Dissertação de Mestrado

Inatel
Instituto Nacional de Telecomunicações

IoT-based Smart Trap Solution for Pest Control in Sustainable Agriculture

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OCTOBER / 2021



IOT-BASED SMART TRAP SOLUTION FOR PEST CONTROL IN SUSTAINABLE AGRICULTURE

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Dissertação apresentada ao Instituto Nacional de Telecomunicações, como parte dos requisitos para obtenção do Título de Mestre em Telecomunicações.

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Santa Rita do Sapucaí
2021

Figueiredo, Vitor Alexandre Campos
F475i

IoT-based Smart Trap Solution for Pest Control in Sustainable Agriculture. / Vitor Alexandre Campos Figueiredo. – Santa Rita do Sapucaí, 2021.
67 p.

Orientador: Prof. Dr. Samuel Baraldi Mafra.
Co-orientador: Prof. Dr. Joel José Puga Coelho Rodrigues
Dissertação de Mestrado em Telecomunicações – Instituto Nacional de Telecomunicações – INATEL.

Inclui bibliografia.

1. Internet das Coisas 2. IoT 3. Controle Sustentável de Pragas 4. Identificação de Insetos. 5. Fazendas Inteligentes. 6. Mestrado em Telecomunicações. I. Mafra, Samuel Baraldi. II. Coelho Rodrigues, Joel José Puga III. Instituto Nacional de Telecomunicações – INATEL. IV. Título.

CDU 621.39

Ficha Catalográfica elaborada pelo Bibliotecário da Instituição
CRB6-2718 – Paulo Eduardo de Almeida

Biblioteca Ministro Sidnei Bilac Pinto

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“A condor flies high and its shadow makes me stare at the sun.”

Suryavan Solar

I dedicate this achievement to my parents,
Maria das Graças Campos Figueiredo *and* ***Antônio Pereira de Figueiredo****,*
my first teachers.
And to my godmother of baptism, ***Célia de Paiva Lima****, who has always supported me*
with her valuable prayers

Acknowledgments

First of all, I want to thank God for the gift of life, love, intelligence, and spirituality.

Thank my supervisor, Professor Samuel B. Mafra, for the teachings, friendship, and encouragement.

Thank my co-supervisor, Professor Joel J. P. C. Rodrigues, for wisdom, sympathy, and guidance.

Thank the National Institute of Telecommunications - INATEL, Brazil, for the opportunity and support in carrying out this work.

Thank Gisele Moreira dos Santos, from the academic records section who always provided precise guidance with her sympathy and competence. And to all teachers for the valuable teachings, especially the José Marcos C. Brito, Guilherme Augusto B. Marcondes, Carlos Nazaré M. Marins, Felipe Augusto P. Figueiredo, Guilherme P. Aquino and Luciano L. Mendes.

Thank my friends and Masters colleagues who made all the difference. Specially to Mauro Cruz, Elvira Diogo, Flávia Fernandes, Diego Cuba, Cláudio Lopes, Anderson Rios, Pedro Villela, Danielly Bravin, Bruna Ferreira, Diego Amorim, Eduardo Teixeira, Werner da Silveira, Aline Aires, Élcio do Rosário, José Rodrigo dos Santos, Douglas Amante, Manoela Miziara and Marília Souza.

Thank my always present family. To my mother, Maria das Graças, who always motivated me to keep studying. To my father, Antônio, from whom I inherited the gift of "inventing things", always taking an interest in my ideas and helping to build them. And to my brother Felipe, Ph.D. in Agronomy, who advised me on coffee culture subjects.

Vitor Alexandre Campos Figueiredo

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List of Abbreviations and Acronyms

4G	Fourth Generation of Telecommunication
5G	Fifth Generation of Telecommunication
6LoWPAN	IPv6 over Low Power Wireless Personal Area Networks
Agrofit	Sistema de Agrotóxicos Fitossanitários
AI	Artificial Intelligence
ANVISA	Brazilian National Health Surveillance Agency
BAN	Body Area Network
BLE	Bluetooth Low Energy
CBB	Coffee-berry-borer
CNC	Computerized Numerical Control
CSI	Camera Serial Interface
CV	Computer Vision
DC	Direct Current
EFD	Elliptic Fourier Descriptors
Gbps	Gigabits per second
GPIO	General Propose Input and Output
GPRS	General Packet Radio Services
GPS	Global Positioning System
GUI	Graphical User Interface
HTTP	Hyper Text Transfer Protocol
IBGE	Instituto Brasileiro de Geografia e Estatística
IFSULDEMINAS	Instituto Federal do Sul de Minas
IIRA	Industrial Internet Reference Architecture
IoT	Internet of Things
IoT-A	Internet of Things Architecture
IPv4	Internet Protocol version 4
IPv6	Internet Protocol version 6
JavaEE	Java Enterprise Edition
JSF	Java Server Faces
JSON	JavaScript Object Notation
LAN	Local Area Network
LBP	Local Binary Patterns
LoRa	Long Range
LoRaWAN	Long Range Wide Area Network
MAN	Metropolitan Area Network
MDF	Medium Density Fiberboard

mm	Millimeters (measurement unit)
MQTT	Message Queuing Telemetry Transport
OS	Operation System
OSI	Open System Interconnection
PAN	Personal Area Network
PIXEL	Picture Element
QoS	Quality of Service
QR Code	Quick Response Code
RAMI	Reference Architectural Model for Industry
RDF	Radial Distance Functions
REST	Representational State Transfer
RFID	Radio Frequency Identification
SDG	Sustainable Development Goals
Sinan	Sistema de Informações de Agravos de Notificação
SOA	Service Oriented Architecture
TCP	Transfer Control Protocol
TCP/IP	Transfer Control Protocol/Internet Protocol
UDP	User Datagram Protocol
UN	United Nations
URI	Universal Resource Identification
USB	Universal Serial Bus
UTP	Unshielded Twisted Pair
V	Volts
VGA	Video Graphics Array
WAN	Wide Area Network
WiFi	Wireless Fidelity
XML	Extensible Markup Language

Resumo

Com o aumento da população mundial, a demanda por alimentos está assumindo proporções inéditas e garantir a segurança alimentar (capacidade de produzir alimentos e disponibilizá-los à população atendendo às necessidades mínimas nutricionais) representa uma questão de enorme preocupação para grande parte dos países. A expansão das áreas de cultivo é uma das consequências diretas desta demanda. No entanto, à medida que as plantações se expandem, um ambiente adequado é promovido para a reprodução e estabelecimento de insetos indesejáveis devido a abundância de alimento e, por vezes, ausência de inimigos naturais. Estes insetos (conhecidos como "pragas") se alimentam dos grãos, frutos e folhas causando degradação da colheita e consideráveis prejuízos financeiros. Como método de controle, a aplicação de pesticidas químicos é amplamente utilizada nas lavouras o que encadeia outros problemas: intoxicações de pessoas e animais, contaminação do ar, solo, e água em geral. Desenvolver soluções ecologicamente sustentáveis e com custo viável para o controle de pragas apresenta-se como um desafio mas também uma oportunidade para garantir a desejável segurança alimentar com alimentos de qualidade, saudáveis e livres de venenos. A utilização de tecnologias avançadas na agricultura tem o potencial para desenvolver tal controle sustentável. A combinação de tecnologias como Internet das Coisas (do Inglês, *Internet of Things* – IoT) e Computação em Nuvem (do Inglês, *Cloud Computing*), Inteligência Artifical, e Visão Computação oferecem propostas de automatização e monitoramento de lavouras, armazenamento dos dados coletados, execução de análises computacionais para tomada de decisão, e visualização avançada de dados. A cafeicultura tem alta relevância no agronegócio brasileiro e, assim como outras culturas, também enfrenta o desafio do controle de pragas. Um dos insetos mais prejudiciais às lavouras de café é conhecido como "Broca-do-café" (*Hypotenemus hampei*) e esta dissertação explora a necessidade de controlar sua população propondo uma inovadora solução onde agrega as mais avançadas tecnologias e o estrito alinhamento aos conceitos de sustentabilidade na produção de alimentos de qualidade. Portanto, ao longo da concepção desta dissertação, foi realizada uma revisão da literatura relacionada à Broca-do-café para conhecer sua biologia, seu ciclo de vida e as principais abordagens de controle populacional apontando as respectivas vantagens e desvantagens. Uma outra revisão da literatura foi o levantamento e análise das abordagens para identificação de insetos, enfatizando quais classes de insetos são mais adequados em cada processo de identificação. Considerando os requisitos tecnológicos, ainda foram realizadas outras duas revisões: a primeira sobre os principais conceitos envolvidos no paradigma IoT enfatizando a Agricultura 4.0 (IoT aplicado na agricultura). E a última revisão foi sobre os principais conceitos de Visão Computacional

como arcabouço para implementação da identificação de insetos por análise de imagem. Em seguida, uma solução integrada é proposta combinando uma armadilha inteligente com sensor de localização por Sistema de Posicionamento Global (em Inglês, *Global Positioning System* – GPS), câmera para adquirir imagens de insetos, hardware e software embarcados para análise de imagem, e atuadores para captura ou expurgo de insetos. Por fim, a armadilha inteligente integra-se via rede celular a uma camada de software, conhecida como *Middleware*, cuja função é receber os dados, armazená-los em um banco de dados, para que a aplicação *Web* desenvolvida, via *Internet*, possa acessá-los e apresentá-los ao usuário final. A solução foi validada primeiro para encontrar o valor otimizado para o limiar de binarização dentro da rotina de Visão Computacional e, segundo, para assegurar a transmissão integrada de dados, desde o ambiente rural, passando pelo Middleware até a aplicação do usuário final. Por fim, a solução é demonstrada e está pronta para o uso em lavouras de café. Portanto, este estudo propõe uma solução altamente tecnológica para controle sustentável de pragas na cafeicultura e com a possibilidade de ser usada em outras culturas agrícolas.

Palavras-Chave: IoT, Internet das Coisas, Visão Computacional, Controle Sustentável de Pragas, Identificação de Insetos, Armadilhas Inteligentes, Fazendas Inteligentes, Agricultura Sustentável, Agricultura Digital, Agricultura 4.0

Abstract

With the increase in the world population, the demand for food is assuming unprecedented proportions, and ensuring food security (capability to produce food and make it available to the population meeting the minimum nutritional need) is a matter of enormous concern for most countries. The expansion of growing areas is one of the direct consequences of this demand. However, as plantations expand, a suitable environment is promoted to reproducing and establishing undesirable insects due to the abundance of food and sometimes the absence of natural enemies. These insects (known as "pests") feed on grains, fruits, and leaves, causing plantation degradation and considerable financial losses. As a control method, chemical pesticides are widely used in plantations which chains other problems: poisoning of people and animals, contamination of air, soil, and water in general. Developing environmentally sustainable and viable cost-effective solutions for pest control presents a challenge and an opportunity to ensure desirable food security with quality, healthy and poison-free foods. The use of advanced technology in agriculture has the potential to develop such sustainable control. The combination of advanced technologies such as the Internet of Things (IoT), Cloud Computing, Artificial Intelligence (AI), and Computer Vision (CV) offer proposals for automating and monitoring plantations, storing collected data, performing computational analysis for decision making, and advanced data viewing. The coffee culture is highly relevant in Brazilian agribusiness and, like other cultures, it also faces the pest control challenge. One of the most harmful insects to coffee plantations is known as "Coffee-berry-borer" (CBB) (*Hypotenemus hampei*), and this dissertation explores the need to control its population by proposing an innovative solution that combines the most advanced technologies and the strict alignment with the concepts of sustainability in the production of quality food. Therefore, throughout the dissertation conception, a review of related literature was carried out to know biology of CBB, its life cycle, and the main approaches to population control, pointing out the respective advantages and disadvantages. Another review was the survey and analysis of insect identification techniques, emphasizing which classes of insects are most suitable in each identification process. Considering the technological requirements, two additional reviews were carried out: The first was about the main IoT concepts highlighting the Agriculture 4.0 (IoT applied in agriculture). And the last review was about the concepts of Computer Vision as a framework to implement insect identification by image analysis. Next, an integrated solution is proposed which combines a smart trap with a location sensor by Global Positioning System (GPS), camera to acquire images of insects, embedded hardware and software for image analysis, and actuators to capture or purge insects. Finally, the smart trap integrates via mobile network into a

software layer, known as *Middleware*, whose function is to receive the data, store it in a database so that the developed Web application, via *Internet*, can access it and present it to the end-user. The solution was validated firstly to find the optimized value for the binarization threshold within the Computer Vision routine and secondly to ensure the integrated data transmission from the rural environment through the Middleware until the end-user application. Finally, the solution is demonstrated and is ready for use in coffee plantations. Therefore, this study proposes a highly technological solution for sustainable pest control in coffee culture and with the possibility of being used in several other agricultural cultures.

Keywords: IoT, Internet of Things, Computer Vision, Insect Identification, Sustainable Pest Control, Smart Traps, Smart Farming, Sustainable Agriculture, Digital Agriculture, Agriculture 4.0

Chapter 1

Introduction

THE importance of agriculture for humanity is unquestionable as it supplies foods, beverages, medical products, and industrial raw materials. Such importance becomes even more remarkable because of the 21st century challenges. According to United Nations (UN), in 2024, the world population will exceed 8 billion and, by 2050, about 9.5 billion. The world population growth increased per capita income, and the rural exodus to cities is expanding the demand for foods exponentially [1]. As one of the essential means for food-producing, agriculture has this great challenge to face, perhaps the most significant challenge in humankind history [2–4].

Researches worldwide claim that it will be required to expand global food production by 70-100%. Food production around the globe uses about 34% of the land and spends about 69% of fresh water. The issue of food distribution and waste is another worrisome point: Not all produced food reaches those who need it. About 1.3 billion tons are wasted each year, which represents 33% of all food production worldwide. This wasted amount is four times what it would take to feed the more than 800 million people who suffer from malnutrition [5]. Fortunately, several types of research have been elaborated about it and have highlighted the most promising strategies to increase food production and optimize logistics and distribution to reduce waste along the food supply chains [6, 7].

Increasing food production is related to raising productivity per area and expanding the cultivable areas. Nevertheless, as the agricultural frontier expands, unwanted enemies (named by "pest") are attracted by food abundance causing severe damages to plants (grains, fruits, and leaves), decreasing the harvest production and financial gains.

Several pest control approaches and the most applied chemical pesticides (insecticides, herbicides, and fungicides) [8]. Even representing a solution for a pest problem,

pesticides end up causing new issues: People and animals have been constantly poisoned, and the natural environment has been damaged pesticide residues have contaminated the soil, rivers, lakes, and groundwater. In Brazil, for instance, people poisoned by pesticides have increased year after year. Furthermore, with the frequent use of pesticides, the pests naturally acquire resistance against the pesticide´s active ingredient. Therefore, new chemical formulas and new products are launched every year, which has increased the plantations maintaining costs for the farmers and, consequently, decreasing their profits. Therefore, the development of cost-effective and ecological sustainable pest control approaches becomes a significant challenge. At the same time, it represents an exciting opportunity to ensure food security including high-quality, healthy and poison-free foods.

Technological innovation has a major role in transforming a sustainable food production system [9, 10]. In recent years, several technologies have been applied in solutions for agriculture, and the term Agriculture 4.0 has been popularized. Paradigms such as the Internet of Things (IoT), Cloud Computing, Big Data, Artificial Intelligence have provided the technological platform to Agriculture 4.0 [11].

Additionally, academic studies have also been carried out, conducting surveys and proposing IoT-based solutions for pest control in rural areas and urban areas. For example, outstanding contributions were made to insect identification and management of the *Aedes aegypti* mosquito, a severe public health problem in Brazil and the world [12–15]. These articles exploit insect identification by measuring the wing-beat frequency through acoustic and optical sensors approaches. The image-based insect identification using a camera sensor is a practical approach as well. Furthermore, the research articles such as [16] and [17] have aggregated an essential contribution to the subject and exploit the image-based analysis for insect classification through the Computer Vision approach. This approach proved more efficient for insects with compact bodies and tiny wings (beetles, ladybugs, etc.). In contrast, the acoustic and optical approaches are more suitable for mosquitoes (large wings and tiny body insects). Computer Vision is understood as the computational science field that deals with digital image processing where operations as acquiring, filtering, segmentation, and classification are performed over images to generate valuable information about them. In simple words, Computer Vision is the science capable of interpreting the world around.

Inspired by available technologies and academic researches, many companies such as AgroSmart [18] and Tarvos [19] have created advanced products and services to support agricultural operations, such as water-saving thought smart irrigation linked to real-time soil analysis, plantation monitoring to improve yield and local weather

information providing. These products and services have been successfully applied to various cultures such as soy, corn, sugarcane, and coffee, helping rural producers to overcome problems inherent to agricultural activity. For instance, coffee farmers worldwide have been fighting to control a pest known as Coffee-berry-borer (CBB), a small beetle that feeds the coffee fruit causing enormous qualitative and quantitative losses. For this pest, the control by chemical pesticides has became more expensive with each harvest, and the efficiency has become increasingly low. Therefore, the coffee culture demands new alternatives for pest control with cost-effective and high efficiency. Guided by research [20] and related works about CBB biology, insect identification by image analysis approach using Computer Vision and Internet of Things paradigm, an IoT-based solution is proposed that includes a smart trap with computational capacity. Since coffee plantations occupy large areas, the smart trap must be moving throughout the area, and a real-time positional monitoring feature has been aggregated. This feature uses Global Positioning System (GPS) sensor on-board to read points of capture location and an application (Web interface) for data viewing supported by an interactive map library. As a bridge between the smart trap and the application, a middleware layer was placed to store data coming from smart trap and provide it to the application. The constrained connectivity conditions in rural areas were also considered, and a local storage mechanism for offline periods was implemented.

