource use and higher productivity [4].

AI plays a crucial role in analyzing these vast amounts of data. Machine learning algorithms can predict crop yields based on historical data, optimize planting schedules, and even detect early signs of diseases or pest infestations in crops [5]. These AI-driven ideas allow precision agriculture, where water, fertilizers, and pesticides are used more effectively, reducing costs and minimizing environmental impact; this is accomplished thanks to the different technologies used, such as sensors, Global Positioning System (GPS) or the Internet of Things application (IoT) [6].

The adoption of digital technologies in agriculture not only improves crop management but also has the potential to address global challenges, such as food security and climate change [7]. This potential is underscored by a report from the United Nations Food and Agriculture Organization (FAO), which predicts a 70% increase in global food demand by 2050 [8]. Integrating technologies like artificial intelligence and big data in agriculture can help predict crop yields, optimize fertilizer and pesticide use and reduce food waste, contributing to a more sustainable future [9].

Moreover, digitalization facilitates traceability and transparency in the agricultural supply chain, ensuring the safety and quality of food that will guarantee consumer confidence [10]. Modern consumers demand detailed information about the food's origin and quality. Through blockchain and other distributed ledger technologies, it is possible to track every stage of a product's lifecycle, from

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farm to table, ensuring the authenticity and quality of the final product [11].

The use of drones and IoT sensors in agriculture has also enabled more precise and real-time monitoring of fields, contributing to more effective management and reduced operational costs [12]. This technology provides farmers with critical data that can be used to improve planning and decision-making, thereby increasing productivity and reducing environmental impact, as in the case of water, where more than half of water consumption is attributed to crop irrigation. The improvement of the irrigation system will be essential to reduce consumption; this can be achieved thanks to different monitoring technologies, in this case, the monitoring of evapotranspiration [13].

AI, a key player in the digitalization of agriculture, also aids in automating repetitive tasks, such as weeding, harvesting, and sorting of produce. This practical application of AI saves time and ensures high precision and efficiency in these tasks, freeing human labor for more complex decision-making processes [14].

The digitalization of agriculture represents a significant opportunity to transform the agricultural sector, enhancing efficiency, sustainability, and resilience to global challenges. Integrating advanced technologies, such as digital twins and AI, promises to optimize farming operations and prepare them for a more sustainable and technologically advanced future [15].

One of these digital technologies could also be holograms. Holography is an application of optical physics, specifically the science of interference and diffraction of light and waves. It enables the creation of three-dimensional (3D) images, which, in contrast to two-dimensional (2D) images, provide enhanced detail and information due to the depth and relief characteristics of holograms. Furthermore, holography is a technology applicable to diverse fields and sectors, rendering it a multidisciplinary concept. These applications encompass medicine, engineering [16], and agriculture [17]. As with other technologies, this multidisciplinary concept has evolved into digital holography, advancing classical holography to a more sophisticated level. Digital holography possesses the capability to integrate real and virtual aspects of the world through its 3D resolution, positioning this technology within mixed reality systems. This technology can significantly enhance user engagement due to low latency, as users can interact vividly with holograms through immersion without the need of special glasses, thereby stimulating multiple human senses simultaneously through haptics, smell and taste. This type of multi-sensory technology is called mulsemedia. Moreover, an additional advantage of augmented reality technology, such as holography is its capacity for integration with multiple other technologies, a concept commonly referred to as multimodal technology or interface [18].

This research is organized as follows: Section I provides an introduction of Agriculture 4.0, emphasizing the transformation and digitalization of traditional agriculture with means of digital technologies, such as IoT, AI and specifically holography. In Section II, the related work regarding intelligent agriculture and farming, LLM, various types of digital holography are discussed. The chatbot-integrated holographic system applied to digital agriculture is being proposed in Section III along with the system's architecture and communication algorithm. Section IV presents the simulation results and evaluates the performance of different language models. Finally, Section V concludes the paper with a summary of the findings, implications of AI and holography in digital agriculture and suggestions for future research directions.

II. Related Work

In recent years, the integration of advanced technologies into agriculture has gained significant attention. A noteworthy contribution is the intelligent agriculture system developed by Xu et al. [17]. This innovative system employs holograms to provide real-time monitoring and management of crops. By projecting holographic data related to crop growth, soil conditions, and irrigation needs, farmers are empowered to make informed decisions without the necessity of being physically present in the field. This advancement not only enhances agricultural management efficiency but also significantly reduces water resource consumption. Looking ahead, future developments in the field of intelligent agriculture could include the integration of AI for predictive analysis and the use of drones for remote monitoring. Such advancements exemplify the potential of technology to transform traditional agricultural practices into more sustainable and efficient methods, showcasing a promising future for the industry.

