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# A cloud-based and flexible architecture for beans images processing

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# ABSTRACT

Food quality is a paramount feature in agriculture technology, analyzing and classifying properly grains requires specialized work (Gomes and Leta, 2012). Nowadays, advanced computer vision technologies are available in vast life environments, however they require a software intensive approach to acquire and process a large amount of data at an acceptable level. In parallel, cloud-based services became full featured and highly available through different types of data networks. These advances together empower the Industry 4.0 solutions to accomplish flexible needs in modern factories. In this work we present an extensible architecture that allows decentralization of the digital image processing suitable in food quality context. We integrate modern computer technologies to decrease the latency between the Edge of image acquisition and Data Centers, leveraging IIoT technologies into the food quality control systems. This approach lets the end user capture images using low or high technology cameras and process them using cloud based technologies. The proposed approach, also, describes architectural components that allow an easy way of adding and combining new components for automatic image processing.

Keywords: Image Processing · Architecture · Corn beans classification

# 1. INTRODUCTION

Food quality is a paramount feature in agriculture technology. Not only detecting corps quality, anomalies and classifying is critical and tedious work (Gomes and Leta, 2012), it often requires specialized skills and trained personnel (Gómez-Ríos et al., 2019). Recent advances in computer vision have made technology ubiquitous to processing vast amounts of data in cloud environments (Van der Merwe et al., 2010). We the advent of Industrial Internet of Things (IIoT) or Industry 4.0 (Salman et al., 2018), decentralization of pre-processing and centralization of processing architectures are starting to give birth of a whole new kind of applications that will allow to process big amounts for data, using specialized and not specialized hardware, until latency between the Edge and the Datacentre drops to acceptable processing levels. In this work we present an extensible image-processing architecture that addresses the above issues. This architecture was developed in the context of PAUTIRE0007650TC<sup>1</sup> project which will require a software intensive architecture for image detection and classification.

#### 2. RELATED WORK

(Jacobsen and Ott, 2017) describes a medium size data streaming architecture suitable to cloud environments for image processing. Their approach to image processing in the cloud is similar to proposed work in the aspect that no hardware change is required and that network use optimization is paramount. On the other hand, our approach compromises processing at the Edge in order to gain flexibility and processing in the cloud. Another cloud base image processing architecture is (Wang et al.,2013), which provides a large-scale real-time monitoring for meteorological monitoring and natural disaster warning and uses maximum likelihood classification (MLC). Although their approach uses a similar queue-based MapReduce approach, ours focus on flexibility providing an extensible pipe-and-filter architecture.

<sup>&</sup>lt;sup>1</sup> PAUTIRE0007650TC: Sistema experto de visión para la clasificación automática de frutos/semillas de plantas oleaginosas.

#### 2.1 Image Processing Techniques

Regarding the image processing techniques, most of the related works have been using Artificial Neural Network (ANN) of some sort. This is to expect, due to the powerful capacity and remarkable precision that this technique has demonstrated during the past years (Chauhan et al., 2018). Because of this nearly ubiquitous property of image detection and classification tools, we have decided to separate the related image processing work into those that use ANN, and those that use some other technique.

Seed	Use	Image Processing Technique	Reference		
Soy	ANN	The back-propagation type of Artificial Neural Networks (ANN) of the Multi-Layer Perceptron (MLP) type in conjunction with Principal Component Analysis to reduce the dimensionality of sample features, and then be able to predict diseased samples of soybeans.	(Kezhu et al., 2014)		
		Multispectral images and Convolutional Neural Networks to soybean classification.	(Zhu et al., 2019)		
	Some other technique	Regression algorithms of Partial Least Square type and Artificial Neural Network to detect fungi in soybeans using Near Infrared Spectroscopy (NIR).	(Wang et al., 2004)		
Sunflowers	_	Multispectral images. They use Convolutional Neural Networks, Support Vector Machines (SVM) and Bayesian Networks.	(Bantan et al.,2020)		
Table 1. Image Processing Related Work					

#### 3. PROPOSED ARCHITECTURE

#### 3.1 Non-functional requirements

Non-functional requirements (NFRs) are the constraints imposed on a system that define its quality attributes (Glinz, 2007) (Chung, 2012). These quality attributes impose constraints over the different components of the system and help assure that it meets the users requirements. The image processing system required by project PAUTIRE0007650TC required flexibility for adding and removing image processing components, the of open standards to ensure interoperability and scalability to support large amounts of data processing, if needed.