1.1 Motivation

Sustainable development has become a central concept in the 21st century. It is a way of understanding the world as an interaction of man and the environment, seeking to predict and raise awareness of human attitudes in different dimensions (economic, environmental, institutional, and social) [21].

Today, the entire world has been calling for actions to eradicate poverty and hunger, protect the natural environment, forests, and animals, and ensure that all human beings over the planet can live with dignity by enjoying prosperity, happiness, liberty, and peace. In 2015, the United Nations (UN) instituted 17 Sustainable Development Goals (SDG) with 169 associated targets to overcome the most significant challenges of our time, take care of the planet and improve all lives [22]. In particular, Goal 2 is related to food production and agriculture and declares, “End hunger, achieve food security and improved nutrition and promote sustainable agriculture”. Therefore, the whole agriculture has a crucial role in overcoming the challenge of producing food for the current world population, and the growing population that is projecting in future years.

Simultaneously, agriculture must transform itself into more sustainable, which means environmental correctness, economic viability, and social fairness.

In coffee culture, the advances to make this kind of culture more sustainable have been slow, mainly in the pest control theme, where the chemical pesticide approach is still the most used. Considering that Brazil has large areas of coffee plantations, sustainable approaches such as homemade traps or cultivating natural pest enemies is impractical as it requires too many workers at the full-time dedication. Therefore, chemical pesticides are more practical because they can reuse the most available machines on the farm and demand fewer dedicated workers. Even considering that the cost of the pesticides approach has increased year after year (due to individual cost itself or higher frequency of application), the large-scale applicability factor still carries more weight for the coffee producers. However, this scenario has an excellent opportunity to promote the new agriculture: the development of an alternative pest control solution without using any chemical products and which are low cost, efficient and practical has a substantial competitive advantage as it brings together all the advantages of the pesticide approach and also aggregates the sustainability factor.

Advanced technological paradigms such as IoT and Cloud Computing can be applied in this solution development and aggregate a lot of value, for example, with the possibility of remote plantation operation monitoring in real-time and the pest eradication process analysis by reports, charts, and geographic map.

The coffee plantation management using sustainable technological approaches will provide significant benefits: a) complete support for the production of high-quality poison-free coffee; b) increase productivity as lesser fruits are damaged or ate; c) leverage financial profit due to the higher quality and more quantity; d) minimally environmental impact, preserving soil, water, air, animals and plants; e) avoiding the poisoning of farm workers, final consumers or any other people. Finally, once this alternative solution works perfectly in coffee plantations, it can be adapted and reused in other cultures helping to transform traditional agriculture into the desired sustainable agriculture and supporting the Agenda 2030 in Brazil and the world.

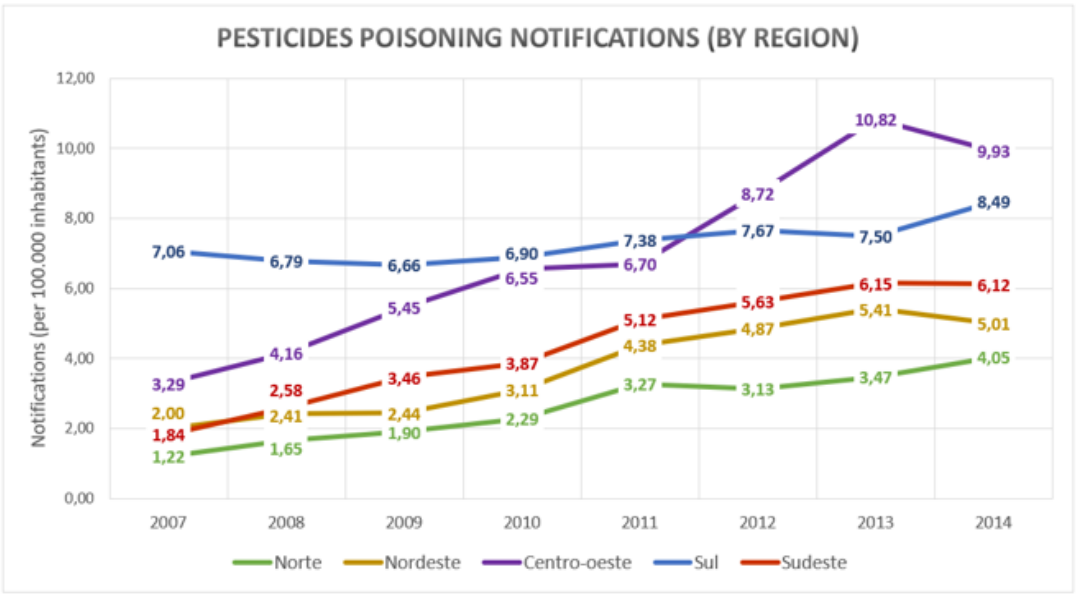
1.2 Problem Definition

As demand for food increases, agricultural frontiers have been expanded where vast green areas are created or even densified (more plants per area). Naturally, all kinds of insects are attracted by the plethora of food, causing agricultural production degradation and consequent financial losses for the farmers. Although there are already several

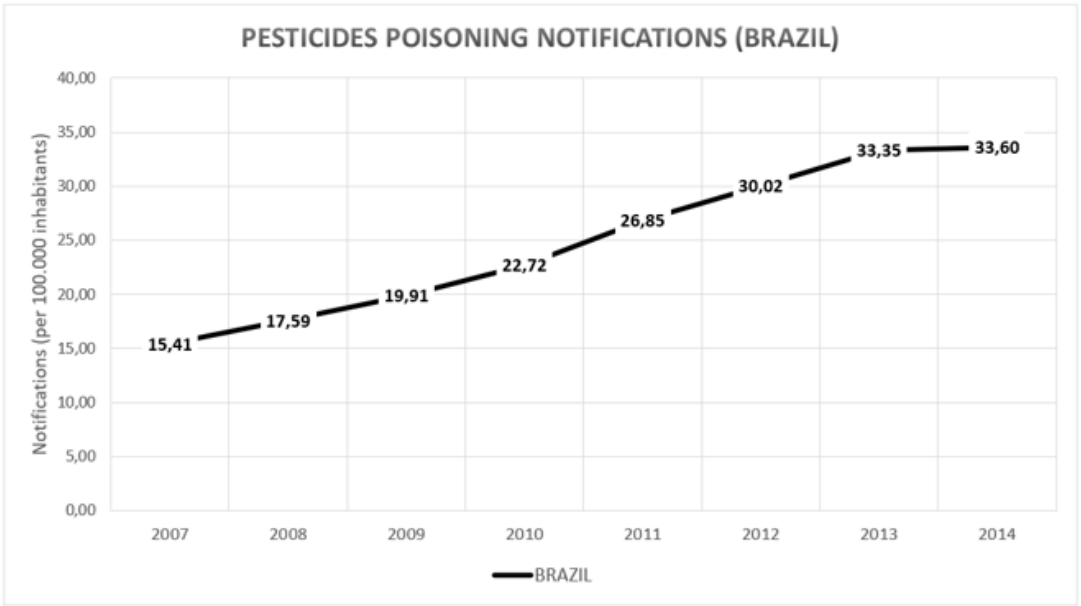
approaches to control unwanted species (or "pests"), the direct application on plantations of artificially synthesized chemical products in industrial laboratories is still the most used approach, mainly for logistics and practicality reasons, where the process can be mechanized covering large areas time-efficiently and requiring few workers to execute it. As a result, Brazil holds the title of the largest consumer of chemical products (known as "pesticides"). In 2008, it surpassed the mark of 700 million liters legally traded. Among the plantation that most induce the consumption of pesticides in Brazil, the soy, corn, sugarcane, cotton, citrus, and coffee stand out, representing together 87% of the total volume sold, As identified by ANVISA (Brazilian National Health Surveillance Agency), the Brazilian pesticide market had increased 190% in 2000-2010 period, against a world market growth of 93% in that same period [23]. However, pesticides have had a medium efficiency, with the cost rising constantly, and their most serious disadvantages are negative environmental impacts and public health problems due to chemical toxicity.

According to WHO (World Health Organization), the cases of acute poisoning, including mass poisoning from contaminated food and occupational exposure in agriculture, constitute the most serious health hazard associated with pesticides used for agricultural purposes [24, 25]. In 1990, the WHO has estimated that about 1 million accidental human pesticide poisonings each year in the world, with about 20.000 reported deaths. The pesticides are absorbed by the human body through the respiratory and dermal routes and, to a lesser extent, also via the oral route. Once in the human body, they can cause acute or chronic intoxication, characterized by nausea, vomiting, disorientation, difficulty breathing, bleeding, seizures, coma, and death [26]. Between 2007 and 2011, there was a 67,4% increase in new cases of non-fatal occupational accidents due to pesticides, and the poisoning coefficient increased 126,8% [27]. Furthermore, the pesticides poisoning notifications had increased in all Brazilian regions in the 2007-2015 measured period [28]. Figure 1.1 demonstrates the poisoning notifications evolution according to each Brazilian region and the country total. Both graphs demonstrate that poisoning notifications have continuously increased over the years, representing a severe Brazilian public health problem.

The environmental impact of agricultural pesticides is another worrisome factor [29]. Studies estimate that only 0.1% of pesticides applied for pest control effectively reach their target pests. So 99.9% goes to "somewhere else" in the environment where they adversely contaminate soil, water, groundwater and the ecosystem atmosphere [30]. Concerning the presence of pesticides in water, their residues are directly toxic to aquatic organisms mainly fishes. When the residues reach the groundwater becomes even more problematic since it is a major source of drinking water in many



(1)



(2)

Figure 1.1: *Brazilian pesticides poisoning notifications. (1) By Brazilian region; (2) Total of Brazil. Source: Sinan, IBGE and Agrofit*

countries [31]. When present in the soil, the pesticides can trigger processes such as degradation by soil microorganisms, chemical degradation (e.g., hydrolysis), absorption by organic and mineral soil, uptake by plant roots, and reach underwater flow. The terrestrial effects also can be expanded in birds population, beehives, and another beneficial arthropod [32]. Pesticides may volatilize into the air. Their movement in the atmosphere can reach over very long distances, as evidenced by the presence of ocean fog and including the arctic snow [33].

Pesticides resistance is another attention factor. During the last 100 years, the number of individual cases of resistance to pesticides has been cumulative. As a result, a lot of time, effort, and money have been involved in discovering and developing new pesticides or upgrading existing formulas [34]. Therefore, pesticides are becoming gradually more toxic, more expensive, and requiring even more applications during each plantation cycle. A direct consequence, the agricultural maintenance costs have been upraised, negatively impacting on financial profits. Therefore, as declared in [35], the need for agrochemicals reduction in agriculture is urgent. The current agriculture has to adopt environmentally and healthy friendlier practices and also considering key factors such as low cost and practicality. Modern technologies, such as IoT, Cloud Computing, geographical information systems, new insect identification techniques, insect traps with computational capacity, and mature software libraries fit this context. An innovative technological solution may be designed for agriculture and leading to pesticide reduction or total abandonment. The generated benefits can improve life quality, protect the environment, and leverage the national economy.

1.3 Research Objectives

The main objective of this dissertation is to present an IoT-based solution for pest control addressed to coffee culture. The solution meets the requirements to build more sustainable agriculture and represents an advanced alternative pest control approach against the current ones. Furthermore, the solution should be capable of eradicating the Coffee-berry-borer (CBB) pest at a competitive cost-benefit without any environmental impact. To achieve the main objective, the following partial objectives should be performed:

- Review of literature about insect identification approaches;
- Review of literature about digital image processing and Computer Vision;
- Review of literature about the Coffee-berry-borer biology, damages, and available population control approaches;

- Proposal and construction of prototype (physical structure, hardware, and software) of insect trap with intelligence to capture only the insect of interest with the real-time monitoring capacity with data viewing application;
- Performance evaluation, demonstration, and validation of the complete solution.

1.4 Main Contributions and Publications

The main contribution of the research presented in this master thesis is helping to transform current agriculture into sustainable agriculture, starting in coffee culture. The smart trap adoption for pest control in coffee culture has the potential to revolutionize the way how coffee farms are managed.

During this research, one academic paper was published in a National Conference:

- V. A. C. Figueiredo, S. B. Mafra, and J. J. P. C. Rodrigues, "A Proposed IoT Smart Trap using Computer Vision for Sustainable Pest Control in Coffee Culture," in *XII Simpósio Brasileiro de Computação Ubíqua e Pervasiva* (SBCUP 2020), *LX Congresso da Sociedade Brasileira de Computação* (CSBC 2020), Cuiabá, MS, Brasil: 16-20 de Novembro, 2020, pp. 201–210.

1.5 Document Organization

This document is organized into five chapters: Chapter 1 describes the motivation for this study, the problem definition, main research objectives, main academic contributions, publications, and finally, this document organization.

Chapter 2 presents the review of literature of most relevant subjects for this study, such as concepts of IoT, the cataloged knowledge about the Coffee-berry-borer insect, insect identification approaches, and the Computer Vision theory.

A proposed solution for coffee culture pest control with the description of insect identification approach using Computer Vision based on embedded hardware and software, IoT reference model, integrated communication with a *middleware* platform, and the development of data viewing Web application is presented in Chapter 3.

Chapter 4 presents the demonstration and validation of the integrated solution, including experiments such as integrated data communication and embedded processing.

Chapter 5 presents the main conclusions of this dissertation, showing the important learned lessons and some promising suggestions for future works.

Chapter 2

Related Works

THIS chapter carries out the review of literature of most relevant concepts related to IoT, Coffee-berry-borer, and Computer Vision. First, the main concepts of IoT as technologies and verticals are also described highlighting the Agriculture 4.0 (IoT applied to Agriculture). After, the biology of the Coffee-berry-borer (CBB) pest is reviewed as well as its most typical methods of control. Moreover, the main insect identification approaches are reviewed, and relevant points are raised as advantages, drawback, and inherent applicability. In the end, the concepts of Computer Vision are reviewed in order to build a knowledge base about digital image processing and analysis. The above concepts will support the theoretical framework for this research and provide relevant insights for the proposed solution.

2.1 Background on Internet of Things

The Internet of Things (IoT) is a new technological paradigm where devices, sensors, mobile phones, and all kinds of computers are connected to the Internet and can interact with each other, promoting intense machine-to-machine communication. IoT can be considered the new era of computing where devices are ubiquitous and systems are online, any time and everywhere, to smartly gathering information around us [36].

The services provided by IoT can benefit a multitude of application areas or verticals (Figure 2.1). Agriculture of precision, environmental monitoring, infrastructure and management for smart cities, industrial process automation, health care, home automation are just a few examples of promising domains for IoT applications [37].

This session goals to present the relevant IoT concepts within the scope of this research. The available architectures of reference, suitable network protocols will be reviewed, and, finally, the IoT applied to agriculture will be deepened, emphasizing

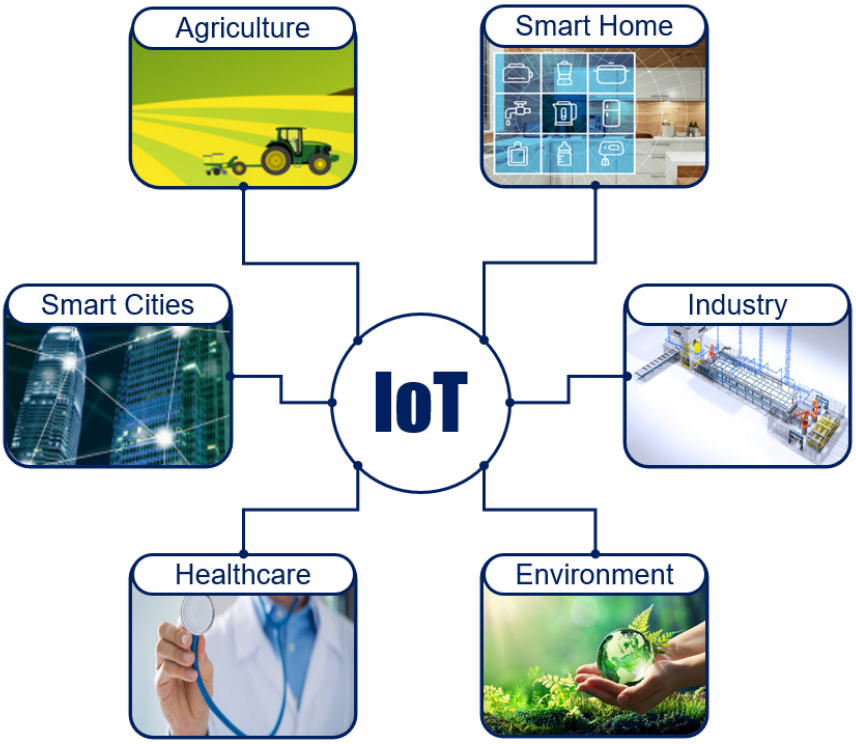


Figure 2.1: *Illustration of several IoT verticals*

their benefits and open opportunities.

2.1.1 IoT architecture reference model

The Internet of Things (IoT) paradigm has a fundamental role as a key facilitator of integration of uncountable application solutions and communication technologies, such as identification devices [38], wired and wireless sensors and actuators networks [39], improved communication protocols and distributed smart objects. The world of IoT predicts physical, digital, and virtual objects interconnected in-network supporting higher class applications. The smartness of objects comes from the automated data processing of an existing state or environmental state in which it is immersed. These data are transmitted to a processing node where they are analyzed and, considering others data acquired from various source objects, then an appropriated sensing profile is determined. A meaningful actuation profile is then built and transmitted back to the smart objects. Therefore, the IoT segments or verticals need to be standardized by a reference architecture model in order for the smart objects can be connected, and requirements such as reliability, mobility, availability, scalability, performance interoperability can be reached to execute their services efficiently [40].

