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Article

The Effectiveness of AI: Feedback on the Project to Counteract Food Waste

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ABSTRACT

Background: Project-Based Learning (PBL) has proven effective in developing students' knowledge and skills. This approach was applied with engineering and Bachelor students to tackle an international challenge focused on resource preservation. The paper presents the technical validation of an AI-based system for automatically sorting potatoes: those deemed "good" are for human consumption, while "bad" ones (with black spots) are redirected for animal feed. The solution emerged from a study of the project's functional specifications and eight months of development. The initiative received support from industrial and institutional partners.
Methods: The study utilized a PBL approach to develop an AI-driven solution for automatic potato sorting.
Results: Technical development involved implementing a Convolutional Neural Network (CNN) for image classification. A SICK Inspector vision camera was used for real-time image processing. A dataset of 808 grayscale potato images was created for training. The trained model was embedded in the camera for autonomous classification. Performance metrics such as precision, recall, and accuracy were used to validate the sorting model. A Proof of Concept (PoC) including a range of industrial solutions (Internet of Things (IoT)) was thus validated.
Conclusions: This internationally awarded project has demonstrates that AI can be effectively applied to reduce food waste by automating the sorting of agricultural products. This approach opens up opportunities for large-scale industrialization, particularly in the agri-food industry.

KEYWORDS: potato; project-based learning; engineer and bachelor levels; artificial intelligence; counteract food waste; international challenge

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INTRODUCTION

PBL is an instructional approach designed to enhance students' motivation, attitudes, and skills. For several decades, it has often been cited as a highly effective teaching strategy [1,2]. Problem-based learning approaches, a subtype of PBL, involve presenting learning tasks as complex, multifaceted problems [3–5]. When meticulously crafted and executed, these problems can immerse learners in challenging endeavors while offering support and feedback. They promote deeper thinking, inquiry, and self-explanation, fostering motivation through the presentation of relevant and captivating challenges. While diverse approaches to PBL exist, they typically adhere to six fundamental principles [6]: prioritizing student-centered learning; employing small group dynamics; facilitating learning through tutors or guides; emphasizing problem orientation; viewing the problem as a tool for acquiring knowledge and problem-solving skills; and promoting self-directed learning. Projects and challenges are distinguished mainly by their length, which often exceeds that of conventional educational activities. However, it is essential to note that the duration of a project must be defined from the outset. This period, extending from the start to the end of the project, is characterized by a process known as "learning", as described by Levitt [7], an irreversible dynamic process during which we evolve from a phase where ignorance or lack of knowledge prevails, but where all possibilities are open, to another where the level of knowledge reaches its peak and all room for manoeuvre has been exploited. This time constraint must establish consistency in the actions taken and in the management of the organizational structure of the group or work teams.

Consequently, constant vigilance and anticipation of the necessary actions are essential to avoid any slippage inherent in the complex problem-solving process (Figure 1).

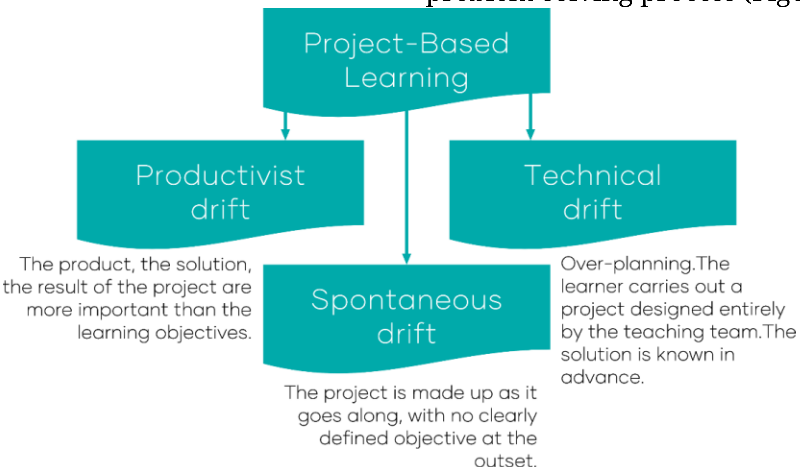

Figure 1. Possible drifts from PBL.

As teachers, we have found that student enthusiasm for a project is closely linked to several factors: the attractiveness of the subject, its ability to motivate, its playfulness and its practicality. The selection of the subject for the experiment stems naturally from the current challenges facing industry. France's technological training and research sectors are essential drivers of the nation's industrial and economic advancement. These sectors serve as foundational pillars, fueling innovation, fostering talent, and propelling growth across various industries. They must attract the best students and prepare them to contribute to the development of companies in a variety of fields. Many innovation-driven companies and start-ups have made France their home, and their growth will largely depend on the emergence of new talent. This is why it is imperative that industry and higher education work closely together. The profound changes that industry is undergoing raise several crucial questions about the content of training programs:

- ✓ Which skill areas should be developed first?
- ✓ At what level of training should we concentrate our efforts?
- ✓ How should we structure our training provision?
- ✓ What teaching methods are the most appropriate?
- ✓ Should we envisage changes in teaching approaches?
- ✓ What equipment and infrastructure are needed to teach these new subject areas?

These issues, which are at the heart of today's challenges, require in-depth reflection and active collaboration between the higher education sector and industry to best prepare students to meet social and economic challenges. Higher education, particularly in the technical, technological, and scientific fields, already offers partial solutions by providing training programs tailored to various aspects of these challenges. However, skills needs are evolving rapidly, requiring a rapid expansion of these training programs. In this article, we highlight the scientific challenge linked to the industry of the future, artificial intelligence, and the preservation of resources by minimizing food waste. We detail the whole process and methods that were adopted, setting out the tools that were put in place to prevent the pitfalls inherent in this challenge. The aim of the work was not to validate a competition between different algorithms for potato discrimination (Figure 5). Instead, the goal was to demonstrate that functions currently marketed by different manufacturers (hardware, software, services, etc.) can be efficiently combined to meet a technical and environmental need. In the following section, we outline the scientific backdrop of the challenge as detailed in Xplore-2023 [8] and delineate the constraints that encapsulate this challenge. This paper is divided into 5 sections. Section 2 describes the international challenge, Xplore 2023, for students, universities, and engineering schools. Section 3 presents the topic of the project our team submitted to this sustainable development competition. The various results are described in Section 4. We end with promotion, communication, and a conclusion.