The importance of accessibility in digital environments is further emphasized in research by Alabi et al. [19], which focuses on visually impaired users. Their study highlights the critical role of assistive technologies, including screen readers and adaptive user interfaces, in facilitating access to information. Implementing these technologies shows that improving digital accessibility can lead to greater participation by all users, particularly those with disabilities. His research findings underscore the need for inclusive design on digital platforms and the responsibility of developers to ensure that the needs of various user groups are considered. By prioritizing accessibility, developers can create more equitable digital environments. It is intended to use this type of technology in libraries to avoid discrimination in these environments.

The development of tools aimed at improving communication for individuals with speech disabilities has also seen significant advancements. [20] Janai et al. introduced a sophisticated text-to-speech and speech-to-text conversion tool that leverages advanced natural language processing algorithms. This tool provides rapid and accurate conversion between text and voice, facilitating smoother user interactions. Its implementation across various applications has positively impacted the daily lives of those relying on such technologies, highlighting the importance of innovation in communication aids. By enhancing accessibility, these tools empower individuals with speech disabilities, fostering more significant inclusion in society.

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Another significant area of development is in the realm of Large Language Models (LLM), as presented by Brown et al. [21]. Their work on models like GPT-3 represents a groundbreaking shift in how machines comprehend and generate human language. With their transformative potential, these models utilize vast datasets and sophisticated deep learning algorithms to produce coherent and contextually relevant text, which has transformed numerous applications, from content generation to academic research assistance. The capabilities of large language models extend far beyond mere Natural Language Processing (NLP); they also facilitate human-computer interaction, making technology more intuitive and user-friendly. This technological leap has opened avenues for new research, creativity, and productivity across various fields.

As previously noted by Xu et al. [17], the utilization of digital holography can be a significant asset in agriculture. The digitalization of classical holography has given rise to various holographic techniques [22]. Computational holography employs computers to generate holograms. This technique offers the advantage of adapting and manipulating holographic projections through computational parameters; however, considering the substantial data requirements of holographic projections, high bandwidth is necessary, which can be addressed through the use of algorithms and Deep Neural Networks (DNN) [23].

Iterative holography also utilizes specific algorithms, such as the Gerchberg-Saxton algorithm. As the name suggests, iterative holography continuously refines projections to reconstruct a holographic image, phase object, eliminate twin images (although beneficial in agriculture [24]), and overcome physical barriers and obstacles of the real world [25]. While this technique may result in poor image quality methods, such as the Constrained Complex Total Variation (CCTV) regularizer exist [26] to preserve image resolution.

Another method of creating holograms digitally without the use of lenses is Fourier-based holography [27], in which a reference wave enables the retrieval of phase information about any type of wave, such as light, electron, and X-ray, scattered by an obstacle, simply by using Fourier Transform to reconstruct images.

The method shown in [28] is applicable to various disciplines and provides the capability to generate Computer-Generated Holography (CGH), which leads to the next type of digital holography. The CGH method can work with incoherent light and generating high-quality holograms through the use of algorithms. Its flexibility and versatility make it suitable for Virtual Reality (VR) and Augmented Reality (AR) [29].

Next, there is Deep Holography (DH), which also utilizes DNN to execute phase aberration corrections. Additionally, DH not only gives rise to other types of digital holography, such as tensor holography, but it also addresses one of the major challenges in holograms, which is the elimination of twin images [30]. Considering the importance and relevance of twin images in agriculture, holography may be a suitable technology in digital agriculture.

Finally, very similar to CGH is tensor holography, which is the most realistic form of digital holography. Tensor holography employs DNN and Machine Learning (ML) and can also be referred to as a physics-informed DNN technique. This technique has the capacity to project real 3D volumetric images in air, making it not only the most computationally intensive digital holography technique but also the most intricate. Scholars argue that tensor holography requires 4000 pairs of RGB-depth images for training and provides the full potential of holographic video communication, thus enabling maximum user engagement and satisfaction [30][31]. Tensor holography is the type of holography that is desired to achieve revolutionizing digital agriculture. As discussed by Huang et al. [32], holography provides 6 Degrees of Freedom (DoF), involving an immersive and realistic experience in 3D movement and rotation, physically allowing users to engage with holographic projections. This again supports the relevance of holograms in digital agriculture.