There are various models and reference architectures available for IoT. Each group or company specifies its own, which often causes technological and functional conflicts

and becoming complex the task of standardization. Among the relevant reference models, it is possible to mention initiatives such as Reference Architectural Model for Industry (RAMI), a reference model started in Germany driven to industry sector adding manufacturing and logistic details. Another initiative is called Industrial Internet Reference Architecture (IIRA), which has a strong focus on industry and is supported by a consortium formed by AT&T, Cisco, GE, IBM, and Intel. The Internet of Things Architecture (IoT-A) is another initiative and deliveries a detailed architecture and model from the functional and information perspectives [41].

Many projects focus on a typical architecture where the non-functional requirements are satisfied by a basic module of a reference architecture. Figure 2.2 illustrates the typical layered architecture. The most essential approaches only consider a tree-layer - application, network, and perception layer [42] [43]. In recent literature, other models add more abstraction to an IoT architecture, such as Service Oriented Architecture (SOA), middleware model, and five-tier model [44].

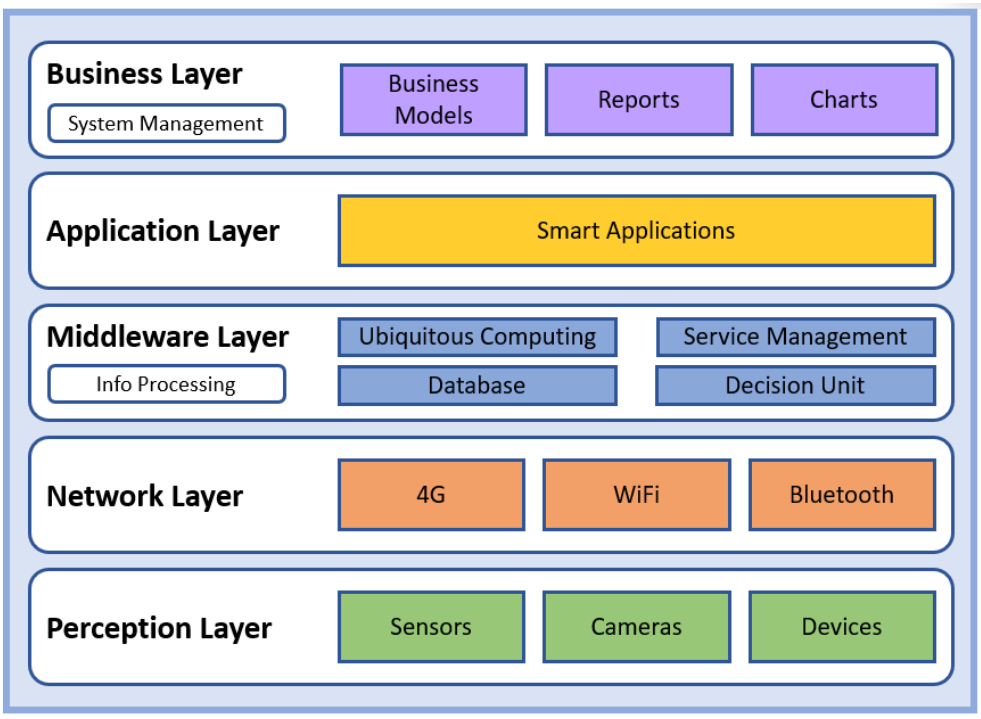


Figure 2.2: *Illustration of layered IoT architecture*

Even with a flexible model, new standard architectures need to be proposed in order to overcome critical factors, especially QoS (quality of service), data integrity, confidentiality, availability, and reliability. Next, there is a brief description of these layers and their roles in IoT systems.

Perception Layer. The perception layer in an IoT architecture has a similar role to the Physical Layer of Open Systems Interconnection (OSI) model because it is

hardware-based and has the responsibility of collecting information from the physical world, process it, and transfer it to upper layer thought available network channels. The collecting processing applies technologies for the detection of parameters of physical characteristics through specific sensors such as temperature, humidity, weight, vibration, etc. Digital camera used for taking a photo of environment or physical objects is frequently considered an advanced type of sensor, and it has become common in recent IoT projects. Moreover, there are specific devices designed for object identification, such as Quick Response Code (QR Code) and Radio Frequency Identification (RFID).

Network Layer. The network layer is responsible for transmitting the collected information in the perception layer to the upper layer through secure channels. According to the system requirements, distinct networking technologies can be deployed, such as Bluetooth, infrared, WiFi, GSM, 4G, 5G, LoRa, etc. In addition to the basic assignments, the network layer can also perform advanced operations such as data encryption and hashing for leverage security levels.

Middleware Layer. Middleware is a software layer that serves as the interface between the IoT components and provides them the capability of intercommunication. This layer follows the Service Oriented Architecture (SOA) approach, and so it is called "Service Layer" in several kinds of technical literature. The middleware layer has some essential functions such as service management, database provider, information processing and has the capability to take autonomous decisions based on gathered results.

Application Layer. The application layer does not directly contribute to the construction of an IoT system, but it is where various services are provider to end-user, such as logistics, retails, etc. This layer is responsible for application management and providing high-quality services to the customer based on the processed information in the middleware layer.

Business Layer: The business layer performs the monitoring and management of underlying layers, manages all IoT applications and services, and providing high-level analysis reports. It is assigning to this layer the responsibility of elaborating business models, reports, and charts which will help managers and executives to make an accurate decision about their business.

Since the advance of IoT systems will exponentially increase network traffic, the IoT solution development depends on technological progress and the design of new architecture reference models.

2.1.2 IoT networks and protocols

The IoT infrastructure employs miscellaneous networks to provide the connection among devices, mobile phones, notebooks, desktops, and high-end servers. This connection can be classified into three categories: Wired, Wireless, and Mobile.

The **Wired Category** interconnects all kinds of immobile equipment and uses physical wires such as Unshielded Twisted Pair (UTP), coaxial cables, and optical fiber. The advantages of wired networks are the low prices of the equipment and the capability to interconnect devices over large distances, including building MAN's (Metropolitan Area Network) and WAN´s (Wide Area Network) systems [45].

The **Wireless Category** interconnects devices (immobile or not) using the electromagnetic spectrum, without any physical wires. The agility to build and operational practicability of wireless networks can be pointed out to its advantages [46]. Generally, this category is used to build LAN's (Local Area Network), PAN's (Personal Area Network), including BAN's (Body Area Network). Some of the most widely adopted types of wireless network are WiFi (employed to build LAN's with star-topology) [47], Bluetooth (used to mount PAN's using point-to-point device interconnection) [48], and LoRa (employed to interconnect devices at long distances with low power consumption requirements and low rate transmission) [49].

Finally, the **Mobile Category** is a network where devices can be mobile, and no installation is required. This category - also knows as Cellular Category - is based on Radio Base Station (RBS) and, at the initial generation, its purpose was only voice communication. Due to increasing market demand, the newer mobile generations have added data communication services. The 3G (Third Generation) have added the General Packet Radio Services (GPRS) as data communication service, and 4G (Fourth Generation) provides data service through the Long Term Evolution (LTE). The 5G (Fifth Generation) is the current generation of mobile network, and it represents a great expectation, whereas a specific 5G branch has been designed to meet the IoT requirements.

Once the connections between devices are established through a network, the data exchange among the nodes will only be possible if strict rules were followed. The set of these rules are the communication protocols. In IoT scenarios, such protocols need to satisfy requirements such as low complexity, low power consumption, security, and performance [50]. The main protocols employed in IoT systems are described as follows:

Representational State Transfer (REST) is a high-level protocol addressed to synchronous communication scenarios. This protocol reuses the underlying HTTP

protocol features such as action demarcations (GET, POST, PUT, DELETE, etc.), well-defined data encoded in JavaScript Object Notation (JSON), and Universal Resource Identification (URI) [51, 52].

Constrained Application Protocol (COAP) is the lightweight version of REST. It also address synchronous communication but uses *User Datagram Protocol* (UDP) which is connection-less and has non-existent acknowledgment support. The COAP is widely employed in IoT systems since it has low overhead and supports multi-casting [53].

Message Queuing Telemetry Transport (MQTT) is a lightweight protocol addressed to asynchronous communication contexts, and it is based on publish/subscribe approach. Its operation consists of the message exchange among devices where a publisher device sends a message to a central server (called of Broker) to a defined topic whose subscriber(s) will receive a message copy. Since it requires low power of computational and low bandwidth, the MQTT protocol has great acceptance in IoT projects [54, 55].

In this work, in order to build and validate the proposed solution, many requirements related to network and protocol were taken into account. The Raspberry Pi was the selected board as embedded hardware, and the requirement for wireless communication was met by WiFi Module natively included on the board. The simple synchronous communication and high-level integration were enough to satisfy the data integration requirement driving the choice for REST protocol.

2.1.3 IoT in rural environments

In this session, Brazilian agriculture is firstly contextualized by presenting its expressive numbers and massive importance for the national economy. The agriculture and technology combination is then introduced as an expansion resource to meet the global demand for food. As valuable examples, some recent researches and innovative startups are mentioned. And finally, the Brazilian government IoT initiatives are exploited, highlighting the aspiration, strategical objectives, main challenges, and great opportunities [56].

Agribusiness is the group of supplies producer companies, rural properties or farms, and processing, distribution, and commerce industries. In Brazil context, agribusiness is responsible for about 1/3 of everything produced in the country, represents 25% of the Brazilian GDP (Gross Domestic Product), and employees an average of 38% of national workers. In the last 20 years, Brazilian grain production has grown approximately 250%, and the cultivated area has expanded by only 50%.

International projections indicate the global demand for food will increase in the next ten years, and the Ministry of Agriculture projects that Brazilian production should grow 27% in the same period. In this scenario, technological advancement in agriculture is essential for the establishment of solid structures in order to guarantee these results. Technology is seen as a relevant factor for increasing productivity, and the main areas of technological action in agribusiness are precision agriculture, management software, decision support technology, and intelligent equipment (IoT).

The term Agriculture 4.0 came embedded in the fourth industrial revolution concept (or Industry 4.0) and refers to the transformation caused by the digital technologies arrival in the agricultural environment inserted in the various production stages, increasing productivity, with lower costs and higher quality. Big Data, mobility, internet connectivity, IoT, and Artificial Intelligence are examples of these digital technologies [57].

In recent years, many IoT types of research have been developed mainly related to environmental sustainability in farms [58]. For example, the researches [59] and [60] describe a smart irrigation solution in order to optimize water usage. Drones usage has also grown considerably for data acquisition through plantations images and has contributed to achieving the state-of-the-art in sustainable agriculture [61].

In the private sector, many entrepreneurs have already assimilated the Agriculture 4.0 trend, and they are launching promising startups as solution providers. The startup AgroSmart [18] offers an integrated platform for intelligent irrigation management that combines soil moisture sensors, digital rain gauges, and mini weather stations. Another promising startup is Tarvos [19], which provides a solution for biological pest control in corn, cotton, and sugarcane cultures through a digital platform for collecting, image analyzing, and recommending the right time to intervene in pest control. Drones began to be used in agriculture to capture aerial images of plantations, but this use had been expanded. The startup SarDrone [62] is a sugarcane culture service provider that applies biological control agents via drones. The startup developed equipment coupled to the drone that transports biological agents. The drone then flies over the crop and releases agents into strategic parts.

The Brazilian government, through National Development Bank (BNDES), Ministry of Planning, Development, and Management, and Ministry of Science, Technology, Invocation, and Communications, elaborated the National IoT Plan (PNIoT) [63], which consolidate the strategic vision for IoT in Brazil for 2018 to 2022 period, highlighting the four priority environments: Cities, Factories, Health and Rural.

The PNIoT for the rural environment was developed based on interactions with spe-

cialists, agricultural producers, academics, and researchers in the sector. The result of these interactions was the declaration of the long-term strategic objectives and aspiration of the IoT for the rural environment. The great aspiration is to increase Brazil productivity and relevance in the world trade in agricultural products, with high quality and social, environmental sustainability, and place Brazil as the largest exporter of IoT solutions for tropical agriculture. The strategic objectives are: a) to increase the productivity and quality of rural production through the use of data; b) Optimize the use of equipment in the rural environment through the use of IoT; c) increase the volume of information and its accuracy in monitoring biological assets; d) promote the adoption of locally developed solutions for environmental challenges.

However, Brazilian agribusiness presents its challenges related to economic, environmental, and social sustainability. For example, it is possible to mention as an environmental challenge that Brazil is the fourth largest consumer of pesticides per hectare (twice the consumption of Canada). There are also negative points in the efficient use of machinery where the index of agricultural machines per area is about ten times lower than in Portugal and 20 times lower than in Austria. Sanitary security is another relevant challenge: in 2017, fresh meat exports to the US were blocked by sanitary irregularities in 11% of imports when the world standard is 1%.

To overcome these challenges, during PNIoT elaboration, the potential applications of IoT in the rural environment were extensively discussed by more than 70 actors from the agricultural sector, and they classified these applications according to their economic impact. Applications considered to have the greatest impact are described in Table 2.1.

The IoT is a unique opportunity, and Brazil is very well positioned to capture its full value. By 2025, IoT will have a greater economic impact than advanced robotics, cloud technologies, and even the mobile internet. The expected impact in Brazil is between US$50 and 200 billion per year, which represents around 10% of GDP. Only IoT in the rural environment, the impact on the economy is estimated to be US$ 21 billion.

For rural environment full implementation of IoT, it is also necessary to overcome some structural barriers mainly related to the lack of connectivity infrastructure, the difficulties in Research/Development/Innovating funding, and the low professionalization of the workforce. However, all these barriers are addressed in PNIoT, and initiatives have been proposed.

Challenge	Application	Description
Efficient use of natural resources and supplies	Weather monitoring	Micro climate and natural resources monitoring by sensors or mini-stations, generating alerts about potential pests, diseases, rains, and supporting decision-making on planting, harvesting, and need for irrigation
Efficient use of machinery	Machine performance management	Real-time monitoring of operations, generating big data that allows monitoring the quality of operations and the impact on culture and predicts the ideal time for machine maintenance
Sanitary security	Pest Management	Monitoring the health of the plantation or pasture that captures images, identifying diseases, weeds, and pests and allowing better phytosanitary control
Animal welfare	Health and feeding monitoring	Monitoring animal health and well-being helping to detect diseases and stress, predicting birth dates, and optimizing livestock feed.

Table 2.1: *IoT applications in the rural environment with the greatest economic impact*

2.2 Concepts of Coffee-berry-borer

This section exploits the pest of interest in this work. Their basic biology features are presented, as well as damages caused and main population control approaches.

The coffee culture has great importance for Brazilian agribusiness representing the main export products. Among the pests that affect production, the pest known as Coffee-Berry-Borer (CBB) (*Hypothenemus hampei*) is one of the most important because of level of serious damages in production [64]. This pest belongs to the entomological order Coleoptera (beetles in general), and their front pair of wings are hardened into wing-cases - as shown in Figure 2.3. The adults have a dark gray body measuring from 0.7 until 1.7mm in length.

The females are responsible for piercing the coffee fruit and putting their eggs. They can attack the green, mature, and dry fruits [65]. The larvae grow inside the fruit, feeding on the seed, which destroying partial or totally the fruit and seed - as seen in Figure 2.4. The most relevant damages caused by CBB [66–69] in coffee plantations are: 1) premature loss of fruit; 2) make seed production unfeasible; 3) reduction of grain weight (quantitative loss): The weight loss can reach 21% per bag (12.6Kg per 60Kg bag); 4) reduction of coffee beverage category (qualitative loss); 5) alteration of the coffee quality indirectly: by piercing the fruit, harmful fungus are capable to penetrating and contaminate the fruit, and the seeds dropping the beverage quality; 6) adding impurity with body fragments.

The financial losses are directly related to new perforated fruit fall, grain hatching,

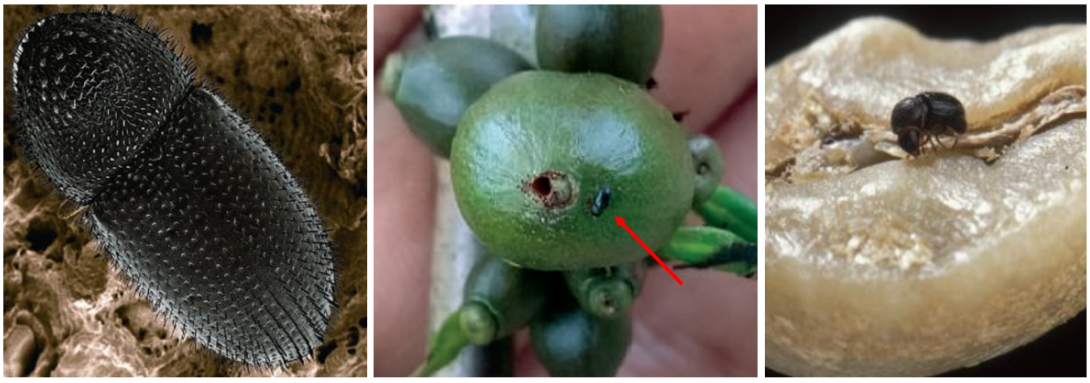


Figure 2.3: *The Coffee-berry-borer (CBB) insect: a) microscopical image; b) over a green fruit; c) over a dry seed. Source: IFSULDEMINAS Campus Muzambinho*



Figure 2.4: *Damages caused by CBB: (a) gallery for oviposition on the fruit seen in longitudinal perspective; (b) gallery seen in transverse perspective; (c) damages in dry seeds. Source: IFSULDEMINAS Campus Muzambinho*

rotting of seeds, viability loss of seed for planting, loss of weight, and lower quality beverage. The losses caused by the CBB are estimated at US$ 500 million annually worldwide.

For CBB population control, there are four main approaches: Cultural, biological, trapping, and chemical control [68, 69]. In the next sections, these approaches are described emphasizing their advantages and disadvantages. In the end, a summarizing table is presented, comparing the aspects of cost, applicability, and level of toxicity.