AN INTERNATIONAL CHALLENGE FOR STUDENTS, UNIVERSITIES, AND ENGINEERING SCHOOLS: XPLORE 2023

The climate crisis is one of the pressing challenges of our era. Upholding freedom and prosperity hinges on our ability to safeguard nature, the bedrock of life on Earth, and adhere to planetary boundaries. Accelerating the energy transition is imperative to meet the requisite pace of transformation. Embracing new technologies and applications on a massive scale is indispensable in shaping a sustainable future—one marked by innovation, intelligence, and enhanced livability. Achieving these goals demands individuals who think beyond conventional boundaries, demonstrating unwavering dedication and creativity in translating ideas into action. Encouragingly, a study examining postgraduate students' knowledge of environmental sustainable development and how they apply this knowledge in their daily lives found that the students possessed a good understanding of environmental issues and were engaged in contributing to sustainable development [9]. In the fashion industry, for example, personalization could be leveraged to encourage more sustainable consumption practices by emphasizing emotional attachment to clothing and waste reduction [10]. Yet we are short of around 280,000 skilled professionals, particularly in the Science, Technology, Engineering and Math (STEM) professions that are so necessary to this ecological transformation [11]. This need will continue to grow over the coming years. Participating in the Xplore 2023 challenge offers teams a valuable chance to contribute to finding the technological solutions essential for a sustainable world [8]. Within this framework, Xplore 2023 aims to ignite and facilitate the realization of young people's ideas for a sustainable future (Figure 2). To bring this vision to fruition, Phoenix Contact, Zvei, V Afrika-Verein, Tech Education, AirFrance, and KLM united their efforts to enable this global challenge. In June 2022, over 170 teams submitted innovative research and development projects across six sectors: Social and Health, Intelligent Mobility, Environment, Intelligent Energy, Intelligent Industry, Digital Technologies, and Education. The jury, composed of eleven members from academia, industry, and associations, delivered their verdict during the Xvention global online conference in September 2022. 100 teams from 30 different countries were selected. Each team was awarded a voucher worth more than €3000 and received free delivery of the components (Phoenix Contact) best suited to its own solution. After a year's work by the teams, accompanied by the delivery of their results in a promotional video, the international jury selected 25 finalists in the 5 categories for an invitation to Germany (Bad Pyrmont, 16 to 21 October 2023). During the event, participants showcased their technical innovations, highlighting all its functionalities and features. Subsequently, the jury selected up to five of the most outstanding ideas in each category. The Orleans team was selected as one of the finalists in the Environment category. The link in Figure 2 can be used to view the video presentation of the 2023 edition [12].

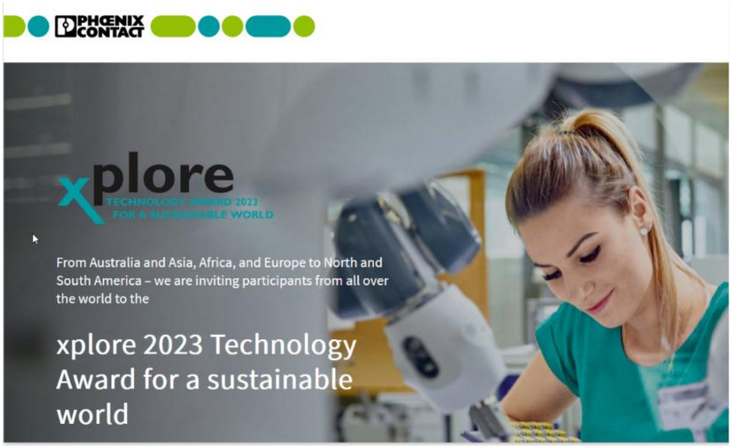

Figure 2. Xplore 2023.

THE TOPIC FOR OUR PROJECT: ARTIFICIAL INTELLIGENCE TO COUNTERACT FOOD WASTE

The Context

Currently, the agricultural and food industry leverages cutting-edge machinery, tools, and Information and Communications Technology (ICT) that harness the capabilities of the IoT. These advancements have heralded the onset of a new era in agri-food production termed 'Agri-Food 4.0,' marked by automation, connectivity, digitization, the integration of renewable energies, and the optimized use of resources within this sector [13,14]. From this standpoint, eradicating global hunger is a key sustainable development goal set forth by the United Nations. To feed 10 billion people by 2050, we need to find the right trade-offs between sustainability, food security and food safety [15]. Under these conditions, the foodstuff already produced will be put to better use. It is possible to propose a hierarchy in an action plan strategy aimed at reducing food loss and waste [16]. In descending order, we can distinguish between reduction at source, reuse or reprocessing of surplus food, recycling of food to feed animals, recovery of energy in the form of biofuels, nutrients in the form of compost or raw materials for industry. As a last resort, we can consider energy recovery through incineration or waste disposal in landfill sites (Figure 3). Over the last decade, food waste has received a great deal of academic, political, economic, industrial, and societal attention. As a factor with negative effects on the environment and resource conservation in particular, food waste is seen as one of the sustainability issues that absolutely must be tackled. Studies indicate that consumers in 'developed' nations represent a significant contributor to food waste [17,18]. Consequently, effectively curbing consumer-related food waste hinges on comprehending the factors influencing consumer perceptions of this issue. In their study, authors Swan et al. [19] draw on recent research on food pedagogies to examine their implications for environmental education. They highlight how both formal and informal practices can teach sustainability through the lens of food. These pedagogies encompass a variety of activities, such as gardening, cooking, and food sharing, aimed at raising awareness about sustainability issues.

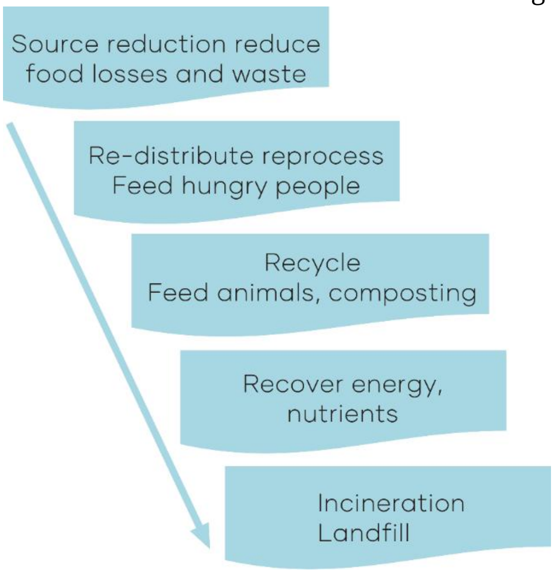

Figure 3. The food recovery hierarchy. From the most desirable—source reduction—at the top to the least desirable at the bottom—landfill (adapted from Vågsholm I, Arzoomand NS, Boqvist S. Food security, safety, and sustainability—getting the trade-offs right. Front Sustain Food Syst. 2020;4:487217 [20]).