While the advancements across these domains—intelligent agriculture, digital accessibility, communication tools, and language models—demonstrate the profound impact of technology on society, it's important to note that they also come with potential risks and challenges. For instance, large language models can potentially perpetuate biases in the training data, leading to unintended consequences. As we continue to innovate, it is crucial to ensure that these technologies are inclusive, sustainable, and enhance the quality of life for all individuals. Embracing a collaborative approach in developing solutions can pave the way for a more equitable and accessible future.

III. Proposed System Framework

Large language models have proven to be a great advancement for artificial intelligence, and natural language processing. Numerous tools, such as ChatGPT, Gemini and Microsoft Copilot are already available for aiding users with faster research by interpreting multiple sources of information and answering questions. Other tools are already being studied to help health professionals to study for clinical education, practice, vascular research and scientific writing [33]. This study proposes a system to make information about different kinds of trees more accessible for people, especially biology students. It is composed of holograms, each of a different species of tree, that are connected to large language models that can answer questions about themselves. Tools for text to speech and speech to text enable the tree to talk with participants without the necessity of text input and output. The general knowledge of AI makes it ready to answer not only possible unexpected questions, but also follow up ones.

A more interactive and playful approach to learning might lead to better comprehension and knowledge retention as other studies suggest [34]. A conversation between a human and a tree allows the user to ask for clarification, or to adapt the technicality of the conversation based on the user's speech. More advanced AI are capable to, in addition to answering questions correctly, interpreting a character, with correct usage of wordplay and even puns related to trees, which contributes to the immersion of the experience.

Figure 1 presents a chatbot-integrated holographic system capable of generating auditory and visual responses through a holographic tree to enhance user interaction. The system initiates with a spoken user input received by a microphone and transmitted in an audio stream via Wi-Fi to the Access Point (AP). The AP subsequently retransmits it to the embedded system. The user input is then converted into text through a voice-to-text translator module. This text serves as the input for the Chatbot. The chatbot's core comprises a language model that analyzes and interprets the input and generates a response based on NLP algorithms. By evaluating the probability distribution of subsequent words, the model ensures conversational coherence and contextual relevance.

The text response is transformed into speech using a text-to-voice module, creating an auditory interaction. Concurrently, the system generates a holographic tree image, and the audio data is transmitted to the speakers over a Wi-Fi network from the embedded system with synchronized transmission to facilitate a conversation with the Chatbot-integrated holographic tree. The holographic tree is animated to match the output speech. The system is proposed to be viewed in an indoor environment, so when the holographic projector is not placed in the same room as in the Wireless Access point, other considerations due to wall loss must be taken into account [35][36]. Overall, the theoretical implications of this system are significant and support educational applications.

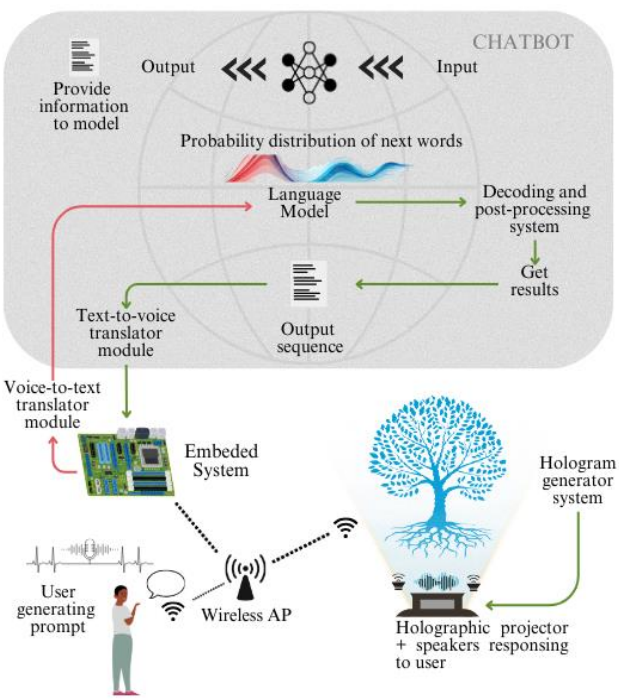

Figure 1. Illustration of the interaction between a user and a chatbot-integrated tensor hologram in a tree form.

Figure 2 represents a communication algorithms flowchart to illustrate the interaction between a user and a holographic system (in this case, a holographic tree). During the initialization phase, the system initiates the interaction and receives and interprets user input. Upon receiving user input, the system proceeds to the system processing stage, wherein NLP and speech recognition are utilized to process the user input, which may be a question or a command. User inputs can be as straightforward as: "Hello, can you tell me about your life as an orange tree?". The subsequent step, "Holographic tree response?", is the point at which the system evaluates whether it can generate a response to the user's input. If a response can be generated, the system proceeds to provide the user with a visual holographic response, which may be factual, educational, or procedural, based on the information retrieved from its database. If the user input is excessively complex or intricate, the system will propose that the user reformulate the prompt. Should the user decline, the system will proceed directly to the finalization stage to conclude the interaction without generating a response. If the user opts to proceed with a new prompt or input, the system will resume the cycle from the user input stage.