2.2.1 Cultural control

The abundance of food in the off-season, originated by the poor harvest, and the failure to collect the coffee fallen in the ground (foundation), allows the development of high populations of the pest to attack the next plantation season. At the time of fruit formation (October to December), the adults of the CBB are still in the crown

of the fruit and cannot penetrate to the seed and lay eggs. The cultural control approach is based on the following procedures: a) proceed with the harvest well done, preferably the selective way; b) avoid leave plantation with remaining fruits; c) eradicate abandoned plantations; d) proceed a rigorous harvest reviewing 15 to 20 day after the harvest (fruits in the plant, and in the soil). Cultural control is basically a manual approach with a low level of mechanization requiring many workers to execute it.

2.2.2 Biological control

There are two main techniques to apply biological control: 1) release a population of CBB natural predators in plantation, such as the "Vespa de Uganda" (*Prorops nasuta*) [70]; 2) application of biological pesticides such *Beauveria bassiana*. It is a fungus that closes the hole made by the CBB in the form of a white tuft. However, these biological pesticides will be efficient only when the relative air humidity is above 65%. Another drawback is that there are insufficient studies about the application in large-scale, and the side effects on local biodiversity.

2.2.3 Trapping control

In smaller farms, the CBB control can be done by handmade traps using plastic bottles [71]. A special substance is utilized to attract the insects, and they would be captured and killed in a water and detergent mixture. This attractive substance could be a commercial product (for instance, the Bio-Broca product from *BioControle laboratory* [72]) or made by Methanol, Ethanol, and coffee powder compound. The recommended traps distribution is about 30 per hectare, replacing the attractive substance every two weeks. Therefore, the traps maintenance demands frequent human interference and is applicable generally on a small scale.

2.2.4 Chemical control

It means the application of toxic pesticides. In the mid-70s, the solution for effective control came up with the registration of the insecticide Endosulfan, which was used for more than 40 years until it was banned in 2013 for being extremely toxic (red stripe, and toxicological class I) [69]. Currently, there are about 11 pesticides on the market varying in cost and efficiency. For example, the Verismo product (from BASF laboratory) [73] costs US$ 62,00 per hectare/year. Considering that is recommended two applications per year, the total cost is about US$ 124,00 per hectare/year, which represents an expressive cost. The chemical control is suitable for large scale with a

high level of mechanization requiring a lower workforce. However, its chemical toxicity represents a serious problem in environmental, natural, and human health contexts.



(a) (b) (c)

Figure 2.5: *Illustration of chemical pesticides applications: (a) Manual application; (b) Tractor-based application; (c) Drone-based application*

Figure 2.5 illustrates a few examples of chemical pesticides applications. The manual application still is widely used, mainly in smaller rural properties. The application using tractors is ideal for large plantations. And new mechanization is gaining ground on modern farms and is based on unmanned aerial vehicles or drones.

	Cost	**Applicability**	**Toxicity level**
Cultural	High	Large scale	Lowest
Biological	Medium	Small scale	Medium
Trapping	Low	Small scale	Low
Chemical	High	Large scale	Highest

Table 2.2: *CBB population control comparative*

This section has described the CBB pest relevant features and its main approaches for population control. The decision about which approach must be applied takes into account aspects such as collateral impacts, scale applicability, and cost. Table 2.2 shows a comparison among these aspects. The challenge is to unite the requirements of sustainability, applicability for large scale, and acceptable cost-benefit. Therefore the creation of new approaches which meet all these requirements would represent an outstanding contribution to the coffee culture.

The following section explores the main insect identification approaches available in academic studies and analyses which one is suitable for CBB identification considering its morphological features.

2.3 Insect identification approaches

Experiments to automatically identify insect species is not a recent practice. The first records on insect flight signals analysis have dated from the second half of the 19th century. The researchers used equipment linked to measuring the sound emitted by the wings during flight, such as a kymograph or chronophotographic. with technological advances in the mid-twentieth century, researchers started to use optical measurement tools such as oscilloscopes and stroboscopes. Several kinds of research have been dedicated to recognizing a direct relationship between the insect morphology and its wing-beat frequency, including the gender classification [74]. In the '80s, studies in the field of biology also proved that the wing-beat frequency is inversely proportional to the size of the insect body, varying between 10Hz and 1,000Hz. [75]. The challenge for researchers was how to acquire the value of these frequencies and further research was carried out highlighting sensors for measuring these frequencies. The acoustic and optical sensor approaches have been divided into research for detecting flying insects by the wing-beat frequency.

In recent decades, with digital photography advances and digital image processing theory, a new approach has been created and has been widely researched: identifying insects by analyzing their images. This approach does not use the wing-beat frequency strategy but rather analyzes, through photographs, their morphological characteristics such as body color, and size, size, and shape of the wings, etc.

Therefore, in this section, these three main approaches for insect identification are reviewed, both analog approaches such as acoustic and optical and the digital approach such as image-based analysis. Each approach is described, and an analysis is carried out on its deployment challenges and also which types of insects are most suitable in the identification process.

2.3.1 Acoustic sensing approach

The earliest experiments to study the wing-beat frequency of mosquitoes come from the biological sciences. The sounds produced by insects are even used as a communication mechanism between them. In related researches, the capture of sounds emitted by the wings of insects is made by electro-acoustic tools such as microphones, and the frequency analysis is performed by analogical oscilloscopes. The countless researches already carried out helped to generate a database for the classification of insects through the fundamental wing-beat frequency. The fundamentals of the approach using acoustic sensors are illustrated in Figure 2.6. The sound emitted by the flying insect is picked up by a microphone and send to an oscilloscope where the signal is

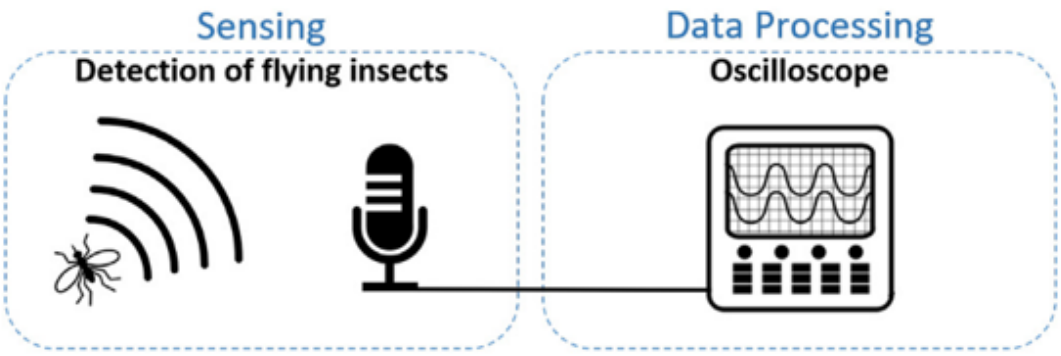


Figure 2.6: *Fundamentals of acoustic sensing approach. Source [12]*

processed.

The challenges of the acoustic approach are related to the sensitivity of sound capture, demanding high precision equipment, as well as the difficulty of implementing filters to eliminate external noises [76]. These challenges have been overcome as microcomputers are used in the process of digitizing, filtering, and analyzing the recordings [77]. However, when experiments are performed in the field, the energy consumption has become another challenge as processing to filter out ambient noises represents a complex task demanding more processing power.

Entomology, a science that studies insects, organizes the insects in orders. The Order Diptera includes the flying insects whose wings have been modified to serve as flight stabilizers, and so their wing-beats can emit enough sounds to be picked up by microphones. Mosquitoes and flies are examples of the Order Diptera [78]. Therefore, the acoustic sensing approach is suitable for identifying insects in this order.

2.3.2 Optical sensing approach

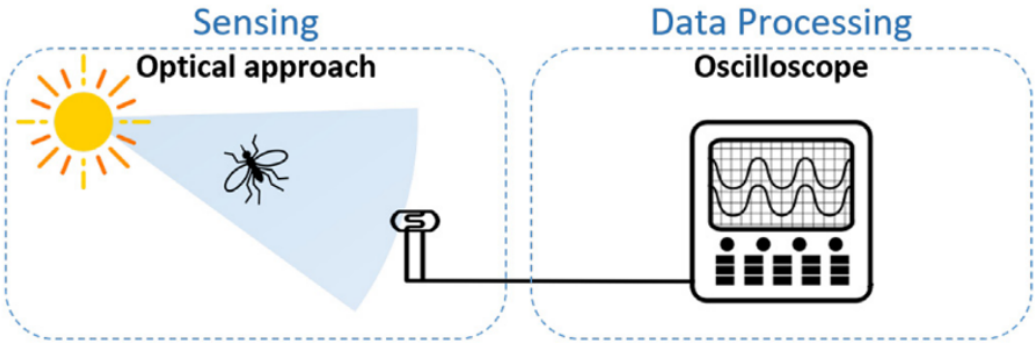


Figure 2.7: *Fundamentals of optical sensing approach. Source [12]*

In 1955, a research was carried out where photoelectric cells perceived the modula-

tion of sunlight when a flying insect crossed the detection field [79]. This conclusion opened the path for studies based on the optical approach to insect identification and classification. The principles of the optical approach operation are shown in Figure 2.7. The insect of interest is placed in a transparent box with an active light beam. Its wing beating causes reflection in optical sensors, photo-diodes. The sensor output is directly connected to signal analysis equipment such as an oscilloscope. The changes in light intensity captured by the photo-diode work as a trigger starting the signal analysis process, representing energy savings. Optical approach researches have evolved gradually over the past decades, where new LED and photo-diode arrangements are designed, and microcomputers equipped with analog-to-digital converter are used [80]. The most recent research innovation is applied Machine Learning in order to improve classification accuracy [81].

The optimized energy consumption is the first advantage of the optical approach over to the acoustic one. The more extensive range of identifiable insects is another advantage. In addition to insects of the entomological order Diptera, insects belonging to orders such Lepidoptera (butterflies), Orthoptera (locust), Odonata (dragonflies) [82] could be identified by the optical approach since their wings are large enough to cause light intensity variations when exposes against light beams.

However, the optical and acoustic approaches have a common disadvantage: during the experiments, the insects have to be in flying for their wing beats could be perceived and then analyzed. Therefore insects "on land" would not be identifiable for neither of these approaches.

2.3.3 Camera sensing approach

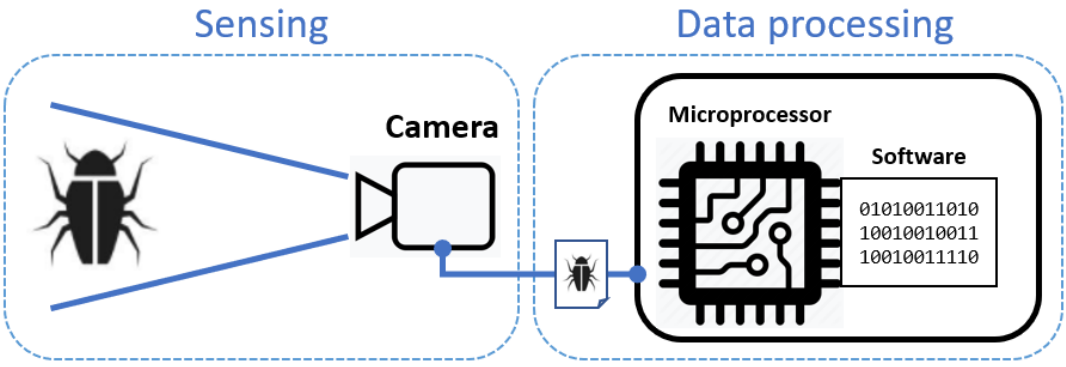


Figure 2.8: *Fundamentals of camera sensing approach*

In this approach, 2D images are acquired by standard digital cameras (even a mobile phone or embedded devices) and so are sent as input to computational routines that

select regions of interest and carry out the identification into known classes - as seen in Figure 2.8. The image-based insect recognition uses morphological features as wings patterns and shapes, body length, width, and colors.

Thus, classic image recognition systems decompose the entire process into three sequential phases: a) Image capture; b) Feature extraction; 3) Classification. Image capture consists of using tools and methods to take pictures of the insect. Feature extraction consists of selecting and extracting useful visual information from the picture. Finally, classification is the phase in which recognition is performed based on information extracted from the processed image [17].

The feature extraction routines range from mathematical models such as Hu moments, Elliptic Fourier Descriptors (EFD), Radial Distance Functions (RDF), and Local Binary Patterns (LBP). Recent researches in visual recognition have applied Machine Learning and Deep Learning models using unsupervised learning, supervised learning, or a combination of both. Noise cancelling, morphological operations, and Gaussian blur can be applied as additional routines [83, 84].

For the classification phase, several classifying algorithms can be used, such as Linear Discriminant Analysis, k-NN classifiers, Support Vector Machine (SVM), Decision Trees, including advanced Neural Networks (NN) [85].

Therefore, the mathematical and computational techniques applicable in this approach are extensive and represent a vast field for future researches and improvements in the area. It is worth mentioning the great advantage of this approach (over acoustics and optics ones) is the fact the insect of interest does not necessarily need to be flying for the recognition process to be performed. Including, when the insect is “on land”, the pictures quality trends to be higher. And finally, all entomological classes of insects might be identifiable by image analysis, regardless of whether they are flying insects or not [86].

The camera sensing approach also has its challenges. The image capture phase must take into account aspects such as lighting, generated shadows, insect positioning, which can induce variations in body shapes, details, or colors. For example, some insects are better recognized by their wing exposure than by their body. These challenges can become more complex in “out-of-lab” or open field environments where these aspects cannot be manipulated, and the use of more sophisticated equipment is restricted.

In summary, the Table 2.3 shows the insect identification approaches comparative highlighting the respective advantages and drawbacks. In the context of this research, camera sensing approach proved to be the most suitable as the Coffee-berry-borer is a

beetle with a compact body and small wings. The difficulties to acquire images were overcome as will be explained further on.

	Advantages	**Drawbacks**
Acoustic sensing	Suitable for big-wings insects; Cheaper equipments.	Difficulty to filter external noises; High energy consuming.
Optical sensing	Suitable for big-wings insects; Low energy consuming.	Expensive equipments.
Camera sensing	Suitable for "on land" insects; All kind of cameras can be used; Cheaper equipments; Low energy consuming.	Difficulty to image capture: lighting, shadowing, positioning.

Table 2.3: *Insect identification approaches comparative*

In the next section, the fundamental concepts of computer vision will be presented, highlighting the issues that will provide all necessary support for image analysis in identifying insects.

2.4 Concepts of Computer Vision

Computer Vision (CV) is a modern field of computer science that makes it possible to emulate human eyes functionality on machines. When an image is presented as input, the system provides an interpreted version as output. In order to provide an output with meaningful results, the image processing must remove all undesired information in the image through filtering or similar operations [87].

This section goals to present the main concepts of CV applied in this research, such as digital image basics and CV typical workflow. These concepts provide the baseline to elaborate the proposed solution in Chapter 3.

2.4.1 Digital image basics

A digital image can be defined as a two-dimensional function *f(x,y)*, where *x* and *y* are spatial coordinates (plane) and *f* is the color intensity or level function [88]. The *x* and *y* values are finite, discrete, and are within the spatial dimensions width (W) and height (H), where $0 \leq x < W$ and $0 \leq y < H$.

The concept of spatial resolution refers to the W and H values of an image, and can change the perception of an image, as can be seen in Figure 2.9, where two images with the distinct spatial resolution are compared. The Figure 2.9(a) has 640x480 resolution

(Width=640 and Height=480), and Figure 2.9(b) has 64x48 resolution – at 100x lower resolution.



(A) (B)

Figure 2.9: *Spatial resolution comparative: (A) 640x480 resolution; (B) 64x48 resolution (100x lower)*

A digital image represents a finite number of elements, commonly called a pixel (acronym for Picture Element). The intensity function for a pixel depends on which color model is being used. The purpose of color models is to allow you to specify colors in a format standardized and accepted by all.

The most common models for representing colors are CMYB (cyan, magenta, yellow, black), and HSI (hue, saturation, intensity) and RGB (red, green, blue). The CMYB model is based on cyan, magenta, yellow and black primary pigments. Most devices which operate on the deposition principle of color pigments on paper (such as color printers or photocopiers) uses the CMYB model. The HSI model allows to separate the hue, saturation and intensity components of color information in an image. Its use is more intense in Computer Vision systems strongly based on color model perception, such as an automated system of fruit harvesting, in which it is necessary to determine whether the fruit is ripe enough to be harvested from its external coloration [89]. And finally, the RGB model was created by inspiration on human perception of colors where the eyes are sensitive to three primary colors (red, green, and blue). Therefore, the intensity function representation of a pixel uses the format RGB(ri, gi, bi), where ri is red intensity, gi is green intensity, and bi is blue intensity. Therefore a specific color is formed by the composition of these three values. In general, image processing systems use intensity ranging from 0 to 255. Most modern graphics libraries represent a digital image in memory as a two-dimensional array where each position corresponds to the pixel and its respective RGB intensity function. It is worth mentioning that, due to its additive nature, the RGB color model is best suited for displaying color in electronic systems such as televisions and computer monitors.

Image Types

There are several digital image types in the image processing scope, but three fit the context for this research.

1. **RGB Images**: the RGB images are colored images composed of the primary colors. As already mentioned, each pixel is the combination of red, green, and blue light intensity, where values range from 0 to 255 (2 power 8). Therefore a pixel demands 8 bits to represent each primary color intensity, totaling 24 bits. It means 16 million colors (255 x 255 x 255) might be represented in the RGB model.
2. **Grayscale images**: the grayscale images are also represented by the RGB model, but all three values are equals. So each pixel has 256 (8 bits) possible values of gray. The notation RGB(0, 0, 0) represents the pure black, but the simplified notation RGB(0) is also used. The pure white is represented by RGB(255, 255, 255) or RGB(255), in simplified form. Moreover, the gray color at 50% is notated by RGB(127, 127, 127) or RGB(127). Therefore, there are 256 possible gray colors.
3. **Binary images**: Binary images are the simplest type to represent a digital image. Each pixel has two possible values (black or white) demanding only 1 bit. Reusing simplified notation, in binary images, the white is represented by RGB(255) and the black is represented by RGB(0).