The European Union (EU) has been engaged in essential work since 2019 on this crucial issue. A document has been compiled to outline the analysis of directives enacted in May 2019 concerning a standardized methodology and quality standards for establishing a consistent system to measure food waste levels across EU Member States. The Waste Framework Directive mandates Member States to monitor food waste production and implement measures to mitigate its volume. However, the absence of a standardized and dependable method for quantifying food waste levels within the EU complicates assessing the magnitude of the issue, pinpointing its origins, and tracking trends over time [21]. Food waste occurs at various stages throughout the food supply chain, posing challenges in accurately quantifying its total volume. This waste is generated at various times, with different characteristics, origins, and for different reasons [22,23]. At present, the data available on food waste lacks precision as to its actual quantity. As a result, a distinct legal measure was enacted, namely the Commission (EU) Delegated Decision of 3 May 2019 concerning the measurement of food waste. This decision standardizes current data collection systems and establishes a framework for Member States to implement future measures aimed at more precisely quantifying the food waste generated. Drawing on their experience gained from observing 15 companies within the catering and bakery sectors, Strotmann et al. [24] introduced an innovative participatory concept aimed at addressing the issue of food waste in the food industry. This concept, outlined in a five-phase model inspired by the PDCA (Plan-Do-Check-Act) cycle commonly used in total quality management, encourages employee involvement throughout the waste reduction process. By embracing a Total Quality Management approach, employees not only contribute to the design but also actively participate in implementing measures to combat food waste. The authors emphasize how this participatory approach raises employee awareness, fostering a stronger sense of commitment and responsibility within the company. To assist managers in this endeavor, the authors produced a handbook tailored to guide organizations in reducing food waste. This manual offers a comprehensive overview of methodologies to be employed at each stage of the improvement cycle, highlighting the significance of these steps, and providing guidance on effective measurement and documentation of results. In general, the combination of this participatory approach and the managerial guidebook serves as a vital tool in reducing food waste and improving resource utilization within the food sector, marking a substantial advancement towards accountable and sustainable management of food resources.

The Expression of Requirement

In France, Law 2020-105 of 10 February 2020 (Article L230-5-1) addresses the fight against food waste and promotes a circular economy framework [25]. Food waste encompasses any food originally intended for human consumption that is lost, disposed of, or spoiled at any stage of the food supply chain. To combat food waste, it is essential to raise awareness among producers, processors, distributors, consumers, and associations regarding their responsibilities and engage them in concerted efforts. The law prioritizes actions to combat food waste in the following order:

1. Prevention of food waste.
2. Utilization of unsold food suitable for human consumption through donation or processing.
3. Redistribution for animal feed.
4. Utilization as compost for agriculture or energy recovery through mechanization.

Combating food waste involves raising awareness and training all stakeholders, mobilizing stakeholders at local level, and regularly communicating with consumers, as part of local waste prevention programs. For example, the GASPILAG program initiated in the Centre-Val de Loire region (France) takes a regional approach to the issue of food waste [26]. The program defines food waste as “any food intended for human consumption which, at any stage in the food chain, is lost, thrown away or spoiled,” rendering it unsuitable for human consumption. GASPILAG primarily focuses on analyzing the factors contributing to the prevention of food waste, adopting a distinct perspective that it is “a territorial issue, rather than solely a ‘food chain’ concern” (Figure 4). In France, food losses and waste amount to 10 million tons of products annually, with an estimated commercial value of 16 billion euros [27]. This wastage signifies an unnecessary depletion of natural resources, including arable land and water, and results in avoidable greenhouse gas emissions. The French Environment and Energy Management Agency (Ademe) estimates that these emissions represent 3% of the nation's total GHG emissions. Moreover, waste could be prevented, thereby obviating the need for treatment and the associated management costs. Every stage of the food chain—from production to processing, distribution, and consumption—plays a role in food loss and waste. According to the Ademe study on the state of food waste masses and management across various stages of the food chain [28]:

- ✓ 32% occurs during the production stage,
- ✓ 21% arises during processing,
- ✓ 14% is attributed to distribution,
- ✓ 33% occurs during consumption.

During the consumption phase alone, this translates to 30 kg per person per year of food losses and waste at home (which includes 7 kg of untouched and still-packaged food waste), alongside losses and waste generated in communal or commercial foodservice facilities.

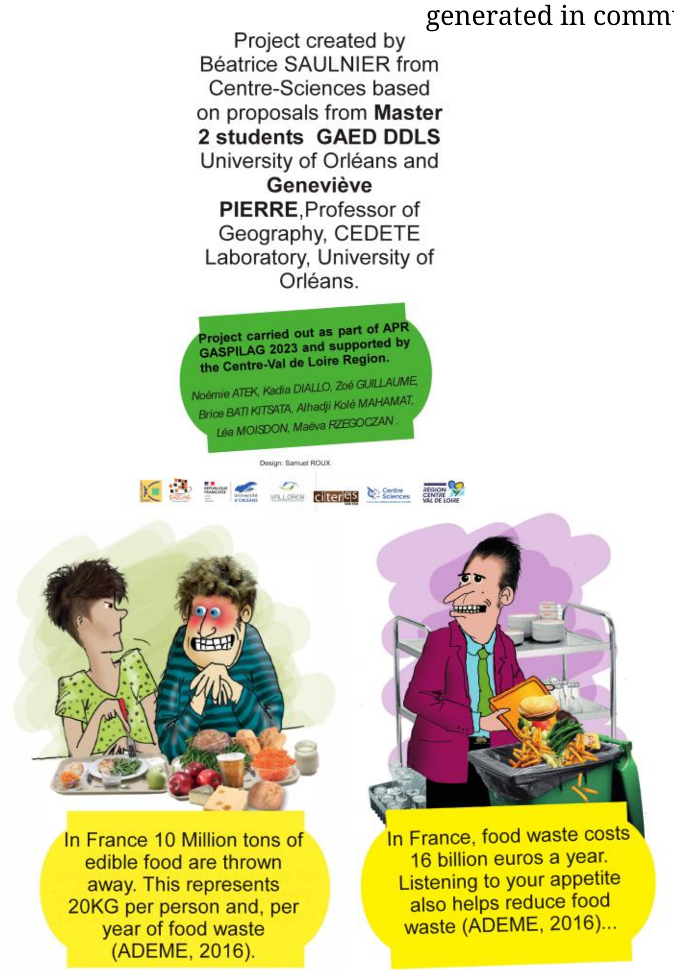

Figure 4. A few drawings to highlight the project [26].

With this in mind, we wanted to develop a technical solution that would include a development and application component for artificial intelligence, while at the same time providing some answers to the issues associated with food waste. Our work focused on one vegetable in particular, potatoes. Potatoes play an important role in vegetable crops and in human health and nutrition [29]. Against this backdrop, several specific studies have been carried out [30]. Very often, we buy potatoes packaged in nets, even though these vegetables have unfortunately already spoiled. This spoiling is visible in the black spots on the washed skin of the potatoes. Once peeled, these potatoes cannot be eaten because the flesh inside is grey. These potatoes are therefore waste. The technical specification for our project was to be able to separate good potatoes (for human consumption) from bad potatoes (for reuse as animal feed) before they are sold. The project therefore involves validating the technical concept of this automatic sorting (Figure 5).

