A Digital Countryside Notebook for Smart Agriculture and Oranges Classification

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Abstract: We present a digital countryside notebook designed to help land owners to monitor the operations performed on a cultivation. The system helps to collect and trace information over time through the developed mobile App. This guarantees the traceability of the product. Our system has many advantages, such as the easy collection of information and the reduction of the time in the analysis of the information acquired. To improve and automate the process of data collection, the system uses a classifier to label images of oranges during the plant monitoring.

1 INTRODUCTION

Agriculture is one of the most important economic sector and source of employment. In the next forty years, the agriculture production should be increased by 60%. This means to duplicate the production per hectare, but in some areas the production can't be increased over 39%. Nowadays, in some areas the production is actually decreasing (United Nation, 2017).
Smart Agriculture is the application of ICT into agriculture domain. It aims to introduce important innovations in the whole agricultural production sector. One of the main goals is to increase the productivity by reducing both, economic costs and natural resources (such as water).
Most of the solutions for Smart Agriculture are based on Internet of Things (IoT) (Prathibha et al., 2017), i.e. devices which are capable of acquiring data to be analyzed to help the land owner a better management of the production. Considering that in the middle of 2017 the world's population numbered nearly 7.6 billion (United Nation, 2017), and that continues to grow, it is important to build smart infrastructures which can be useful to increase agriculture production. Indeed, it is estimated that the population will be 9.8 billion in 2050 and 11.2 billion by 2100. Thanks to IoT infrastructures, the land owner can be able to connect devices and collect information of interest in agriculture domain. Different devices are used to help agriculture become smart, such as drones, sensors to drive irrigation pumps, solar panels for energy production, sensors to monitor humidity, etc. (Varghese et al., 2015; Codreanu et al., 2014; Sathyadevan et al., 2011)
In (Lipper et al., 2014) is described a Climate-Smart Agriculture (CSA) approach useful to transform and reorient agricultural systems to support food security under the new reality of climate changes. In (Gondchawar and Kawitkar, 2016), a smart GPS based remote controlled robot is employed to perform tasks like weeding, spraying, moisture sensing, bird and animal scaring, keeping vigilance, etc. The system includes automatic irrigation with smart sensors and intelligent decision making procedures based on accurate real time field data analysis and warehouse management. In (C. Wouter Bac and Edan, 2014) a review and challenges related to harvesting robots to help crops in agriculture is presented. In (Sales et al., 2015), Wireless Sensor Networks (WSN) are used. The nodes of the network perform acquisition, collection and analysis of data, such as temperature and soil moisture, that can be employed to automate the irrigation process in agriculture while decreasing water consumption. This implicates in monetary and environmental benefits.
In (Murabito et al., 2017) is presented a tool for generating knowledge-enriched visual annotations of 24 fruit varieties which they use to build a benchmark dataset for a complex fruit classification problem.
Growers and breeders of Blood oranges were able to

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identify and collect many somatic mutants, which differed in their major pomological traits, such as fruit size and firmness, pulp and peel pigmentation, and ripening period. In (Caruso et al., 2016), a dataset of 88 varieties of blood orange is collected. Pomological parameters, such as fruit weight, equatorial diameter, polar meter, width of central axis, peel thickness, number of seeds, juice yield, total soluble solids, acidity, pH, peel color index, pulp color index, total anthocyanin, are analyzed trough principal component analysis (PCA). In our experiments, we used the subset of this dataset containing only the images. In particular, we have been considered three orange species, namely, “Tarocco a Buccia Gialla”, “Tarocco Meli” and “Tarocco Rosso” (Rapisarda and Russo, 2000).
In this paper, we propose a system useful to monitor land property based on IoT cloud platform. It involves the dislocation of a series of sensors on the agricultural field in order to detect all the interesting parameters to monitor and manage the land property, such as temperature, humidity, solar irradiation, etc. Through a wireless network, a cloud platform receives and examines these data. The proposed system represents a first prototype with respect to a classic countryside notebook. The farmers usually use this document to report every operation on the product, ensuring its traceability. More specifically, we propose a digitalization of countryside notebook and develop a ”K-NN Oranges Variety Classifier” to help the land owner for the automatic labelling of the acquired images of an orange plant among different varieties. The mobile App was developed to work on an Android operating system.
In the following sections, we first describe the building blocks of our system. Finally, we report experimental results and conclusion.