In Computer Vision context, working with RGB images must be taken into account carefully, because it represents a overloaded processing for each color channel (primary color). On the other hand, grayscale images are faster and lighter to be processed, as a single channel is considered. Despite being the simplest image type, the binary images have wide applicability in Computer Vision systems, the binary contrast can perfectly represent the regions of interest selection inside an image. Therefore, the next sections present the techniques for image types conversion that supports Computer Vision processing.

RGB-Gray Conversion

In order to reduce the size of information to be processed, the image conversion from RGB for grayscale is a task almost always performed in Computer Vision applications. However, even low detailed, the grayscale images maintain important object features such as borders, regions, stains, and joints.

The mathematical process involved in grayscale conversion is done pixel by pixel.

The resulting pixel is the weighted sum of red, green, and blue channels. The weighting coefficient is distinct for each channel. Those coefficients were standardized and defined based on the human eye perceptual response for each channel.

For a RGB(*ri*, *gi*, *bi*) pixel, where *ri* is red channel intensity, *gi* is green channel intensity, and *bi* is blue channel intensity, the conversion equation is:

Resulting grayscale pixel = ((0.3 * *ri*) + (0.59 * *gi*) + (0.11 * *bi*))

According the above equation, the red channel has contributed 30%, the green channel has contributed 59%, and the blue channel has contributed 11%.

Gray-Binary Conversion

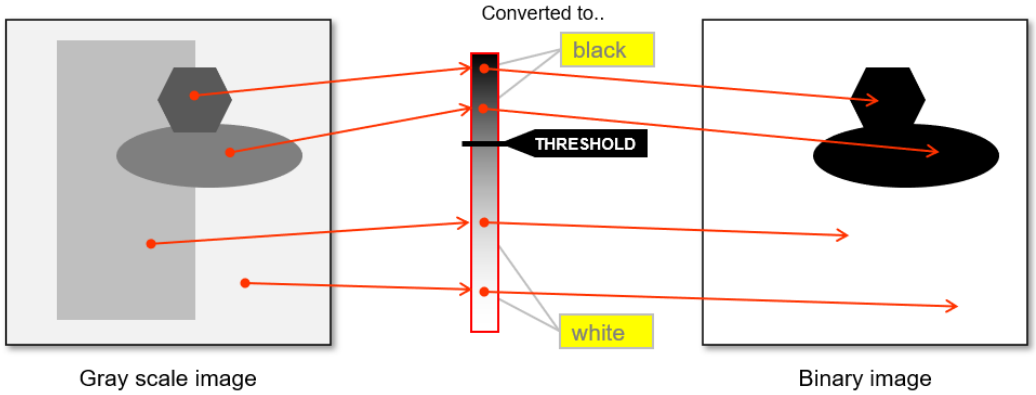


Figure 2.10: *Binarization and Threshold: Each pixel in the grayscale image is compared to the threshold value. The resulting pixel will be black or white.*

As already mentioned, binary images are the simplest image type but are valuable enough for advanced image processing involving Computer Vision systems.

The Gray-Binary conservation is commonly named the binarization process, and its goal is to separate the region of interest from the background plan. The binarization process consists of analyzing pixel by pixel and convert it into a binary pixel. A threshold value in RGB notation must be previously defined in order to be the reference in binary conversion. For example, considering the threshold value is RGB(T), an original gray pixel RGB(x) would be converted to black - RGB(0) or to white RGB(255) according to rules: a) when x is lesser than T, the gray pixel is interpreted as dark and converted to black; b) when x is greater than T, the gray pixel is considered light and converted to white.

Figure 2.10 illustrates how binarization works based on the threshold value. The threshold value can be defined dynamically by a previous image processing using adaptive algorithms or statically by an empirical process. The dynamic definition is

suitable for an unpredictable image associated with contrasting high variance, while the static definition method fits the images with predictable contrast variance.

2.4.2 General Computer Vision workflow

The most of Computer Vision systems follow a typical workflow steps which it is illustrated in Figure 2.11. The **image acquisition** is the first, and it can be done by sensors such as cameras, scanners, and X-rays. These sensors transform the physical light emitted by real objects or scenes into a digital image. Borders and geometric shapes highlighting color histogram, and equalization, geometric transformation are some routines performed during the **pre-processing** step.

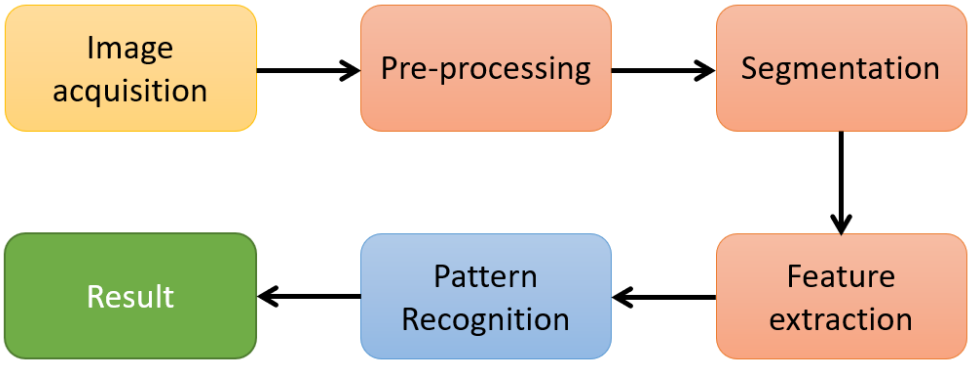


Figure 2.11: *General Computer Vision workflow*

The **segmentation** step consists of separating only the sub-area representing the object of interest, generating a new image and excluding the second plan. Some segmentation techniques are binarization, threshold value definition by adaptive algorithms, and color segmentation [89]. Noise cancelling is a fundamental treatment in segmentation. Noises are minuscule non-relevant points produced by the binarization process, which could disrupt the next steps, including producing mistaken results.

There are several operations can be applied to remove noises. The erosion and dilatation operations are primitive operations and more sophisticated operations can be performed by the combination of them. Both primitive operations uses the *Structuring Element* concept which consists of a pixel matrix that will be traversed through the entire image, pixel by pixel, changing the value of the original pixel. The most common patterns for the matrix is rectangular, elliptical and cross.

The erosion operation is characterized by the corrosion of the edges of the object of interest, resulting in a shrunken version of the object. The erosion operation algorithm consists of superimposing each pixel of the input image with the center of the structuring element. If all points of the structuring element coincide with the object of interest

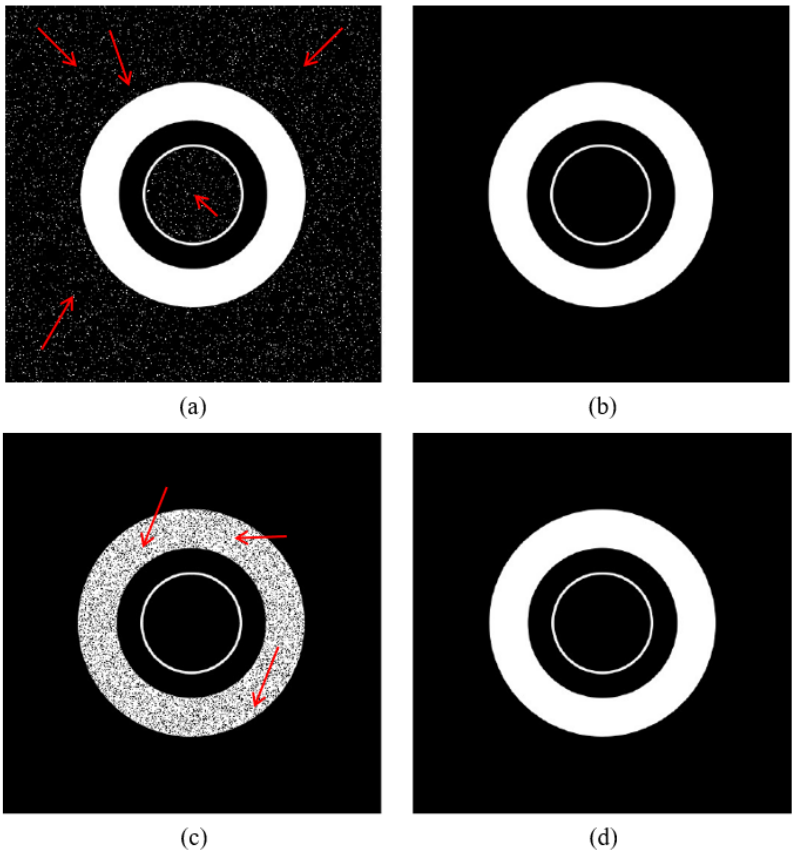


Figure 2.12: *Noise cancelling treatment. Image (a) shows the white noises in black background, and (b) shows the result after the opening morphological operation was applied. In the image (c), the black noises are pointed in white background, and (d) presents the closing morphological operation result.*

points, then only the center point becomes part of the resulting object.

The dilatation operation is the opposite of the erosion operation. In this procedure, the area of the object of interest will be dilated, that is, the object in the foreground will be larger than it was initially. The dilation operation algorithm also consists of superimposing each pixel of the input image with the center of the structuring element. If all points of the structuring element coincide with the object of interest points, then all points become part of the resulting object.

To optimize noise cancelling in images, more sophisticated operations can be performed by combining erosion and dilatation operation. These operations are known as **morphological operations** and there are two types: a) Opening morphological operation aims to remove white noise in black areas and it is characterized by the erosion operation followed by the dilation operation; b) Closing morphological operation removes black noises in white areas and it consists in apply the dilatation operation followed by the erosion operation. Figure 2.12 illustrates noisy image samples and the respective results after both morphological operations were applied.

Feature extraction has the objective of extract information that makes it possible to classify or identify an object. The characteristic of an object can be categorized in aspect (ex: color), dimensional (ex: geometric shape), inertial (ex: geometric center, rotation, and translation), and topology (ex: number of vertices, number of holes)

Pattern recognition makes possible the automatic classification of an object of interest. Therefore, these techniques allow computers to see the world around us, recognizing plaques, pieces, characters, faces human, and all sorts of objects. Advanced pattern recognition processors use algorithms such as Haar Cascade and K-NN Classifiers.

And finally, the **results** are the presentation of what was recognized in the previous step. The results can be presented as textual reports or graphical charts underlining the useful information found. Nevertheless, the most valuable way to present the Computer Vision results is overlaid markings (geometric colored figures and texts) in the original acquired image. For example, Figure 2.13 illustrates the result presentations of two different Computer Vision applications. Figure 2.13(a) is referent to traffic control automation system for Smart Cities where people and cars are instantly distinguished from each other, being able to issue alerts helping to report or even avoid accidents. And Figure 2.13(b) is related to the Computer Vision system applied to agriculture where grape plant elements are automatically recognized (fruits and leaves). This result could provide support to an autonomous harvester robotic, for instance.

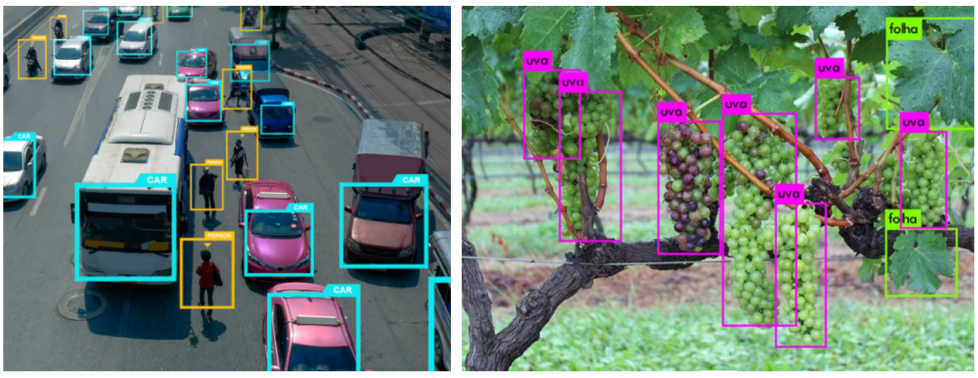


Figure 2.13: *Computer Vision results presentation. Image (a) shows a traffic control system where cars and people are identified across the street. In image (b), a Computer Vision system recognizes the plant elements (fruits and leaves) in grape culture*

This session presented the most relevant Computer Vision concepts used in this dissertation. These concepts were fundamental during creating the proposed solution, where images of insects are processed by software routines over a Computer Vision library and providing their identifications as result.

Chapter 3

The proposal of an IoT-based Solution for Pest Control

THIS chapter analyzes the requirements and concepts leveraged in previous chapters and makes a proposal of technological solution for pest control addressed to coffee culture.

The management of agricultural plantations is related to countless cares, and frequently these cares can represent promising business opportunities for solution providers in agriculture. Within an overall analysis, a new solution (technological or not) needs to meet the relevant requirements such as:

Large scale applicability: Brazil and other essentially agricultural countries have been expanded their agricultural frontier as the growing global increases and mechanization becomes indispensable for this expansion. Therefore, any proposed solution to solve any rural environment issue must necessarily consider the machinery usage level or other automated processes applicable in wide areas.

Acceptable cost-benefit: As any economic activity, rural properties goal at a financial profit by maximizing productivity and minimizing costs. One of the first requirements to be evaluated for a new proposal adoption will be cost-benefit acceptance. For example, modern farms have been adopted advanced solutions for agriculture of precision which expensive initial investment. However, the immediate reduction of production costs corroborates to justify the investment

Sustainability: Sustainable development is a current exigence of the worldwide citizen endorsed by the UN (United Nations) and, therefore, any solution applicable in the rural environment must be in line with this trend, produce the least possible environmental impact and prioritize human and animal health.

One of the most critical care in plantation management is mitigating the damage caused by pests - the plantation natural enemies. Currently, the application of chemical pesticides is the most widespread approach to population control of these pests. However, the control by chemicals meets only the large-scale applicability requirement, missing the economic viability and causing immeasurable impacts on the environment, animals and human health.

Taking this scenario as a reference, this work proposes a new approach as a solution to pest control concerning meeting the sustainable requirements, economic viability and large-scale applicability. The proposal solution employs the most advanced available technologies such as IoT and Cloud Computing. In the next few sections, its general technical features are presented.

3.1 Presentation of pest control solution

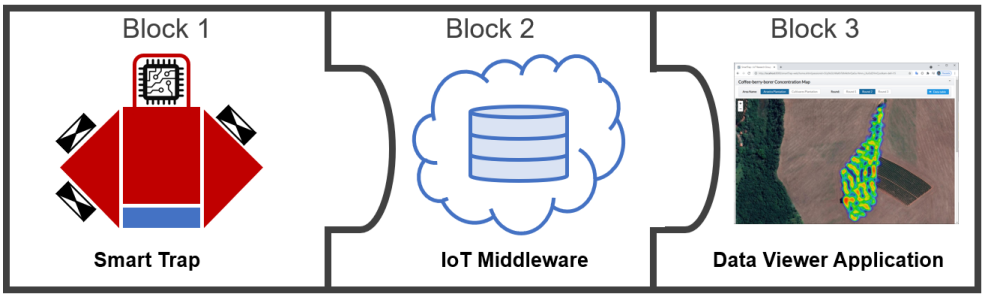


Figure 3.1: *Blocks diagram of the pest control solution*

The proposal pest control solution is an integrated system that consists of three structural blocks - as seen in Figure 3.1. The first and most important block is named Smart Trap and is where the insect of interest (CBB) is attracted, identified and captured. The Smart Trap needs to be in motion to get closer to the insect swarm since the CBB has short flights. Analyzing the CBB Entomological Order, the insect identification approaches based on acoustic or optical would not be suitable. So, the insect identifying will be performed by image acquired by camera sensors. Through its morphology study, the CBB has a rounded body and encapsulated wings. Thus its body could be considered a regular circle, which would make the identification more accurate. The camera will be positioned against a white background to contrast with CBB body color (dark gray). The acquired images could be processed using only basic Computer Vision resources, which demands low processing power. Through the OpenCV library, the software components were developed to execute the Computer Vision workflow. Moreover the Smart Trap has an active mechanism fan-based for

capture/purge [20]. The Smart Trap includes a GPS sensor to publish its geoposition on capture events. According to the IoT architecture reference model, the second block represents the middleware layer, whose responsibility is data storing and providing. Finally, a data viewer application represents the third block which will consult the data stored in the IoT Middleware and present it to end-users who will be enabled to monitor the field operation in real-time and perform all kinds of data analysis.