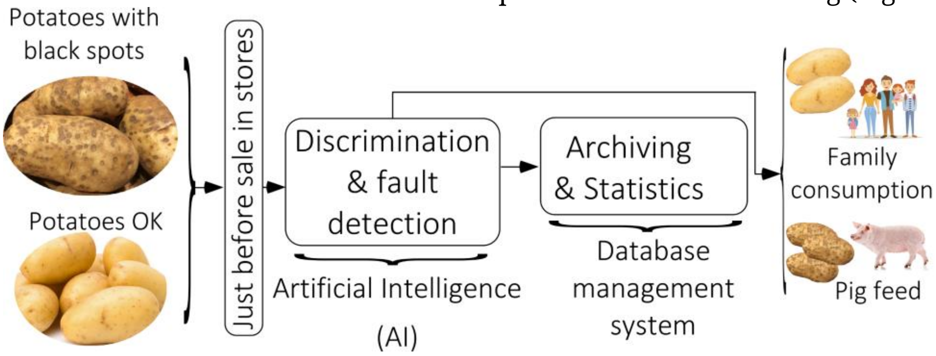

Figure 5. The functional specifications to validate the project concept.

The Selected Solution with Integrated AI

One of the main challenges of the project was to be able to automatically separate potatoes according to the constraints presented in Figure 5. This necessarily involved the implementation of a camera with image processing and classification. For image classification, there are several methods and algorithms that can be implemented as part of Deep Learning [31,32]. In the context of our project, we benefited from the partnership that our university has had with SICK for a few months (Figure 6).

Figure 6. Launch of partnership with SICK in March 2022.

SICK, a technological leader and market leader, offers intelligent sensors and solutions for applications that form an ideal basis for Industry 4.0 [33]. Our work focused on the use of the high-performance supervised algorithm CNN or ConvNets [34–36]. CNN are a subset of neural networks and one of the most potent models for image classification today. Their operation is straightforward: the user feeds an input image in the form of a pixel matrix. This matrix comprises three dimensions:

- ✓ Two dimensions for a grayscale image,
- ✓ A third dimension, depth 3, representing the primary colors (Red, Green, Blue).

Unlike traditional MLP (Multi-Layer Perceptron) models, which consist solely of a classification component, CNN architecture comprises two distinct parts:

- ✓ Convolutional part: This segment aims to extract image-specific features by compressing them to reduce their initial size. Essentially, the input image traverses a series of filters, generating new images known as convolution maps. Subsequently, these convolution maps are amalgamated into a feature vector termed the CNN code.
- ✓ Classification part: The CNN code produced by the convolutional segment serves as input for a secondary component, comprising fully connected layers referred to as an MLP. The function of this component is to amalgamate the characteristics of the CNN code to classify the image.

A conventional layer consists of three procedures: convolution, the activation function, and pooling. The result of a convolutional layer is called a feature map and can be considered as a particular feature representation of the input image. The convolution can be formulated as follows:

$$a_j^l = \sum_{i=1}^{n} a_i^{l-1} * \omega_{ij}^{l-1} + b_j^l \tag{1}$$

where $*$ denotes convolution, a_j^l is the j-th output map in layer l, ω_{ij}^{l-1} is the convolutional kernel connecting the i-th output map in layer $l-1$ and the j-th output map in layer l, b_j^l is the training bias parameter for the j-th output map in layer l. n is the number of feature maps from layer $l-1$.

The activation function is applied to each value of the filtered image. There are several types of activation function, such as an absolute function $f(x)=|x|$, a sine function $f(x)=\sin(x)$, or a Rectified Linear Units (ReLU) function $f(x)=\max(0,x)$. The next important step is pooling. A pooling layer is commonly inserted between two successive convolutional layers. Its function is to reduce the spatial size of the representation and to reduce the number of parameters and computation in the network. During pooling, either the maximum or the average value is computed. Finally, convolutional layers perform normalization of the feature maps, which ensures that the output values of the neurons are on a comparable scale.

These programming models are potent tools enabling image recognition, notably by automatically assigning a label to each input image, indicating the class it belongs to (Figure 7).

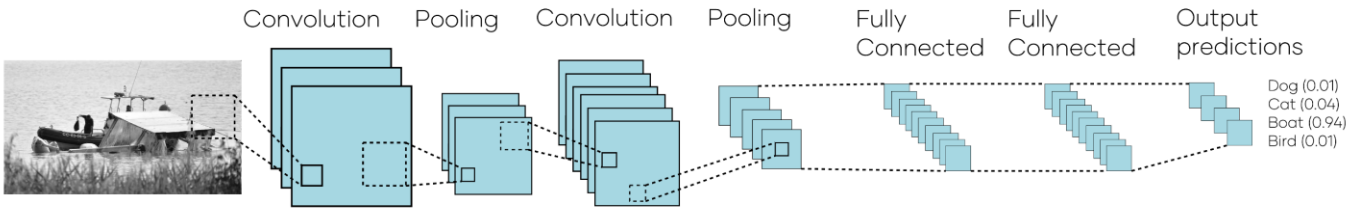

Figure 7. Example of CNN architecture (adapted from Aloysius N, Geetha M, editors. A review on deep convolutional neural networks. In: 2017 International Conference on Communication and Signal Processing (ICCSP); 2017 Apr 6-8; Chennai, India; New York (NY, US): IEEE; 2017 [34]).

These machine learning techniques and the associated decision-making evolve with the new computing capabilities of computers. This development has been documented by various research teams [37,38].

Technical Project Development

The Solution Chosen for Image Processing

Before implementing the camera-based solution, an overall analysis of the requirements and the various constraints was carried out. The initial objective was to validate the concept presented in Figure 8. Under these conditions, different categories of potatoes were identified from a wide range that can be easily bought in a shop. Size, thickness, weight, geometry, and texture were analyzed. Similar work has been carried out on potatoes in the context of defect detection [39,40]. Wang et al. [39] worked with an image database of different potatoes (214×4 images for each category). These potatoes tended to be round. For 3 different scenarios, several constraints were proposed (illumination conditions of the area to be detected, camera height in relation to a potato). In their work, the authors demonstrate the robustness of the different algorithms selected, as well as the rapidity of the learning phase. The algorithms used converged in the learning phase after 26 min. The Region-based Fully Convolutional Network (RFCN) ResNet101 showed better results, with no confusion in the different classes to be processed. Arshaghi et al. [40] proposed a project to classify potatoes and also took the opportunity to present various other projects on vegetables. The authors used a CNN model based on a database of 5000 potato images across 5 different classes. All the images in the database have the same format (120×120), which requires pre-selecting potato sizes. The results show that the learning process converged after 30 min of testing, with some confusion observed between certain classes.