2 PROPOSED SYSTEM

A countryside notebook is an official document which reports all the information collected by farmers which are related to treatments, for instance in case of cultivation diseases, herbicides used, time and method of administration of treatments. The countryside notebook is useful to guarantee the traceability of the product. The filling procedure of the countryside notebook has been done by using paper documents so far. This slows down the collection and analysis of data and strongly limits the amount of information that can be collected. In paper format the information and results of possible analysis aren’t immediately available to both the producer and the consumer. Usually, the countryside notebook contains information

Figure 1: Screenshots of our countryside notebook.

about the company, the lands, the crops, phytosanitary treatments, herbicides used, irrigations, parasitic diseases, ground processing, pruning operations.
We created a digital version of the countryside notebook, as shown in Figure 1. There are many advantages in digitalizing it. As first, it simplifies the acquisition of data. As second aspect, the time for the analysis of collected data decreases. More advantages come from the fact that the proposed countryside notebook is able to automatically process the voice of the operator (speech to text) to transcribe the text related to the different involved tasks. Finally, the proposed system gives to the farmer the possibility to acquire images of the cultivation (oranges in our case) and automatically classify the variety. Hence, with the proposed countryside notebook the full story of a cultivation can be stored and eventually analyzed over years.
Figure 2 shows the overall scheme of the system. The countryside notebook has been developed as a mobile application with a client side implemented in Java for Android platform. It uses RESTful resources from a back-end encoded in NodeJS where data are stored in MongoDB.
We chose model view controller (MVC) as design pattern. This allows to separate the logic of presentation, modification and insertion of data from business logic. In our system, the three main roles are divided as follows: *model* is the Node.js server to manage interactions with MongoDB storage, *view* is an Android user graphic interfaces to capture and display data and *controller* is written in Java with Android SDK to allow interactions between the other two components.
The client side is described as follows. For the user authentication, we created an ad-hoc login page that requires username and password. If the company isn’t registered, can be registered with the appropriate form. After authentication, the user can create a new countryside notebook or view the list of notebooks already presented. For the management of information related to the notebook, it has been implemented a

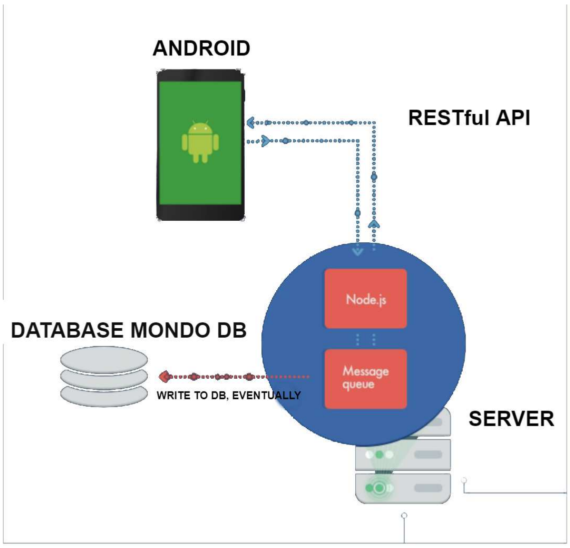

Figure 2: Overall scheme of the proposed System.

Tab-menu with Expandable ListView. In particular to each tab corresponds the state of a plant, whereas to each field in the ListView corresponds to a more specific sub-phase. By clicking on the sub-phase, the ListView is expanded and it shows two clickable fields: ”New” and ”Show All”. Touching on ”New”, an insertion form opens to register a new cultivar card. By clicking on ”Show all”, instead, a list is displayed with the cultivars previously enter with the ability to view, edit and delete them. The last Tab includes soil tillage and cultivation operations (pruning) and it is organized in a similar way to the others.