3.2 Smart Trap

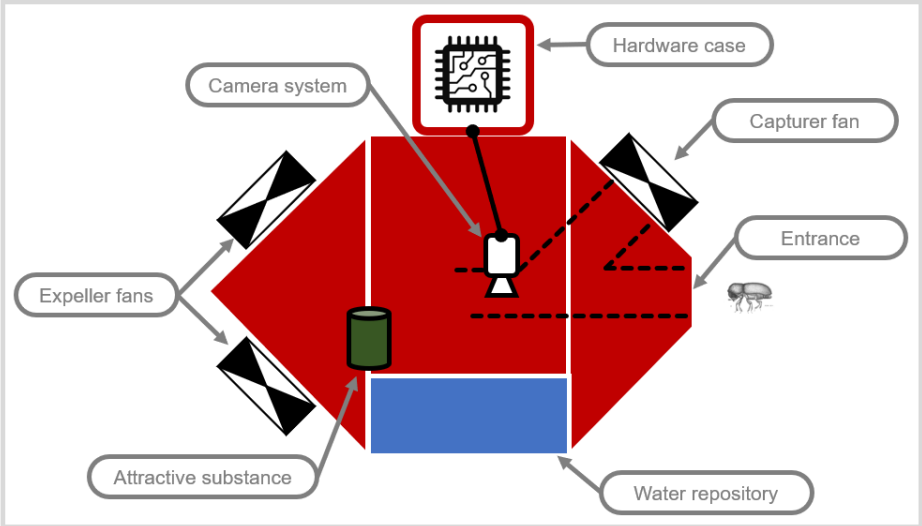


Figure 3.2: *Smart trap details*

The insect trap is considered smart because its structure is equipped with sensors, and a programmable board capable of running custom software enabled to data processing and network communication. The smart trap projected in this solution is composed of a micro camera that constantly takes photos of insects attracted to its interior (a particular substance is placed inside the smart trap to attract the insect of interest). The photos are sent to the microprocessor board, where specialized software performs a thorough image analysis searching for relevant patterns in order to identify the insect of interest. When the identification is negative, three specific fans are activated, generating the airflow inside out and expelling all unknown insect(s). Otherwise, when the identification is positive, the insect is captured by activating the appropriate fan that produces the airflow outside, pushing the insect against a water repository with a viscous liquid, where it is killed. Furthermore, the trap geoposition is retrieved from the GPS module. Next, a textual message is mounted containing the latitude, longitude, total of captured insects and current timestamp. It then is sent to IoT Middleware, where

it is stored in its internal database. Figure 3.2 illustrates the detailed parts explained above.

The next sessions exploit the smart trap functionality and an overview of all hardware components and the communication strategies are presented. And so, a profound explanation is addressed to the software project for this dissertation, highlighting the state machine model, which represents the intrinsic software logic.

3.2.1 General hardware architecture

The proposed Smart Trap is an embedded system assembled by the actuators and sensing components, a relay module that manages the fans activation, a camera system to take photos and a GPS module whose function is to read the current smart trap geoposition whenever an insect is captured. The general hardware architecture of this proposal is illustrated in Figure 3.3. Most components are connected by wire to a Raspberry Pi microprocessor board, except the 12 Volts battery pack, which directly supplies the Relay Module and the WiFi-4G Modem, which establishes a wireless network to the native WiFi Module.

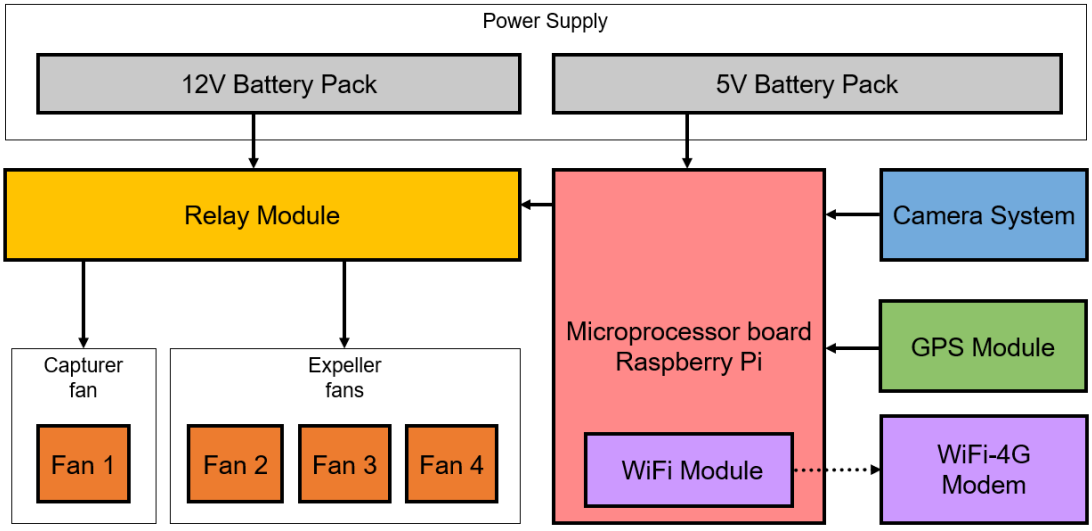


Figure 3.3: *Smart trap hardware architecture*

Raspberry Pi Microprocessor Board

The main hardware component in the proposed architecture is the Raspberry PI microprocessor board [90], due to its programmable capacity and Python language support. Raspberry Pi board was created in 2006 by Raspberry Foundation and its primary proposal is to be used in IoT solutions. This work uses the Raspberry Pi 3 Model A+ equipped with a 1.4GHz 64-bit quad-core processor, 512MB RAM, single USB

2.0 port, native WiFi module, full-size HDMI, and Camera Serial Interface (CSI) for connecting compatible cameras. Its Operating System (OS) supports the installation of open-source packages and libraries at Python Programming Language, which facilitates the development of applications. The reason for picking the Raspberry Pi board is its portability, lower price and small size enabled it to be easily deployed in small containers. Moreover, the Raspberry Pi board is particularly suited for Computer Vision projects, since it has a native camera module port and there is an extensive list of camera models available, from lower cost, high definition, infrared and multi-spectral cameras.

Relay Module and Fans

The proposed smart trap has an active fan-based mechanism to perform insect capturing or expelling. The fans are 12 Volts DC motors enabled to produce enough airflow to push insects. There are three specialized fans whose function is expelling all unknown insects and there is only one fan responsible for capturing the identified CBB´s. Through its two channels the Relay module manages the activation of the fans by transferring them with necessary electric energy.

GPS Module

The Global Positioning System (GPS) was developed by the United States Department of Defense and its essential function is to identify the receiver location on the surface of the earth. Currently, the GPS is the widest and accurate resource to determine a point on the earth surface and the GPS-enabled devices trends to have competitive prices. The smart trap operation in the field consists of moving it through the plantation in order to get closer the the probable CBB swarms. Whenever a capture occurs, the current geoposition is retrieved from the GPS module and the capture event information is registered for posterior analysis. The geoposition is defined by latitude and longitude pair and it is vital for end-user monitoring the trapping operation as well as performing the pest concentration analysis.

Camera system

The camera system is composed of a micro-camera compatible with Raspberry Pi and two infrared LED's for illumination adjustment. These parts are assembled on the same board and connected to Raspberry PI through a suited flat cable. The micro-camera has a 5 MP sensor and manual focus adjustment to facilitates photographing objects at short distances. The camera system is installed in the trap entrance where

the micro camera takes the insect photos, and infrared LED's balance any variations in luminosity.

Communications

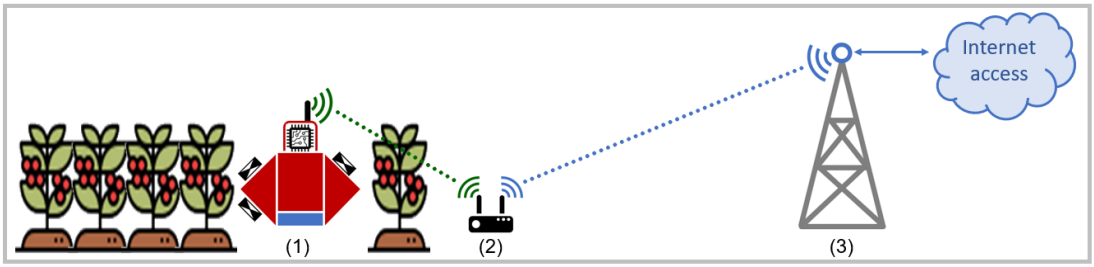


Figure 3.4: *Communications of the proposed solution. 1) Within a coffee plantation, the smart trap communication is based on WiFi networking; 2) In plantation border, the WiFi-4G Modem is placed playing the bridge role between the smart trap through WiFi and near accessible 4G base station; 3) The 4G base station provides the internet access to previous network elements.*

Internet access is essential to smart trap to reach the IoT Middleware where the trapping data is stored. As shown in Figure 3.4, the connecting between the smart trap and internet is established in two steps: a) The Raspberry Pi board, through its native WiFi module, connects to the WiFi-4G Modem; b) The WiFi-4G Modem establishes communication to 4G mobile network which provides the necessary internet access. However, in rural environments, the 4G signal trends to be unstable and it was fundamental the develop of a local storage mechanism as redundant data storing. Then the mechanism frequently monitors the internet access and pushes the locally stored data to middleware whenever the access turns online.

Power Supply

The power supply system consists of external rechargeable battery packs. The first battery pack supplies 12 Volts energy directly to the relay module, transfering energy to activate the fans. The second battery pack provides the 5 Volts energy are responsible for supplying the Raspberry PI board directly and, indirectly, others modules connected to it. The GPS module connects to the USB interface, the Camera system uses the native camera connector and the Relay module is connected in GPIO pins, all are supplied by 3.3 Volts coming from the Raspberry Pi board.

It is valuable to mention that all devices are widely available both in physical and on-line shops at a low price, making the proposed solution exciting and cost-effective. Figure 3.5 shows all hardware devices used in proposed solution. In the end, in order to organize and protect the hardware components, a simple case made of MDF has been projected and mounted.



Figure 3.5: *Image of Smart Trap devices used in the proposed solution*

3.2.2 General software architecture

The smart trap operation consists of a computing cycle where it identifies the entrant insect and takes the decision to capturing or expelling the insect. The software components have been developed in the Phyton programming language [91] and the Computer Vision routines extend the OpenCV library in its Python version [92].

A state machine diagram has been modeled to represent the Smart Trap operation and three main states were leveraged, as shown in Figure 3.6.

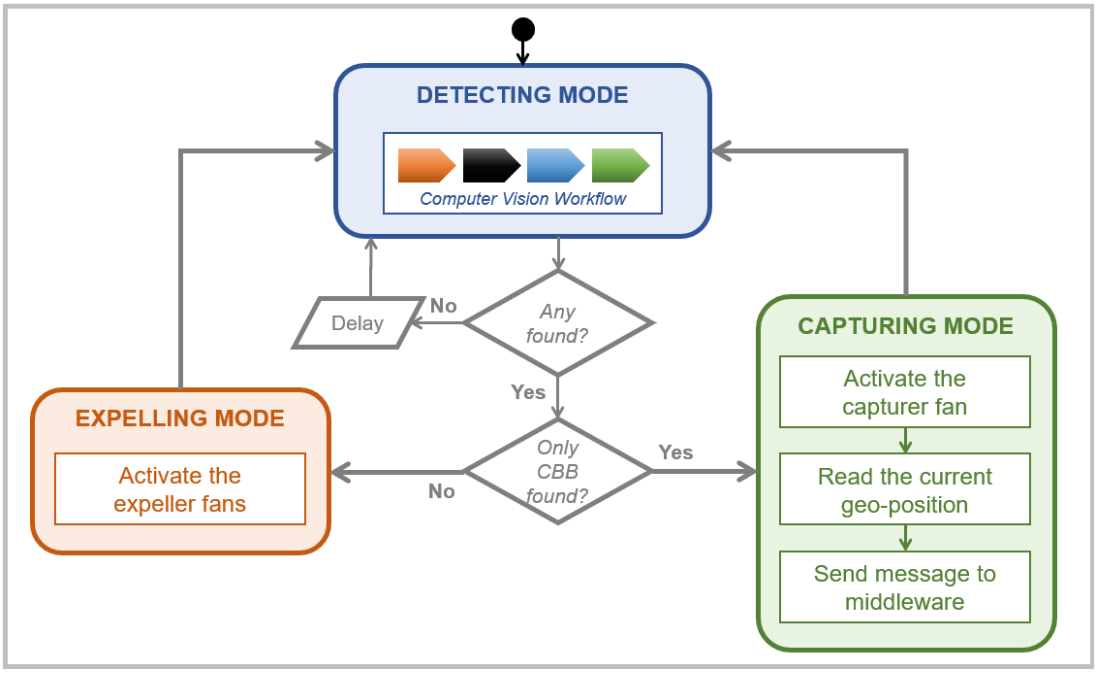


Figure 3.6: *Smart trap state machine diagram*

The **DETECTING MODE** is the initial state and consists of cyclic processing

based on executing Computer Vision Workflow (explained in Section 4.2) and interpreting the received result. If no insect was detected in the result, the processing sleeps for a few configurable milliseconds until it is restarted. Otherwise, if at least one unknown insect was detected in the insects group, the state machine goes to EXPELLING MODE, where the whole group will be expelled. However, if the result indicates that only CBB were identified, the state machine then transitions to CAPTURING MODE, where a series of actions will be taken.

The **EXPELLING MODE** activates the three expeller fans and thus produces enough airflow to expel all insects (unknown or not) out of the trap. It is worth the mentioning of agriculturally valuable insects such as bees and ladybugs should never be caught. Thus, any unknown insect will be expelled. Figure 3.7(b) illustrates the expelling airflow mechanic. Once the expelling action is finished, the state machine reverts to the DETECTING MODE state.

Finally, **CAPTURING MODE** is the most complex process and consists of capturing all insects identified as CBB and notifying the event. First, the capturer fan is activated, generating the airflow pushing the specimens against the water repository where they will be caught and killed. Figure 3.7(a) shows how capturing airflow works. Next, the current geo-position is retrieved from the GPS Module and a message is created containing the latitude, longitude, total of captured CBB and the current timestamp. Finally, the message is sent through the available connection to IoT Middleware, where it is stored. As soon as the submission is complete, the state machine then goes back to the DETECTING MODE. It is valuable to mention, in a rural environment, the off-line connection probability is high, turning impossible the message sending. A redundant storage mechanism has been developed to overcome this situation, where the message is temporally stored in a local file. Once connection is re-established, all local messages will send to IoT Middleware.

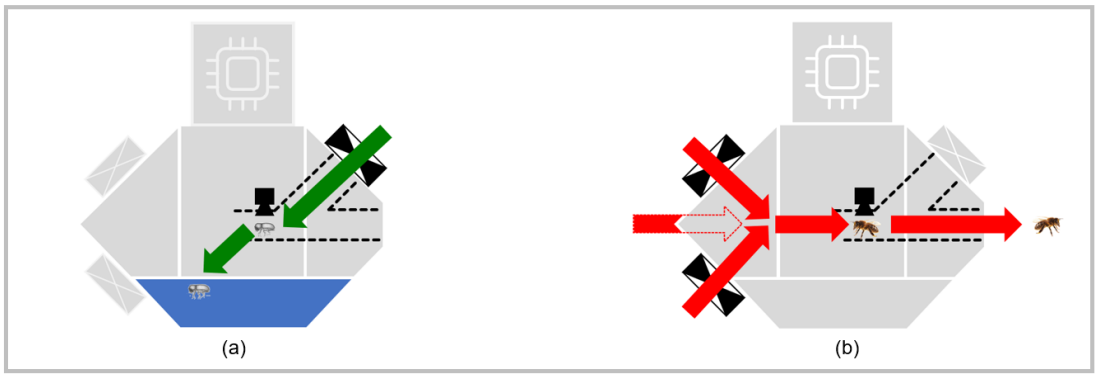


Figure 3.7: *Illustration of airflow produced by fans: a) The only one capturer fan produces airflow pushing the CBB against water repository; b) The three expeller fans generate the airflow to expelling eventual useful insects*

3.3 IoT Middleware integration

IoT Middleware is the software layer responsible for integrating data from devices on-base systems, allowing their communication and providing the collected data to upper layers [93]. Therefore, IoT Middleware is a reliable platform deployed between devices and applications for communication among "things" with heterogeneous architectures, interfaces and operation systems [94]. Within the smart trap solution, the middleware plays a fundamental role since it receives all data sent by Smart Trap and stores it in its internal database. So the end-users will be enabled to query all stored information and then performs all kind of analysis and reporting. In the proposed solution, the IoT middleware platform selected was the **In.IoT Middleware** [95] whose prominent role is to turn available the collected data in the field for the end-users. Despite the In.IoT Middleware supports several protocols. The REST interface has ever been sufficient to meet the data integration requirements for this work.