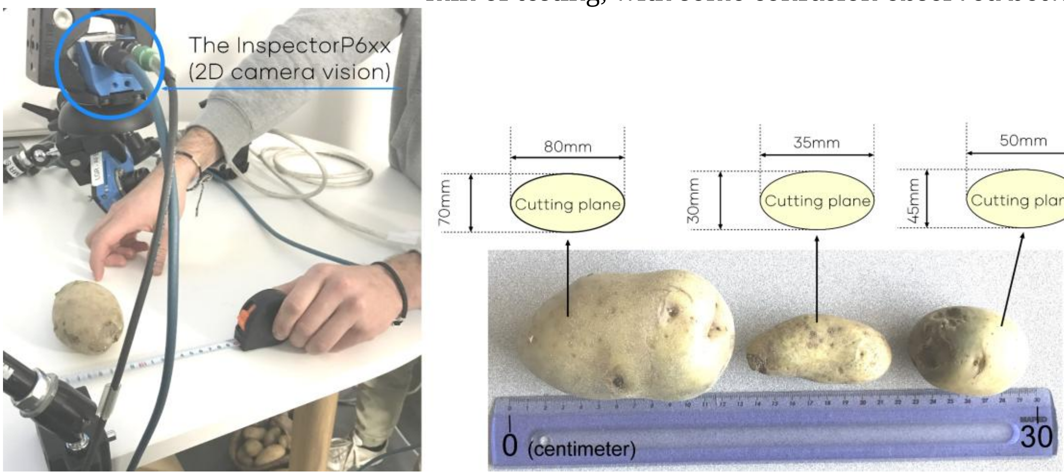

Figure 8. The different categories of potatoes.

The InspectorP6xx (2D camera vision) is a programmable vision sensor tailored for industrial applications that require high-resolution images over extended distances (Figure 9a). Programmed via the SICK AppSpace development environment software on a Station (PC), this device can be customized to suit various tasks. Depending on the application, developers can create a browser-based graphical user interface (Human Machine Interface (HMI)) to allow operators to influence the application parameters. The device boasts multiple interfaces for control, programming, and operation, activatable as required via development environments, a Programmable Logic Controller (PLC), or applications. Primarily intended for industrial and logistics applications, these devices adhere to industrial standards for ruggedness, interfaces, and data processing, though they are not classified as safety components under the Machinery Directive 2006/42/EC [41]. The InspectorP6xx product family is integrated into the SICK AppSpace ecosystem, comprising software tools and programmable sensors or devices. See Figure 9b for an overview of SICK AppSpace.

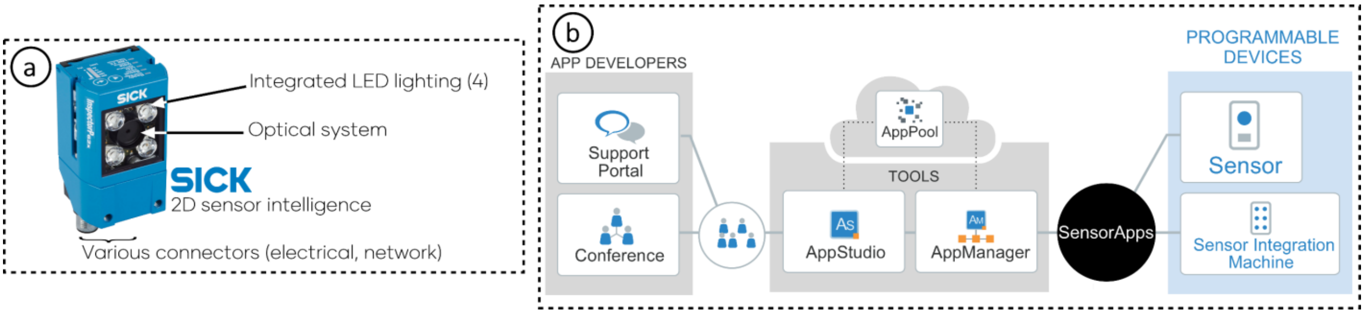

Figure 9. SICK camera and AppSpace.

SICK AppSpace encompasses various components and resources tailored for seamless development and management of SensorApps (Figure 9a). The preliminary and tedious work consists, after validation of the environmental context of the camera (height, light, contrast, etc.), in recording a collection of photos of the different potatoes. The camera configuration tool is hosted by the manufacturer, SICK. Resource-intensive processing is carried out on the manufacturer's Cloud to obtain the camera configuration files. In our case, we created a database of 808 greyscale photos (Figure 10). The three classes ("OK", "Bad" and "Nothing") were labeled by the expert's feedback. All photos were captured under the system's functional usage conditions (Figure 16b). The use of a dome that emits red light made it possible to very effectively isolate the photo acquisition and the quality of the results. The camera processes photos based on a grayscale. The different parameters are: Max trigger frequency with current acquisition settings (42.5 Hz); Exposure time (1215 μs); Focus (300); Contrast (1.1); and Brightness (3.5).

SICK does not propose to compare different algorithms against each other. The available toolbox includes a CNN, and we aimed to validate the solution proposed by SICK within an industrial application. At the end of the learning phase, a model presented in the form of a correspondence matrix is proposed (Figure 11b). The diagonal of the matrix (blue) must be complete for an optimal result and therefore without confusion between the different classes proposed upstream. The other cells must therefore contain the zero value. If this is not the case, the photo database will have to be enriched to make the model more robust (no confusion possible between classes). Figure 11a shows the evolution of the results between training and evaluation. The result is available after 16 min of CNN calculations. In the working environment offered by SICK, AI metrics, confusion matrix data, F1 scores and a table summarizing model performance are not available. This is unfortunate as it would be useful for more results to be made available at the end of the learning phase.

Once the model has been established, the camera can host it in a JSON file (Figure 12). During the learning phase with the CNN model, we initially encountered a few minor issues, such as a lack of photos in the database. As with any industrial development, there are various adjustment phases before the system is finalized and delivered. The camera then becomes a fully autonomous technological object that understands the rules of the game. The next stage of the work involved validating the recognition of the different potatoes (Figure 12).