In order to guarantee system scalability, we implemented a client server architecture. The application server has been implemented in *NodeJS* and Storage of the data was made in *MongoDB*. Images are captured from the smartphone ’s camera, encoded into base64 strings and sent to the server. Similarly, the server sends the strings encoded to the client that provides the decryption. The timestamp is generated on the server side and sent to the client that will make it visible every time insertion and modification operations are carried out. This approach guarantees the authenticity of the timetables and dates of compilation of the countryside notebook.

The implementation of the digital countryside notebook facilitates the process of information management. In order to improve and further automate the process of analyzing the information acquired, we insert a form called ”K-NN Oranges variety classifier”. This form is related to the management of orange crops. During the orange harvesting phase and when filling out the appropriate form in the countryside notebook, the operator can take pictures of the product that has just picked up. These photos are attached to the other information included in the countryside notebook. The pictures taken are stored on the remote server. The server automatically runs the classification module that identifies the variety of orange under consideration and sends the result of the classification to the application client-side.

The K-NN Oranges variety classifier module is based on the Bag of Visual Word representation paradigm (BoVW) (Bosch et al., 2007; Battiato et al., 2010; Farinella et al., 2014; Farinella and Battiato, 2011) to extract features. This approach converts the set of local descriptor into the final image representation. This technique was first proposed for text document analysis, but it is applied to images by using a visual analogue of a word. To extract the BoW feature from images, we detect regions/points of interest, compute local descriptors over those regions/points, quantize the descriptors into words to form the visual vocabulary and find the occurrences in the image of each specific word in the vocabulary for constructing the BoW features (or a histogram of word frequencies). A k-nearest-neighbor classification algorithm (K-NN) is used on the BoVW representation for classification purposes (Bishop, 2006).

3 EXPERIMENTS AND RESULTS

In this section, we show and discuss the results of the ”K-NN Oranges variety classifier” module. It is an image classification module of oranges that takes input a digital image of an orange view in section (cut in half) returns the variety of it.

3.1 Dataset and Preprocessing

The dataset used for test purpose have been provided by the public organization called Consiglio per la ricerca e la sperimentazione in agricoltura (C.R.E.A). The dataset is composed by 1,391 images of three orange species, namely, Tarocco a Buccia Gialla, Tarocco Meli and Tarocco Rosso (see Figure 3). For each class, the oranges were collected from four different points of view but, in our experiments, we consider only sectional view.

We crop the images with a rectangular box of size (height, width)= $\left(h+\frac{h}{4},\ \frac{h}{2}\right)$, where h is the distance between the center and the border of the orange, as shown in Figure 4.

3.2 Results

The K-NN Oranges variety classifier is based on Bag of Visual Word Model (BoVW) algorithm for feature extraction. In our case, we use Daisy (Tola et al.,

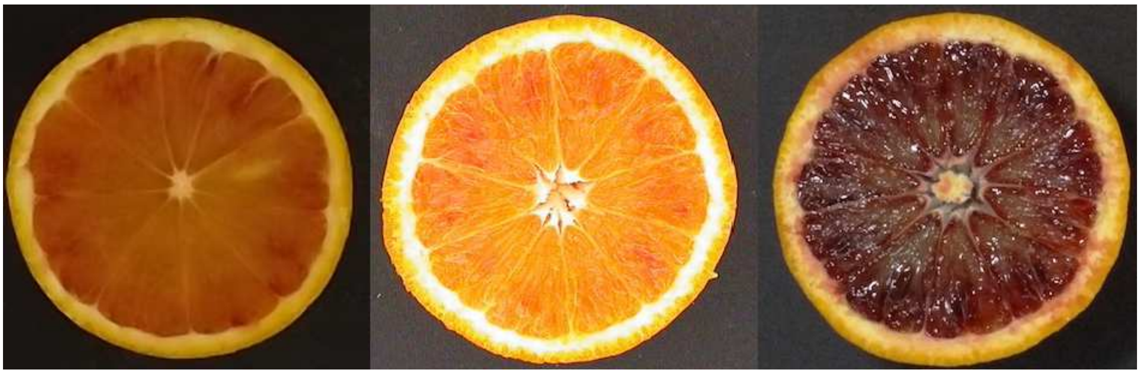

Figure 3: Examples of oranges varieties. From left to right: Tarocco a Buccia Gialla, Tarocco Meli and Tarocco Rosso.