During the holographic tree response stage, the system creates an immersive volumetric 3D hologram or tensor hologram, as previously explained. The system's response is adaptive, dynamic, and interactive, enhancing user experience through engagement. Following this stage, the user has the option to continue the interaction or terminate it. Should the user wish to continue, the system loops back to the input stage and maintains the flow of interaction, leading to deeper engagement. However, if the user opts to end the interaction, the system transitions to the finalization stage, concluding the cycle. This design enables the system to process various types of queries, including factual and complex questions.

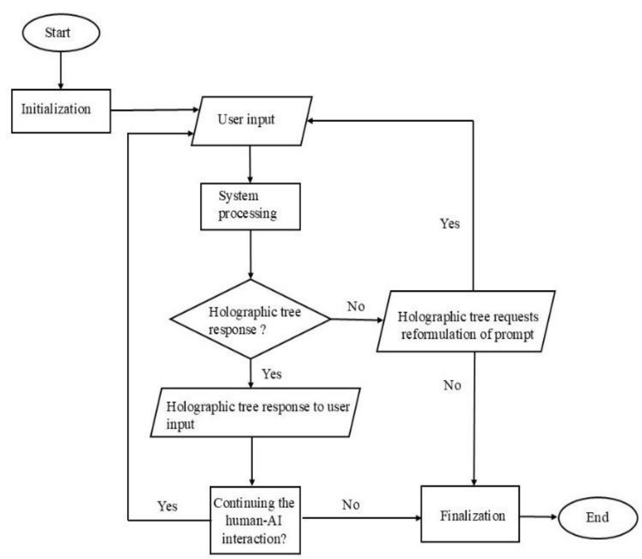

Figure 2. Communication algorithms flowchart framework between a user and a holographic tree.

It is a versatile system applicable to diverse domains and topics. To contribute with immersion, text to speech tools have also evolved to better pronounce words, add intonation, pauses and stress to the voice. Neural networks are also employed to this task, as they are capable of generalizing patterns that are not always present on the learning phase [37]. Advancements were also made with multilingual models, an extremely useful feature in our use case since LLM are capable of synthesizing text in multiple languages [38]. Those same models can also simulate different voices from short audio files, to add variety for different types of trees.

By combining those three consolidated technologies with holograms, it is possible to build a prototype of the proposed system and test its performance based on some metrics: answer correctness, its preciseness and character impression.

Other metrics, such as response time were considered, but all tested models presented near-real time answers, sometimes even faster than human interaction timings, thus it was not measured. This study conducted evaluations on three pertinent and freely accessible large language models: OpenAI's ChatGPT, Google's Gemini, and Microsoft's Copilot. The same set of prompts were input across all of them to avoid inconsistencies. The models were asked to "Pretend that you are an apple tree that talks. I'm going to ask you questions about your biology and you should answer as you were this tree". Afterwards, the three models were asked a series of questions on the subject.

All the models were able to answer the questions correctly. However, only ChatGPT and Microsoft Copilot played a role of a talking tree. Google Gemini answered in the first person, as requested, but did not simulate the ludic text of a cartoonish tree.

As an example, Table 1 presents the answer to the prompt mentioned in the last paragraph. Questions about apple trees were made, from simple ones, such as "What varieties of apple trees exist", to more technical ones: "What amount of organic matter in the soil is necessary for the proper development of the apple tree and its fruit?" The AIs could answer both types of questions precisely, with no contradiction between them.

On average, the answers from the three systems were two paragraphs long. Copilot had more succinct answers and GPT the longest ones. None of them had single-line answers, even for the most direct questions, i.e., "How much water do your need to grow healthily?". Overall, the answers are the length expected from an informative conversation.

IV. Simulation Results

Figure 3 represents the recorded time measurements for each module during the testing phase. The elements are ordered according to their occurrence in the proposed interaction. Initially, the Speech-to-Text (STT) delay represents the time between the conclusion of human speech and the completion of its transcription. Subsequently, the GPT Start to Answer delay indicates the interval between prompt input and the initial output from GPT.