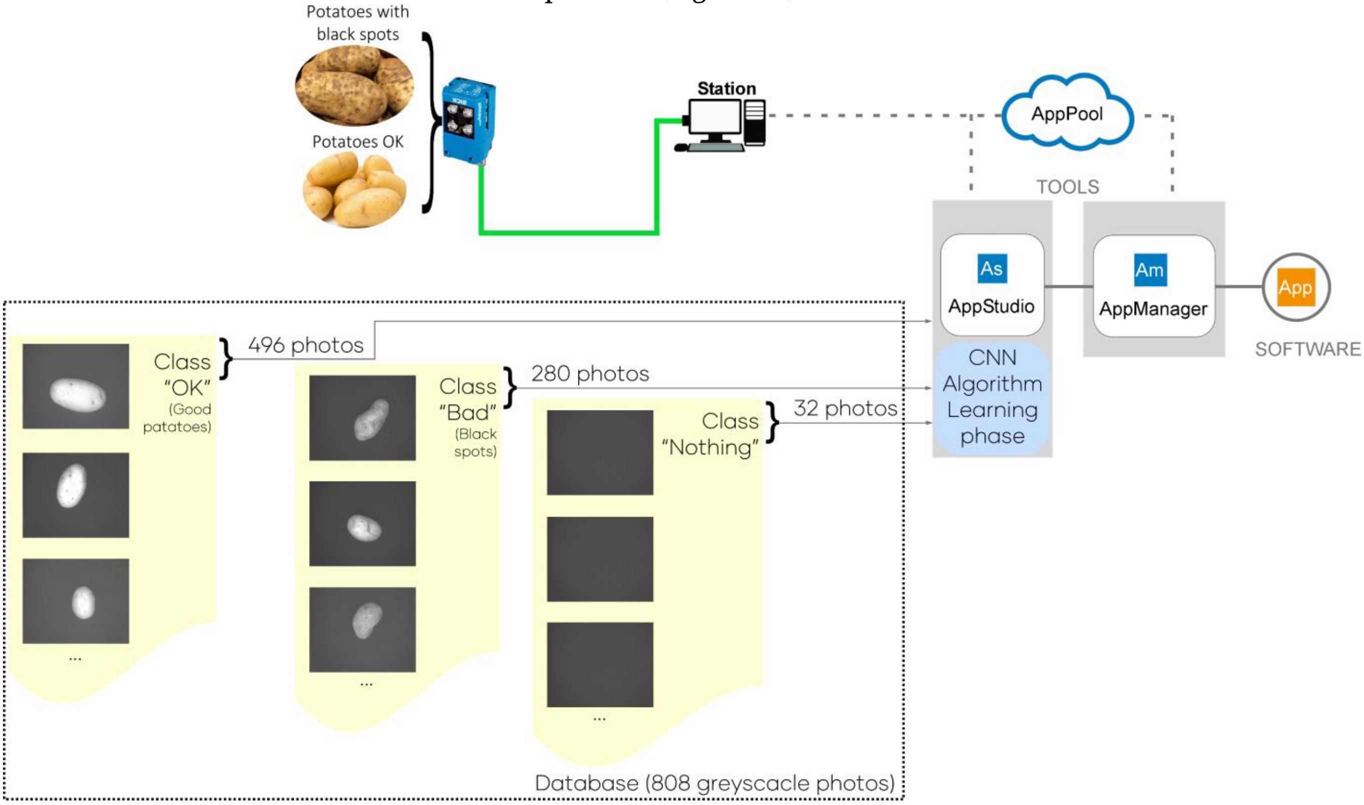

Figure 10. Class generation and creation of the database (photos) before the learning phase.

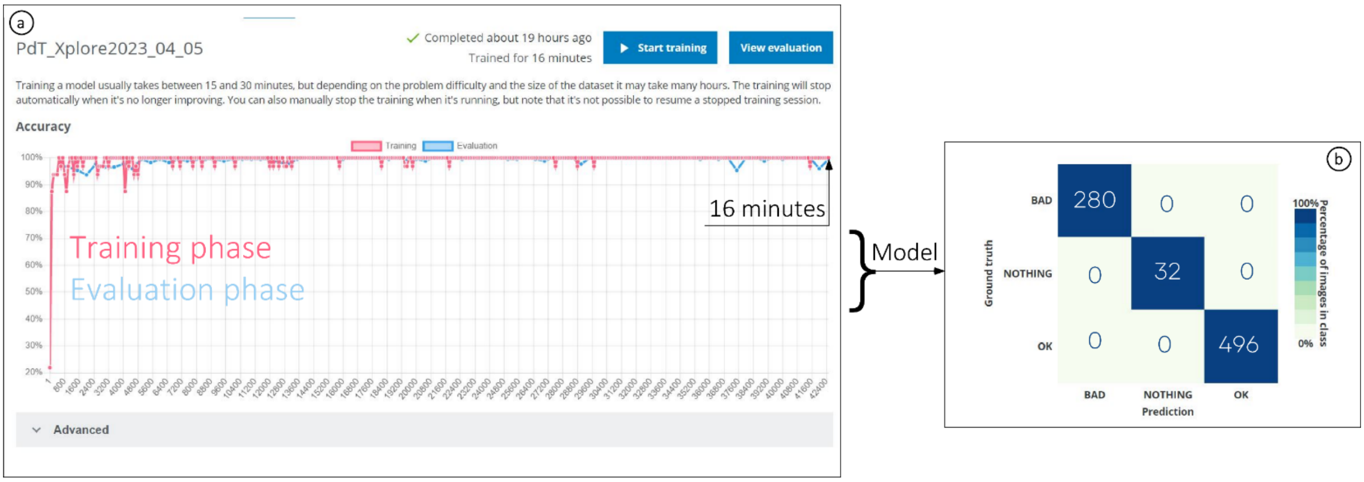

Figure 11. Learning phase, model evaluation and confusion matrix.

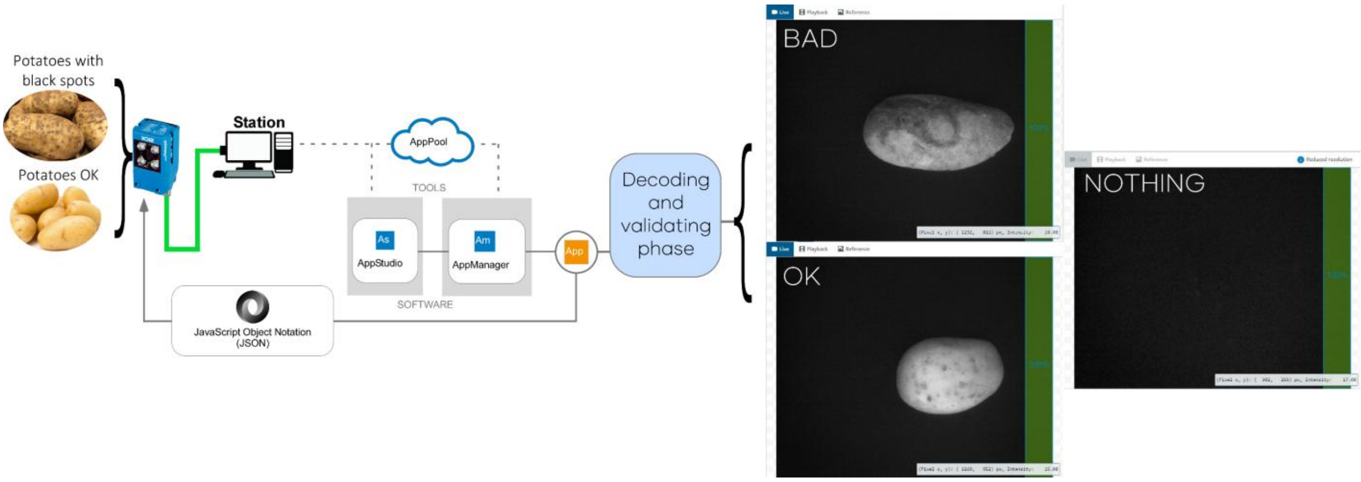

Figure 12. Testing the model after it has been embedded in the camera.

Detailed Architecture of the Selected Digital Network

Figure 13 describes the network architecture that has been implemented. This architecture responds to the numerous requirements and technical obstacles that can be encountered in industrial contexts in terms of monitoring and checking the conformity of manufactured products. The rules of the competition specify that each project had to integrate products from Phoenix Contact. As part of a common exchange protocol (Profinet), the first challenge was to get a third-party product (camera, SICK) to communicate with a PLCnext (Phoenix Contact). The Web Panel was also a Phoenix Contact product, which also uses the Profinet protocol. The second challenge was to meet the need for a robust model hosted in the camera capable of discriminating between potatoes. The third challenge was to create a local database from an OPC UA channel [42,43]. This database is hosted on a RaspberryPi-based solution. The fourth challenge combined data storage and processing in a reporting application (Excel). Finally, the fifth challenge was to provide complete control and command of the system's various actuators (electrical and pneumatic). The mechanical part is detailed in Figures 15 and 16.