#### 3.2 Components

In order to achieve the non-functional requirements needed to process the amount of images without having to incorporate special and expensive hardware, we have proposed and implemented the image processing architecture that is shown in Figure 1. In this section we will explain each of the building blocks, and how its interconnections and compromises aim at achieving the requirements.



Figure 1. Proposed Architecture

#### 3.3 Image Inbound Processing

The first part is the **Image Inbound Processing**, which has the responsibility of ingesting images into the system. This building block exposes two MQTT Queues for clients with very different needs to connect to the system. For readable or browser clients, the queue **cinaptic/json/input** ingest input messages encoded in JSON, while for more performant client and IIoT devices **cinaptic/proto/input** queue accept Protocol Buffer (Protobuf) encoded message. Using protocol buffer as encoding mechanism bring performance improvement as well as extensibility to the processing pipeline (Maeda, 2012). Also, an additional benefit of using Protobuf is the support in different programming languages to automatically generate compliant code.

```
ł
  "created at": "2022-10-01T13:49:51.141Z",
  "source": "MQTT",
  "devece id": 451cc5e5-d143-4b48-95ad-9e778edb2e08",
  "location": {
    "latitude": -27.451159,
    "longitude": -58.979154
  },
  "metadata ": {
   "lote": "1"
  },
  "image": {
    "name": "IMG_20210915_172252924.jpg",
    "mime type": "image/jpeg",
    "data": "/9j/4AAQSkZJRgABA..."
  }
}
```

Listing 1.1. JSON Encoded Inbound Processing Message for a image

Listing 1.1 shows an example of part of a JSON encoded message sent to the Image Inbound Processing sub-system. In this message we can see some of the fields that the system will use to route and process the image embodied in it. Also, metadata and localization data can be sent as part of the message for aggregation and geo-processing.

#### 3.4 Image Storing and Processing

Image storing and processing services make use of a data storage service, such as relational database, and a message broker service. The first processing step is reading from the inbound queue and decoding from text and binary formats. Afterwards, event messages are persisted in a PostgreSQL RDBMS. The next processing step is to route these messages to the message broker for further processing at the downstream layers.

#### 3.5 Visualization UI

This architecture incorporates a HTML5 client application that enables users to capture images from any camera available on the device where the browser runs. Additionally, users can also choose from existing image files. Once an image is captured or selected, it can be uploaded to the processing system via the MQTT channel. To provide real-time feedback on uploaded images and their processing status, the system retrieves data from the database using the gRPC API. This feedback is displayed on the same web interface, allowing the stakeholders to promptly assess the results of the analysis conducted by the other modules of the architecture. Figure 2 shows a snapshot of the current Web Application Interface used to display the information gathered by the system.



### Persisted images

Date & Time	Device	File Name	Category	Image Thumbnail
3/5/2023 19:49:51	cinaptic_cam	Cap-3/5/2023, 19:49:14.png	Corn	Ð
3/5/2023 19:45:00	cinaptic_manual	File-corn1.jpg	Corn	Ð
3/5/2023 19:41:00	cinaptic_cam	Cap-3/5/2023, 19:40:20.png	Soy	P

Figure 2. Web Application Interface

#### 4. CONCLUSIONS AND FUTURE WORK

We have designed and implemented a software architecture for image processing that is both flexible and scalable. This architecture incorporates open-standard components that allows the user to run it at scale, having it deployed on a cloud-based platform or at the Edge. The distribution of components has a good fit for Industrial Internet of Things (IIoT), allows some of the processing to happend at the Edge, whereas the most CPU or GPU intensive can be leveraged to the cloud. Our next steps would require to extend the different components of the system to support new types of persistence and processing techniques, allowing a wider range of configuration and settings possible.