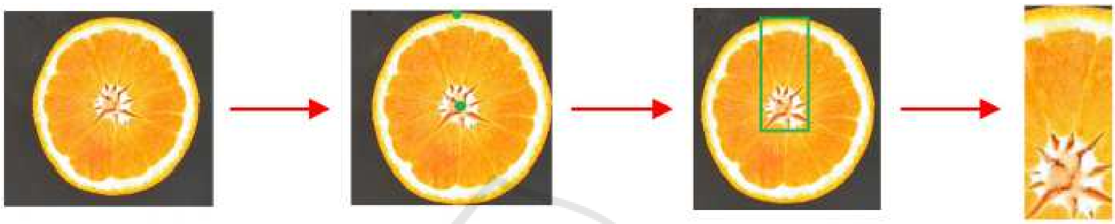

Figure 4: Image cropping.

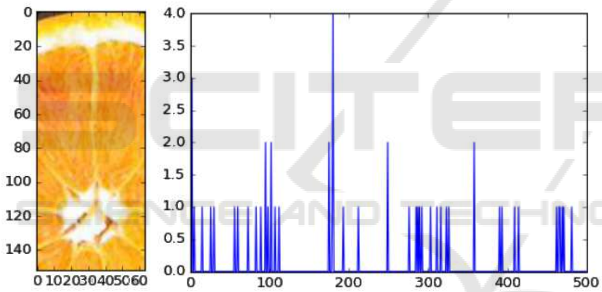

Figure 5: BoW representation.

2010) as local feature to build the visual vocabulary. To create a visual dictionary, we use a k-means clustering algorithm with $k = 500$. The images represent as BoW are used with a K-NN classifier. Figure 5 shows a representation of an orange image.

The system has been tested splitting training e test randomly. The K-NN algorithm finds the three images of training set that resemble the image query. The figure 6 shows the obtained result where the query image is at the top left. Note that the query image is a Tarocco Meli orange and the other images belong to the same class.

We evaluate the K-NN classifier for different values of k. The results of accuracy is shown in the Table 1. We obtain the same values of accuracy for k=5 and k=7. In Table 2, the confusion matrix for $k = 5$ is reported.

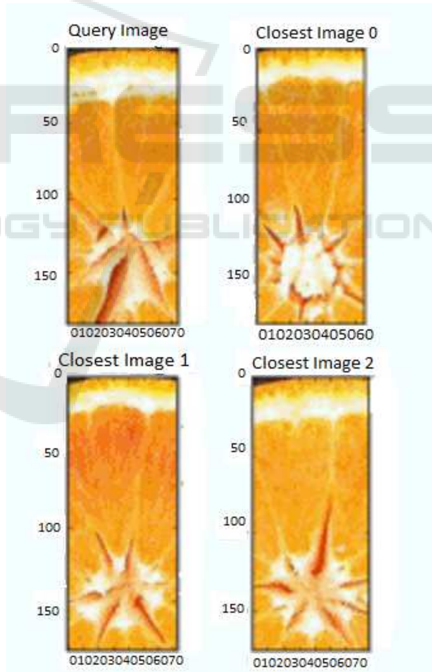

Figure 6: Query result example.

4 CONCLUSION

In this paper, we present a digitalization of countryside notebook for oranges. We want to increase the dataset with other varieties of oranges and we plan to use the images together with physio/chemical data to

Table 1: Accuracy values for different k.

Value of k	3	5	7	9
Accuracy	0.90	0.96	0.96	0.94

Table 2: Confusion Matrix.

	Meli	Giallo	Rosso
Meli	100%	0	0
Giallo	0	86.67%	13.33 %
Rosso	0	0	100%

increase the scientific knowledge of these products. We also plan to extend this notebook for other crops introducing also other analysis tools. The system has been designed to allow the farmer to trace cultivation over time and to collect data that can be automatically analysed.
Future work will be developed to produce automatic procedure which can be used for decision making and comparing advanced methodologies for image representation and classification (e.g. deep learning).

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