3.4 Data Viewer Application

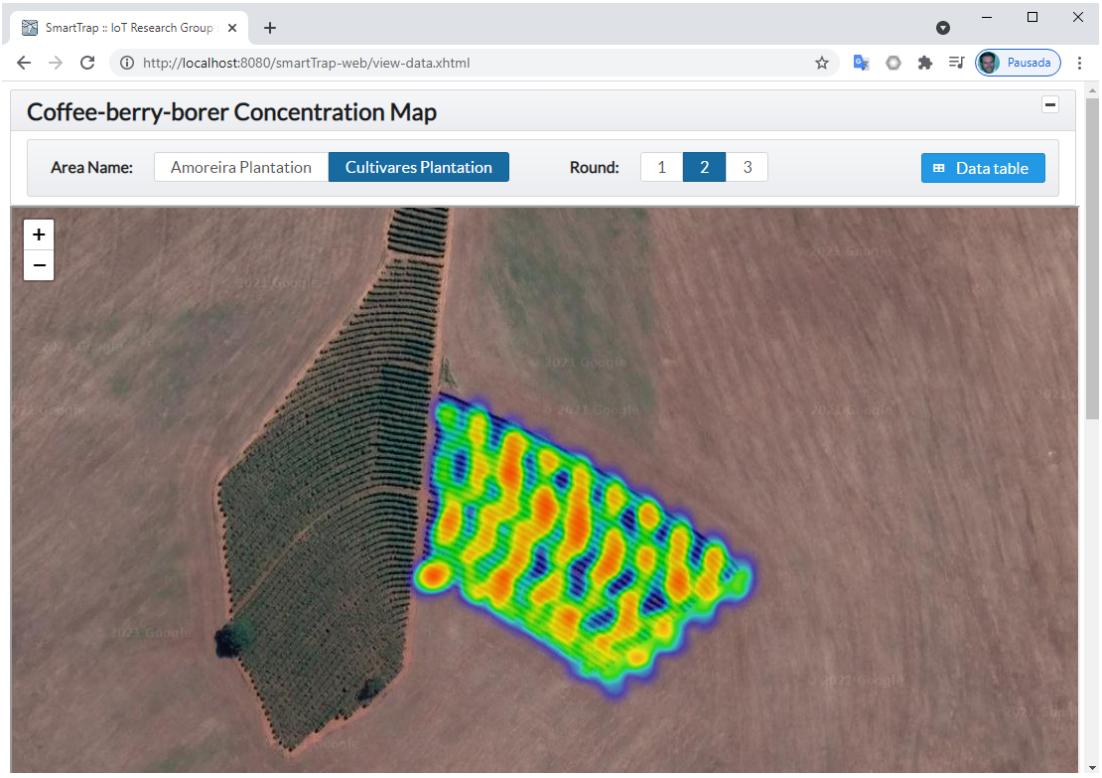


Figure 3.8: *Main page of the data viewer application*

The technology for developing web-interfaced applications has evolved considerably in recent years. Powerful features in programming languages, browser enhance-

ments and modern open-source frameworks have contributed to making web development extremely productive, enabling rich graphical interfaces development with advanced usability. Within this scenario, a modern web application was developed to offer the end-user an advanced experience for viewing the collected data during the Smart Trap operation in the field. Among the various advanced features, the application has a responsive interface. Thus the end-user can access it from desktop, tablet, or mobile phones and the visual elements will be adjusted on-screen automatically. The leading programming platform used in its development was the Java Enterprise Edition [96] and the Primefaces [97] as rich visual components library. The application uses the MySQL relational database [98] and once packaged, it is deployed in the WildFly application server [99] and ready to be accessed. For advanced interactive maps, the Leaflet library [100] was selected since it is an open-source, mature and well-documented project. Figure 3.8 shows the main page of the data viewer application, where a heat map is rendered representing the concentration of captured CBB in a specific plantation.

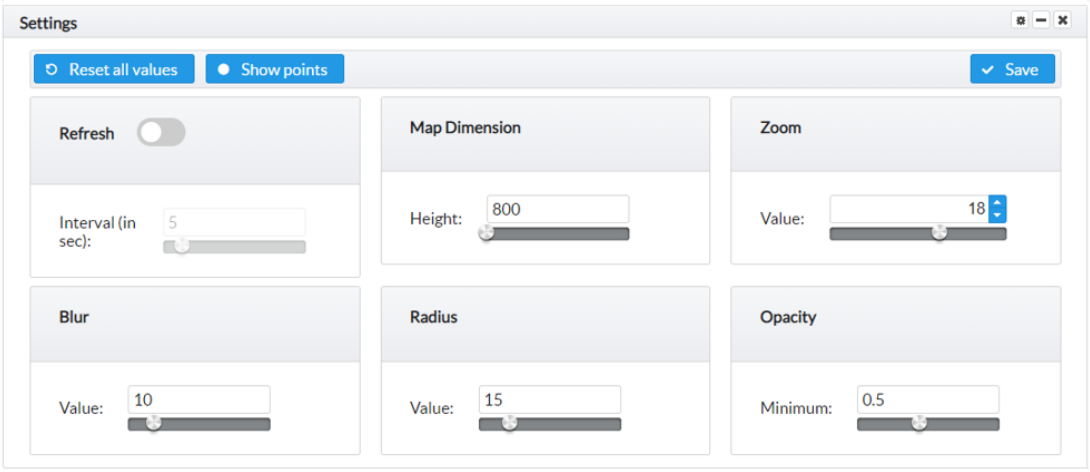


Figure 3.9: *Settings of the data viewer application*

With advanced usability requirements in mind, a series of map rendering settings are available to end-user, such as refresh period, map dimensions, zoom, blur, opacity, etc. Figure 3.9 shows the page with such settings. Through these settings, the user can perform advanced analysis of pest concentration and make decisions based on them. As the last feature, the graphical user interface has been internationalized, supporting to English, Portuguese and Spanish languages.

Chapter 4

Performance Evaluation, Demonstration, and Validation

THE prototype, whose guidelines were described in the previous chapter, has been built and its details are demonstrated in this chapter. First, the physical structure is presented, highlighting the devices and how they were organized. Then the Computer Vision workflow is validated, and an extensive explanation is made. The definition process of binarization threshold is also described and, finally, integrated data transmission is performed and the results are shown in data viewer application in few perspectives.

4.1 Prototype demonstration

The Smart Trap solution explained in the previous chapter has provided the relevant guidelines for building a prototype shown in Figure 4.1.

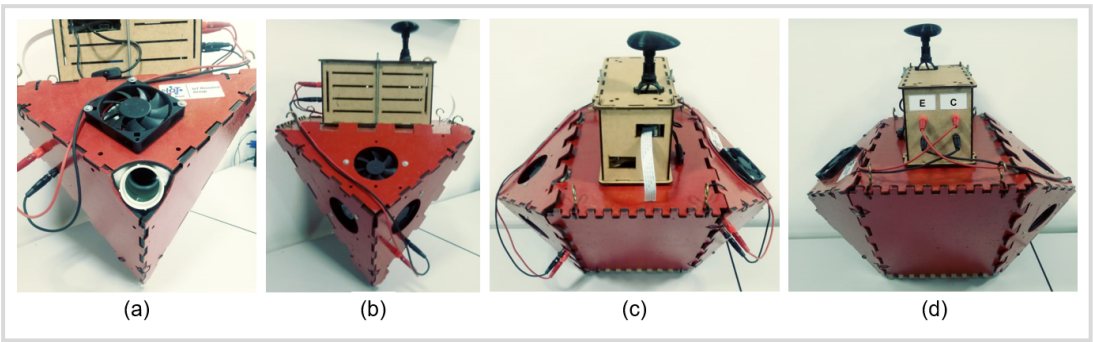


Figure 4.1: *Images of Smart Trap: a) Front view with trap entrance and capturer fan b) Back view with three expeller fans; c) Right view with camera flat cable; d) Left view highlighting the wires for fans power supply.*

The prototype is composed of two main structures, the hardware case and the body case and both whee designed by a CAD software and a laser engraver machine cut their pieces using MDF material. Once pieces have been assembled, the hardware case has been kept unpainted, but the body case has been painted in red to enhance the attraction effectiveness [71]. The front view shows the trap entrance by where the insects enter the trap body. The entrance is made by a PVC pipe which also directs the airflow from the capturer fan. The camera system is also attached to the same tube. By the back view, all three expeller fans can be observed. The camera cable can be seen in the right side view exiting the hardware case and entering the body case. And in the left side view, all power supply wires connecting the hardware case and the respective fans.

Figure 4.2 illustrates the hardware case and how all devices are organized in its interior.

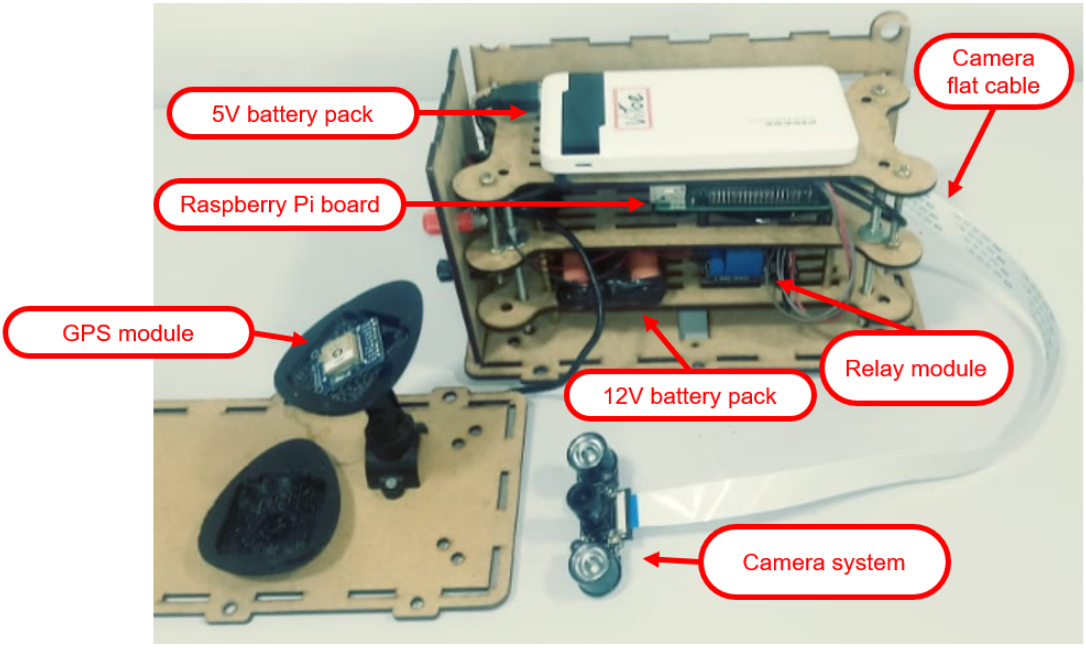


Figure 4.2: *Image of the hardware case interior*

The hardware elements are organized into three floors where the upper one is placed the 5V battery pack for Raspberry Pi board power supplying, the middle one is Raspberry Pi board and finally and 12V battery pack and relay module are placed on the lower floor. The GPS module is attached outside in the cover and a 30cm-length camera flat cable connected the Raspberry Pi to the camera system, which goes inside the body case.

As can be seen in Figure 4.3, the body case contains the camera system, entrance PVC pipe, and expeller fans. In Figure 4.3(a), the camera system is attached by the entrance pipe upside. The downside was painted in white in order to improve the

image acquiring. Figure 4.3(b) shows the detachable part where the expeller fans are installed. In addition, inside the body case will be placed the attractive substance and the water repository where the insects are caught.

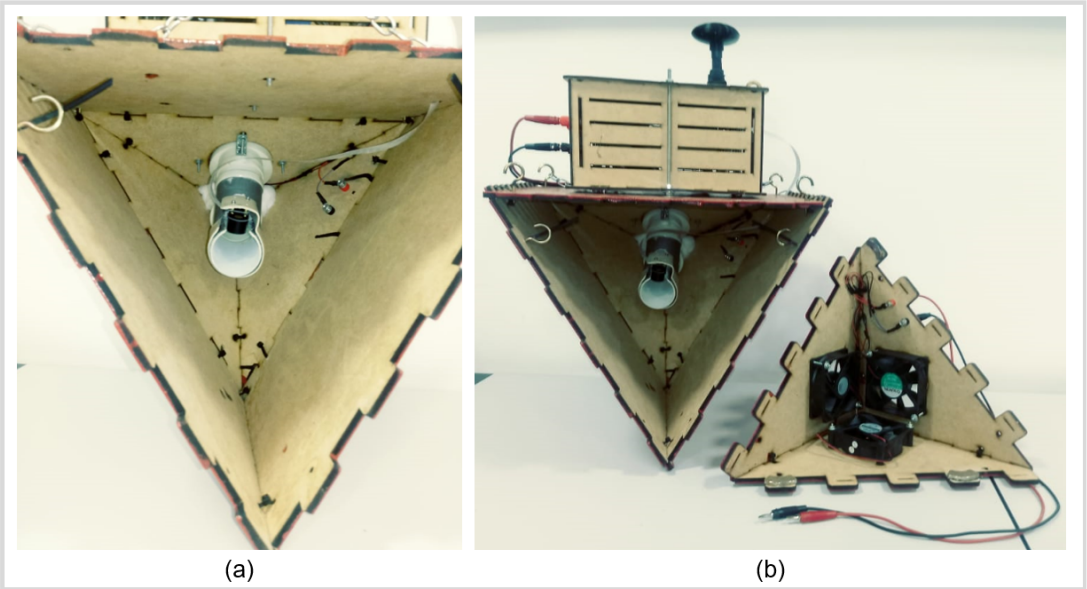


Figure 4.3: *Image of body case interior. (a) The camera system in the entrance pipe; (b) Detached part with expeller fans*

This section describes the validations performed in this work and three main are explored. First, the Computer Vision workflow validates the details related to insect identification by image analysis highlighting their steps. Second, the process of finding the optimized binarization threshold value is explained in deep. Finally, the complete data transmission from field passing to IoT middleware and reaching the data viewer application is also validated.

4.2 Computer Vision workflow



Figure 4.4: *Adapted Computer Vision workflow*

Insect identification by camera sensing has been selected for this work. Computer Vision science is enabled to provide the necessary computational resources to analyze the images of insects acquired by the camera system. Keeping in mind the requirements to identify the insect of interest for this work, the original Computer Vi-

sion workflow has been adapted to meet these requirements. Figure 4.4 illustrates the adapted Computer Vision workflow.

The workflow steps are explained in the following, illustrating the image transformations until the conclusive results from where identification data will be extracted.

4.2.1 Image acquiring

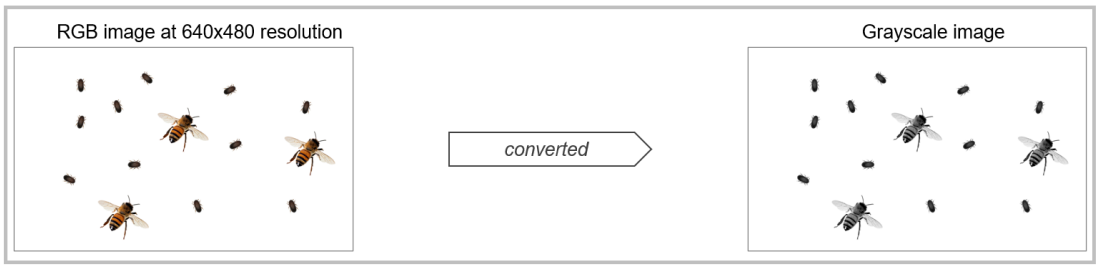


Figure 4.5: *Image acquiring step in Computer Vision workflow*

The camera system attached in the body case entrance is configured to take RGB photos at 640x480 resolution and transferred them to the appropriate software component whose primary function is instantiating the original colored image as a pixel array and then converted it to grayscale image, which will be the input to next step. The Figure 4.5 illustrates the image conversion in this step. Some analyses were carried out involving requirements such as resolution, computational resources for image conversion, and energy consumption. During the laboratory experiments, higher resolutions were tested, but no relevant benefit was added since the the short distance between the camera system and the background (about 4cm). Therefore, it was concluded the 640x480 resolution is good enough for the Computer Vision routines, given that higher resolutions would require high graphical processing and high energy consumption as well.

4.2.2 Binarization

The binarization is a conversion image process whose input image is on grayscale. First, each gray pixel is converted to black or white considering a value of reference, named threshold value. The threshold value can be defined dynamically during a preprocessing routine or statically fixed through an external process. Due to the controlled illumination condition, the fixed threshold value is the appropriate approach in this work and the external process used in its definition is explained in Section 4.3. Once the entire image is binarized, it is inverted where the original white background is inverted to a black area. And the original black area, which represents the insect body,

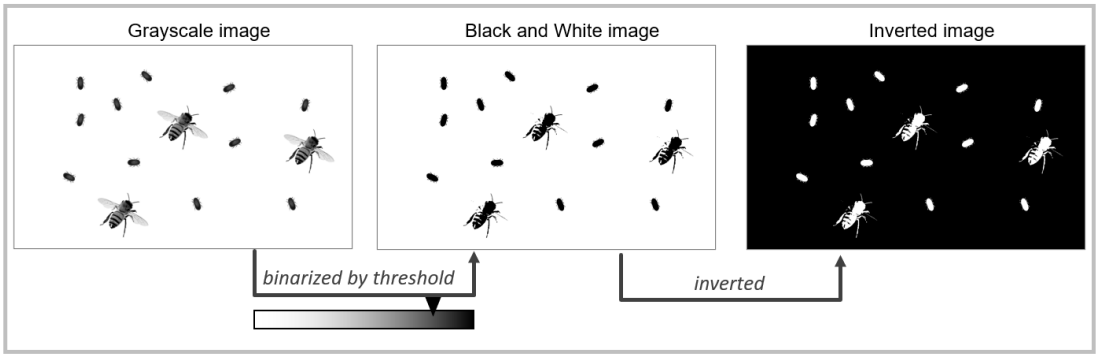


Figure 4.6: *Binarization step in Computer Vision workflow*

is inverted to a white area. Figure 4.6 illustrates the binarization process and frequently the resulting image contains remaining noises which will be dealt with in the next step.

4.2.3 Noise cancelling

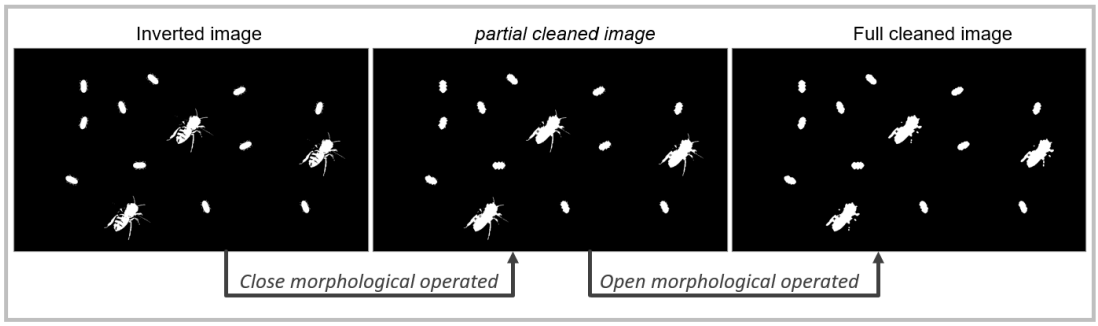


Figure 4.7: *Noise cancelling in Computer Vision workflow*

After the binarization process, some meaningless points could be remained in the image, demanding the additional cleaning process called noise cancelling. Computer Vision science provides the morphological operations to perform such cleaning. The first morphological stage is the close morphological operation and consists of removing the tiny black points inserted in the white area. The second morphological stage, defined as open morphological operation, removes the noising white points in the large black area. Figure 4.7 illustrates the input noised image, partial result and final cleaned image. The expectation is the cleaned image resulting contains only relevant white area representing the insect body.