#### References

Rashad A. R. Bantan, Aqib Ali, Samreen Naeem, Farrukh Jamal, Mohammed Elgarhy, and Christophe Chesneau. Discrimination of sunflower seeds using multispectral and texture dataset in combination with region selection and supervised classification methods. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 30(11):113142, 2020.

Rahul Chauhan, Kamal Kumar Ghanshala, and R.C Joshi. Convolutional neural network (cnn) for image detection and recognition. In 2018 First International Conference on Secure Cyber Computing and Communication (ICSCCC), pages 278282, 2018.

Lawrence Chung, Brian A Nixon, Eric Yu, and John Mylopoulos. *Non-functional requirements in software engineering*, volume 5. Springer Science & Business Media, 2012.

Martin Glinz. On non-functional requirements. In 15th IEEE international requirements engineering conference (RE 2007), pages 21-26. IEEE, 2007.

Juliana Freitas Santos Gomes and Fabiana Rodrigues Leta. Applications of computer vision techniques in the agriculture and food industry: a review. *European Food Research and Technology*, 235(6):989-1000, 2012.

Anabel Gómez-Ríos, Siham Tabik, Julián Luengo, ASM Shihavuddin, Bartosz Krawczyk, and Francisco Herrera. Towards highly accurate coral texture images classification using deep convolutional neural networks and data augmentation. *Expert Systems with Applications*, 118:315-328, 2019.

Dirk Jacobsen and Peter Ott. Cloud architecture for industrial image processing: Platform for realtime inline quality assurance. In 2017 IEEE 15th International Conference on Industrial Informatics (INDIN), pages 72-74, 2017.

Tan Kezhu, Chai Yuhua, Song Weixian, and Cao Xiaoda. Identification of diseases for soybean seeds by computer vision applying bp neural network. International Journal of Agricultural and Biological Engineering, 7(3):43-50, 2014.

Kazuaki Maeda. Performance evaluation of object serialization libraries in xml, json and binary formats. In 2012 Second International Conference on Digital Information and Communication Technology and it's Applications (DIC-TAP), pages 177-182. IEEE, 2012.

Ola Salman, Imad Elhajj, Ali Chehab, and Ayman Kayssi. IoT survey: An sdn and fog computing perspective. *Computer Networks*, 143:221-246, 2018.

Jacobus Van der Merwe, K.K. Ramakrishnan, Michael Fairchild, Ashley Flavel, Joe Houle, H. Andres Lagar-Cavilla, and John Mulligan. Towards a ubiquitous cloud computing infrastructure. In 2010 17th IEEE Workshop on Local & Metropolitan Area Networks (LANMAN), pages 1-6, 2010.

Donghai Wang, Floyd Dowell, M.S. Ram, and William Schapaugh. Classification of fungal-damaged soybean seeds using near-infrared spectroscopy. *INTERNATIONAL JOURNAL OF FOOD PROPERTIES* Vol. 7, No. 1:75-82, 12 2004.

Pengyao Wang, Jianqin Wang, Ying Chen, and Guangyuan Ni. Rapid processing of remote sensing images based on cloud computing. *Future Generation Computer Systems*, 29(8):1963-1968, 2013. Including Special sections: Advanced Cloud Monitoring Systems & The fourth IEEE International Conference on e-Science 2011 – e-Science Applications and Tools & Cluster, Grid, and Cloud Computing.

Susu Zhu, Lei Zhou, Chu Zhang, Yidan Bao, Baohua Wu, Hangjian Chu, Yue Yu, Yong He, and Lei Feng. Identification of soybean varieties using hyperspectral imaging coupled with convolutional neural networks. *Sensors*, 19(19), 2019.