The Different Software Environments Used

In order to meet the technical challenges presented in Figure 13, various software packages were used (Figure 14) to develop the project correctly. Beforehand, a complete assessment of the variables to be processed was validated (inputs, outputs, internal variables, etc.), taking into account the component parts list table and the various diagrams (electrical and pneumatic, not presented in this article). The control-command part of the system housed in the PLC was developed in the PLCnext Engineer software environment. The programming of the automation system complies with the IEC 61131-3 standard, with web-based visualization and open standards such as HTML5 and JavaScript [44]. A detailed prior description of the system's sequential operation enabled the correct algorithm to be established and then coded by associating the information broadcast by the camera in the Profinet network (Figure 13a,b (HMI n°1)).

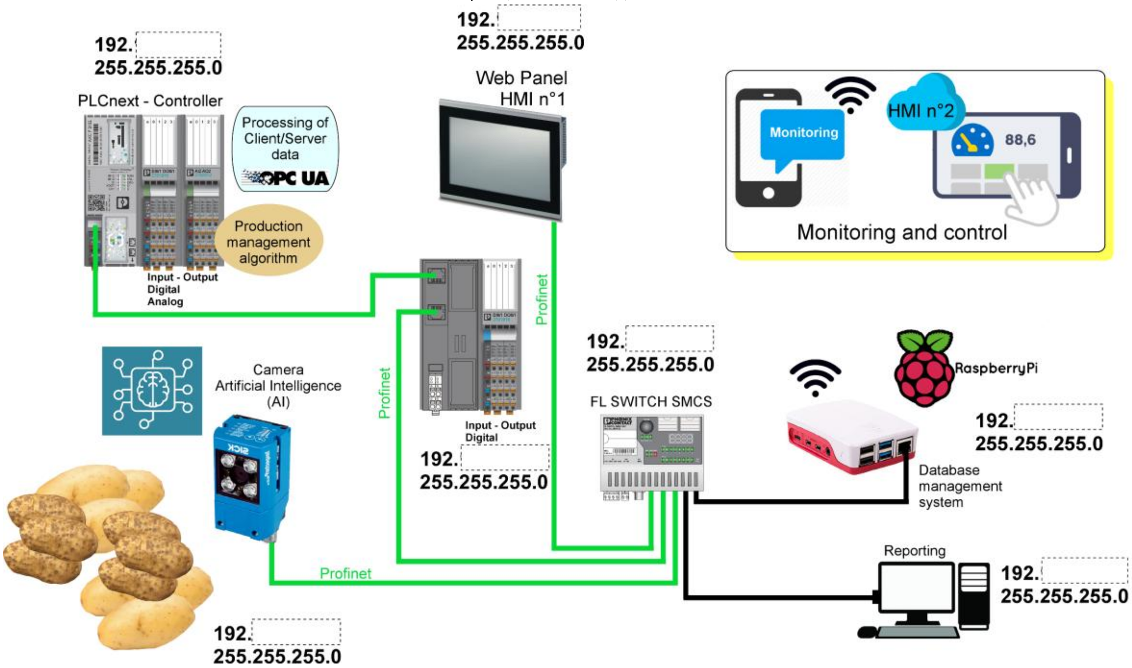

Figure 13. Network architecture.

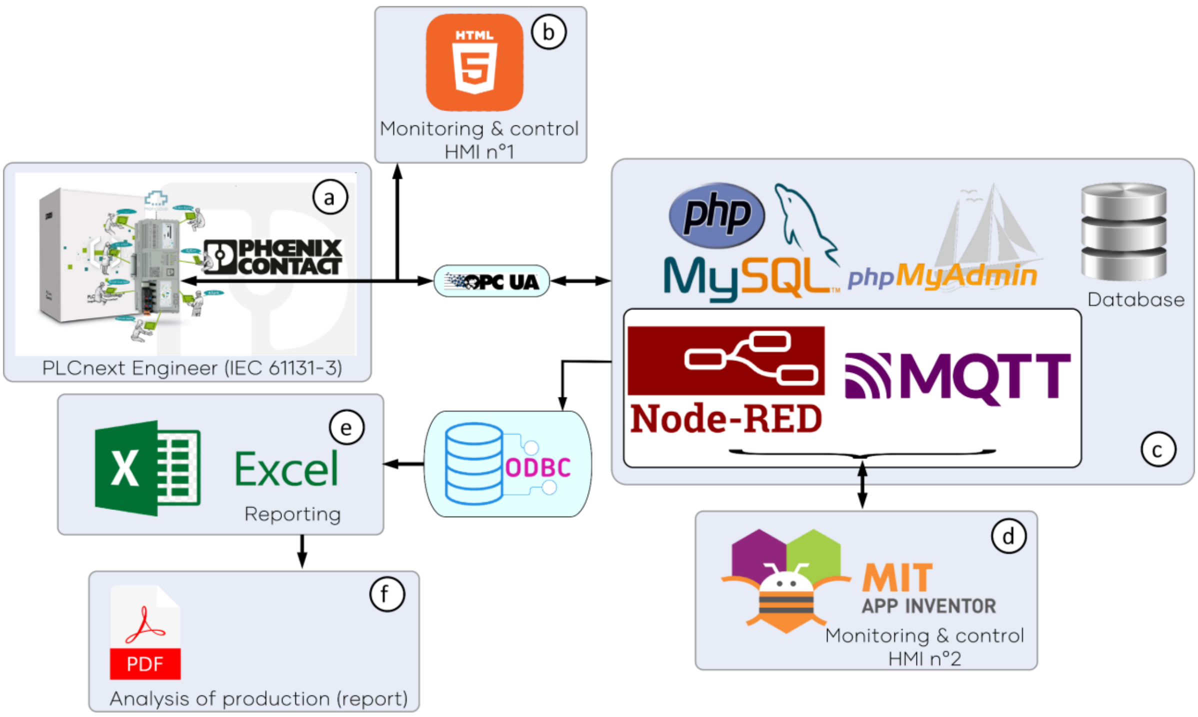

Figure 14. Software and services.

Figure 14c shows the various software packages installed on the RaspberryPI. The creation of the database makes it possible to record the census of the various potatoes, their class and the processing time and date. The system's various operating cycles are also stored (stop/start). A specific Flow developed with Node-Red makes it possible to retrieve the OPC-UA communication channel (filtered data [45]) and process this information directly in the database. For the rest, specific filters were implemented to send information via MQTT (mobile application developed with APP INVENTOR, HMI n°2). HMI application no. 2 (for tablet or Smart-Phone, Figure 14d) was developed using the APP INVENTOR2 platform [46]. The application works with the MQTT server hosted by the RaspberryPI. Each element of the application will read or write to a specific topic under MQTT [47,48]. The various variable contents are then implemented in specific topics in Node-RED [49,50]. An ODBC gateway is required to properly exchange data stored in the database with the reporting application (Excel). Various declarations and parameters must be respected. Numerous tutorials are available on this subject. As with an industrial application, the operator of the production line or system can edit a logbook in PDF documents. This log can then be shared with various departments, including quality, logistics, maintenance, and production (Figure 14e,f).