4.2.4 Contour finding

Once the inverted image has been cleaned, the white area contours are found, producing an array of objects representing the bounding rectangles of the white areas.

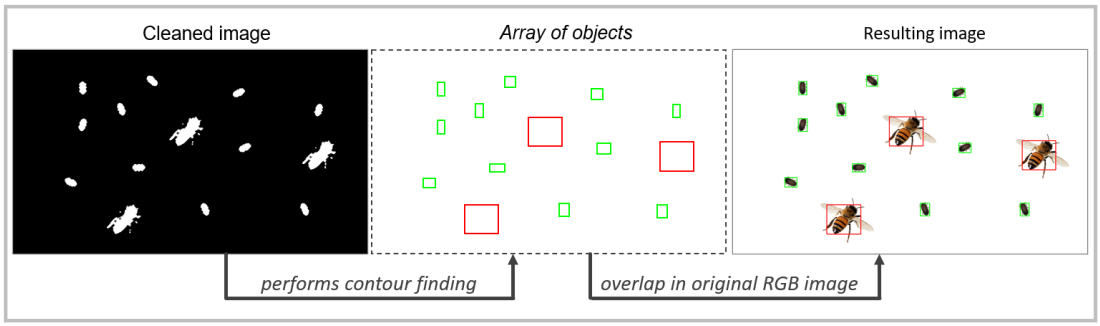


Figure 4.8: *Contour finding in Computer Vision workflow*

Each object keeps the rectangle dimensions and position inside the image. The detected insect is then identified as CBB or an unknown insect based on rectangle width and length. The resulting image combines the original RGB image and overlapping rectangles rendered with a green border for the identified CBB and a red border for the unknown one. Figure 4.8 illustrates the overlapping image process and the resulting image. The array of objects interpretation will define the subsequent actions within the context of the Smart Trap operation. When the array is empty, it means nothing has been found and the Computer Vision workflow is restarted after a programmable delay. When the array contains a mixing of identified CBB and unknown insects, everyone must be expelled to avoid the risk of catching any beneficial agricultural insects. The only condition to proceed with the capture is when only CBB specimens are identified.

This section has delivered how the Computer Vision workflow works, passing thought steps where insect image is acquired, processed, and produces the interpretation about how many CBB and known insects have been found.

4.3 Binarization threshold definition

Within Computer Vision, the binarization process is key to produce reliable results and an accurate threshold value is fundamental for the success of binarization. The threshold value could be calculated dynamically by an approach in a pre-processing stage where contrast and brightness levels are taken into account and then the threshold value is found through statistical calculations. The dynamic approach is ideal for scenarios where image contrast and brightness have high variance. However dynamic calculation always demands high processing costs and energy consumption. For the context of this work, the static approach is adequate since the contrast and brightness of the images are practically constant due to the low interference of ambient light during image acquiring. Therefore, a series of stages was performed through a previous external process to find this static threshold value. This session exploits the details of

these stages. In a first stage, a CBB high definition image with its natural color was selected [101] and then it was submitted to a manual binarization process using image editing software. This manual binarization was carefully processed so that each pixel belonging to the CBB region (body, head and members) and each pixel belonging to the background were binarized meticulously. Once the binarized image was ready, its inverted version was generated. Figure 4.9 shows the three images described above.

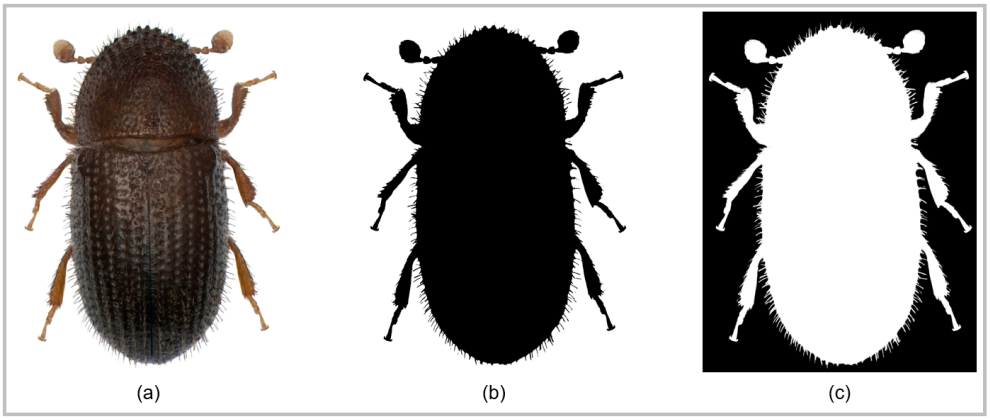


Figure 4.9: *Manual Binarization. a) Original RGB high-resolution image; b) Manually binarized image; c) Inverted image. Source: [101]*

Through the inverted image, an OpenCV routine has calculated the total white pixels, those that belong to the CBB region. A total of 1,844,580 pixels was found and this number will be a constant function to plot the graphs shown in Figure 4.11. The next stage consisted of applying the original high-resolution RGB image as input to the binarization and inversion routine specifically developed for this work in multiple invocations with different threshold values ranging from 10 to 260. Figure 4.10 shows some resulting image samples and their respective threshold values.

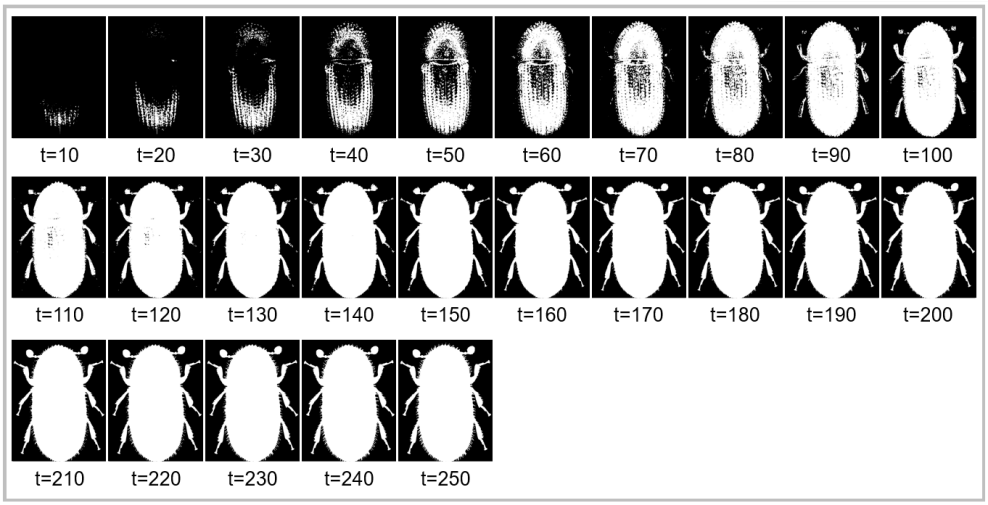


Figure 4.10: *Samples of resulting image generated by applying multiple thresholds (t) values*

On each resulting image above, the total white pixels were calculated and the generated data table (threshold value x total white pixel) has been plotted on a graph illustrated in Figure 4.11(a) as the second function with the X-axis increasing at steps of 10 units. Figure 4.11(b) contains the same plotted functions but in a more detailed perspective on the X-axis, ranging from 155 to 205 intervals and increasing at the step of 1 unit. Both function interception at point 191 indicates the accurate binarization threshold value for CBB identification.



Figure 4.11: *Threshold values and total white pixels graph. a) X-axis from 0 to 255 at the step of 10 units; b) Closer perspective where X-axis ranges from 190 to 200 at the step of 1 unit and interception point is highlighted.*

4.4 Integrated data transmission

The capability to transmit the data collected in the field from an embedded device to an end-user Web navigator passing through an IoT middleware based on cloud computing is meant by integrated data transmission. Therefore, the most relevant IoT feature of this solution is related to this capability.

In this context of work, the rural environment has its challenges where the internet connection can suffer constant instabilities. Therefore, the data transmission mechanism must be prepared to overcome such situations, such as managing a local storage during the off-line period. For that reason, during the field data transmission experiments, both online and off-line scenarios were validated.

The validation experiments consisted of simulated CBB captures in a real coffee plantation named Cultivares located at Coqueiros Farm in Santana da Vargem, state of Minas Gerais. Such experiments have been organized in rounds representing the complete plantation area coverage and, in each round, the spacing between capturing positions was differentiated, representing the CBB population eradication.

To transport the Smart Trap structure through the plantation, it has been installed on a simple transportation rover, shown in Figure 4.12(a). To provide the Internet connection in field, the WiFi-4G Modem, powered by a battery, has been placed in a table on plantation edge, seen in Figure 4.12(b).

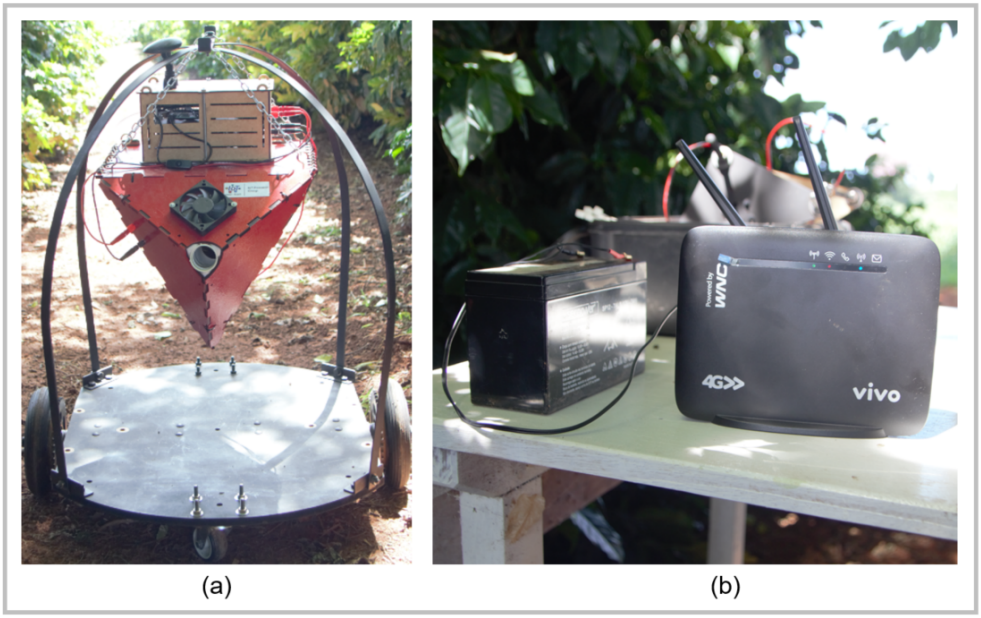


Figure 4.12: *Field experiment equipments: a) Transportation rover ; b) WiFi-4G Modem and its battery*

In each capturing event, the geo-position was retrieved, added to the built message,

and transmitted to the end-user. According to the GPS Module manufacturer documentation [102], positioning precision is around 2.5 meters.

As the collected data of the round reaches the IoT middleware, the data viewer application has been enabled to query them and render them as heat map representing the CBB concentration map. Since the rounds have used different spacing, the heat maps were rendered with different concentrations as expected. Figure 4.13 shows the respective heat maps for the three rounds, starting with smaller spacing and progressing to larger ones.

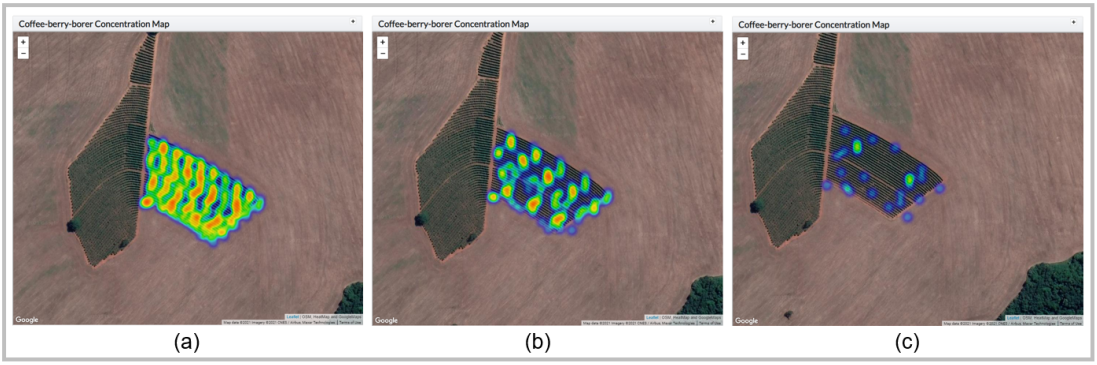


Figure 4.13: *Heat map as data transmission result: a) first-round; b) second round; c) third round*

As a graphical resource of the data viewer application, instead of a heat map, a round can be configured to display only the capturing points, as shown in Figure 4.14.



Figure 4.14: *Capturing points distribution. a) first round; b) second round; c) third round.*

In this visualization style, the displacement of points out of the field can be observed, which confirms the documented GPS module positioning precision. However, such low precision does not represent a disadvantage in the scenario of this work since the rendered heat map is a mere informational resource for the end-user.

The experiments carried out have been able to validate the integrated transmission of data, even in moments of offline connection with the local storage of messages and

automatic re-transmission as soon as the connection is re-established. The expected results in real capture operations, the concentration map would be gradually dilute each round, indicating the CBB population is being eliminated until the last round when nothing will be captured.

Chapter 5

Conclusions

BASED on the studies and experiences gathered during the elaboration of this dissertation, the relevant learned lessons, main conclusions and future works are exposed in the next sections.

5.1 Learned lessons

Throughout this research, valuable lessons have been learned that can support future researchers interested in Agriculture 4.0 and sustainable pest control solutions, as well as software developers to improve insect identification through Computer Vision techniques.

Only one smart trap used in the crop may not be enough to eradicate the entire CBB population since the possible capture period is limited from October to December, which would be short for extensive plantation. Therefore, using multiple traps in parallel could solve this issue.

Another point observed is related to the cost of this solution for small farmers since several traps simultaneously working could make the solution financially impractical. An idea to overcome this scenario would be the service-providing business model where a company would provide the trapping service charging hourly or daily instead of the farmer buying the smart traps.

A third point is related to the material of the trap structure. During field experiments, MDF material tends to be vulnerable to high humidity common inside coffee plantations and new materials must be thought of to replace it. For example, acrylic or lightweight plastic could be tested in this scenario since they are immune to humidity.

5.2 Main conclusions

The expanding number of people on the Earth surface is transforming the world and changes in our habits need to be established for the sake of survival. Therefore, models of economic development that are in synergy with the environment, animals and people need to be adopted, supported and encouraged. This new development model called sustainable development already has the endorsement of the UN and is gradually gaining support from civil organizations across all nations. In this context, technologies such as IoT, cloud computing are available to provide the necessary support for this new model and continue to evolve exponentially.

The focus of this dissertation is agriculture mainly due to its importance in the scenario that presents where the food security of nations will be (and is already being) a high-priority topic. The proposed solution provides a clear answer to what is widely adopted for pest control in the plantations. It is worth mentioning the proposal meets the requirements for its adoption in large-scale agriculture.

Nowadays, the lack of telecommunications network infrastructure in the rural environment represents the hardest barrier to the adoption of a high-tech solution strongly based on data communication. However, the good news is that they already have infrastructure improvements based on modern generations of telecommunications such as 5G and LoRa. Therefore, it is only a time that the rural environment benefits from a high-quality data communication infrastructure.

Everything indicates that in the near future, solutions such as the proposed in this dissertation will be widely adopted on rural properties, contributing to the expansion of what we call sustainable agriculture.

5.3 Future works

During the elaboration period of this work and experiments in the field, some interesting ideas have emerged and could be pointed out as future works.

Developing an autonomous rover capable of moving through the fields would elevate the smart trap proposal to the next level, mainly due to its practicality. The rover could be guided with high-precision geo-processing combined with Computer Vision to detect and avoid eventual obstacles. Non-polluting electric motors could be used supplied by batteries recharged by solar plates installed in its structure. The rover would move at low speed and would be remotely monitored in real-time. Furthermore, a plantation with plenty of rovers working collaboratively would be amazing, and their management could be centralized, decentralized, or hybrid.

A second future work would be to improve the visual computing software to identify multiple pests. Thus the same trap could be used on different cultures such as corn, soybeans, citrus, or sugarcane. Additional Computer Vision techniques could be tested, such as machine learning and deep learning to support multiple identifications. Depending on communication quality, the Computer Vision routines could be executed in a cloud environment releasing the smart trap of such responsibility.

The third suggestion for future work is related to the Computer Vision processing in the cloud environment. As rural connectivity challenges are overcome, the smart trap could transfer each acquired image to a cloud infrastructure, where it would be processed and the result sent back. In this new scenario, the embedded hardware of the smart trap could be simplified (making its cost lower) and the energy autonomy would be extended once the image processing is carried out externally.

Another suggestion would be to use thermal cameras and process the insect image through the infrared spectrum.

In order to ensure the Computer Vision accuracy, another possible future work would be the survey of the false-positive and the false-negative results. Additionally, a comparison could be built using the results obtained from common cameras and a thermal cameras.

During the data transmission experiments, no security-related concerns were taken, since the security was not in the research scope. Therefore, a convenient future work would be to add security configurations, such as using secure transmission channels and encrypting the stored data.

A final suggestion for future work would be to carry out long-distance data communication experiments with modern technologies such as 5G [103] and LoRa [104] and then evaluate the real improvements in connectivity in a rural environment.

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