TABLE I. Answers to the initial prompt

Model	Answer
Chat GPT	Ah, welcome beneath my branches! I am a humble apple tree, deeply rooted in the soil, stretching my limbs toward the sky. What curiosities do you bring? Ask away, and I shall answer as best as a tree can!
Gemini	Okay, I'm ready to be an apple tree! Ask me anything you'd like to know about my life.
Copilot	Alright, I'm an apple tree! My branches are adorned with lush green leaves, and I bear delicious apples. Ask away, and I'll do my best to share the secrets of my tree-ish life with you! 🌳🍏🍎

Third, the total time for a complete answer represents the duration required for the conclusion of GPT operation. This period is not critical for application, as the Text-to-Speech (TTS) module can commence operation as soon as the first phrase is available. Lastly, the TTS Start Delay denotes the time between text input and the initiation of audio output.

Lastly, the TTS Start Delay denotes the time between text input and the initiation of audio output. It is noteworthy that the entire system can exhibit rapid response times to the user due to the potential for task parallelization. The STT module operates concurrently with user speech, resulting in its delay being perceptible only upon the cessation of speech. Similarly, the GPT delay is noticeable only until the completion of the first phrase, at which point, in conjunction with the TTS delay, the system will begin vocalization. The GPT completes the entire answer in approximately 14 seconds, which is significantly faster than the conclusion of TTS.

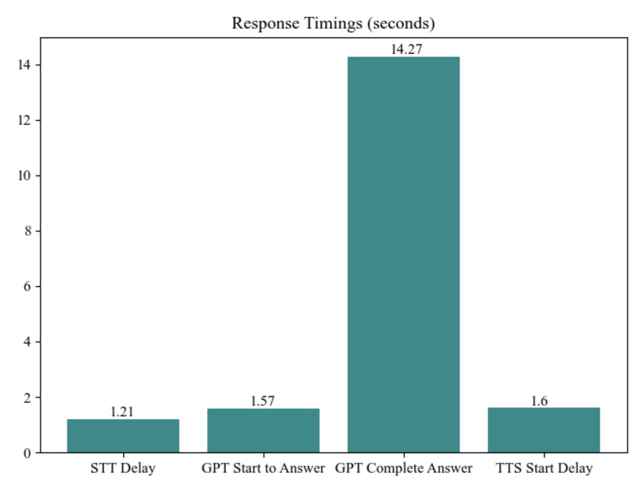

Figure 3. Measured response times for STT, GPT and TTS modules.

Courtesy of IARIA Board and IARIA Press. Original source: ThinkMind Digital Library https://www.thinkmind.org

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Consequently, it can be inferred that the response time delays are sufficiently low to maintain the fluidity of human-like conversation.

As previously noted by scholars [22], transmission delay has a significant impact on user engagement and satisfaction, particularly in the context of enhancing agricultural management efficiency. This graphical representation leads to the conclusion that special attention must be directed towards delay time when incorporating AI and holographic technology in intelligent agriculture to ensure an efficiency in human-AI interactions.

V. CONCLUSION

In this article, we propose an interactive hologram system to present information about plants to humans. This system enables dynamic interaction between humans and machines to learn more effectively, in a ludic way. To do so, four core technologies must be combined: holograms, large language models, text-to-speech and speech-to-text tools. Holograms provide three-dimensional images from the plants studied for better visualization and comprehension of the physical aspects of the tree, in addition to better immersing the user in their learning experience.

Large language models are an efficient way of garnering information, organizing and presenting it to a human in a conversation in the most natural way. Their capabilities of synthesizing text have been used in several areas and can help swiftly accessing information combined from various sources. Tests were conducted with them to extract information about apple trees. The results show how not only do they return precise, correct answers, but also can interpret a role of a cartoonish talking tree, enhancing the experience.

Text-to-speech tools are responsible for receiving the output of the LLM and synthesizing voice. It is crucial for the user experience to have, in addition to the correct pronunciation, intonation, pauses and stress capabilities.

Neural networks have also been employed in the state-of-the-art models due to their potential of extracting patterns from data and generalizing for unseen information. It is also possible for a single network to speak multiple languages, featured with the LLMs.

The experiment is promising, and more research is important to better implement it. For future work, more advanced features could be considered, such as interaction between two plants that have symbiotic relationships. Open source LLM models are also considered to better adjust them to the task. In addition to it, designing tree models with faces that have moving mouths could be an important step towards its implementation.

In the context of holography, a critical consideration for future development is the resolution of current technical constraints in data transmission and latency to facilitate holographic communication and the implementation of interactive holographic projections, especially in digital agriculture. This has consistently proven to be a significant factor during system evaluations when measuring STT, TTS, and GPT modules in human-AI interactions. Our future work will be focused on improving the GPT response time and testing other Conversational AI and AI Chatbots.

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