Study and Design of the Mechanical System

The mechanical aspect required extensive effort and drafting to thoroughly evaluate the merits and drawbacks of various solutions. The initial objective was to validate the concept with its prototype, while ensuring that the system was robust and easy to dismantle. The system's industrialization phase (possible continuation of the project) for more extensive deployment to companies working in the food industry was not at the heart of our constraints and challenges. However, the 'cost' of design and implementation was a very important criterion that was seriously considered. Depending on the technical choices made, the final bill can be multiplied by 10 (conveyor technology, length, sorter, etc.). The various solutions considered, taking into account the advantages and disadvantages, are shown in Figures 15 and 16a. Version V4—02-20-2023 was finally selected. This solution was entered in the final round of the Xplore 2023 international competition. Figure 16b describes the various mechanical settings. A project management approach was launched in September 2022 (Figure 17). Ten months of work were under way.

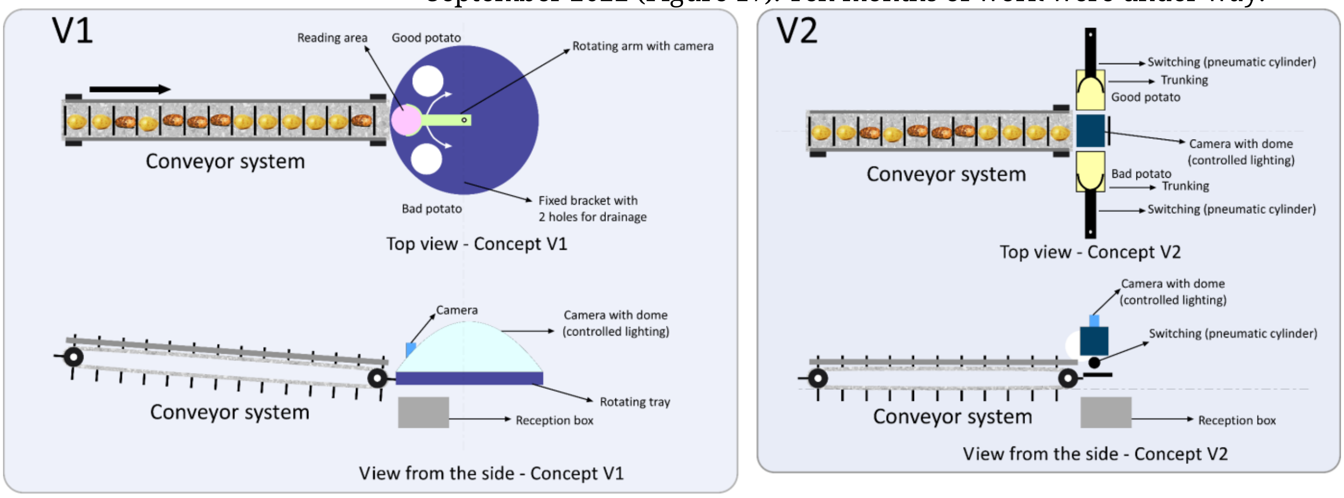

Figure 15. Study and mechanical design V1 & V2.

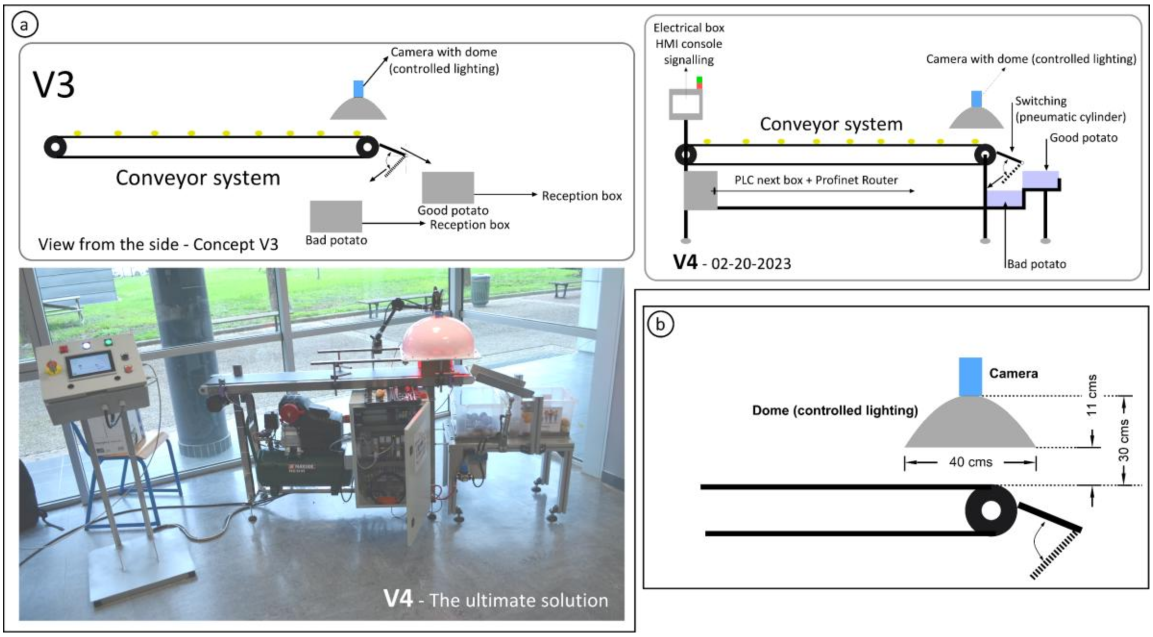

Figure 16. Study and mechanical design V3 & V4.

July 2022, submission of the project proposal.
September 2022, 100 teams from every continent are selected.
Ten months' work.
July 2023, project presentation (video + documentation).
September 2023, qualification of the 25 finalist teams in the 5 categories:
- Social and Health, Intelligent Mobility, Environment, Intelligent Energy, Intelligent Industry, Digital Technologies and Education.
Week of 18 October: final in Bad Pyrmont (Germany).

Figure 17. Major phases of the project.

Project Management and Planning

This project was governed by the construction of a team made up of 7 people (Figure 18a): 2 teacher-researchers from the "PRISME" research laboratory (management) and 5 students (3rd year Bachelor level (option: Supervision of Automation and Networks, University of Orléans, Indre University Institute of Technology), Châteauroux-France, and 4th year engineer level (option: Industrial risks, INSA Centre Val de Loire, Bourges-France)). The management's initial strategy was to put together a team with complementary and particularly enriching viewpoints and skills. Five main Work Packages (WPx) were broken down with different milestones deployed throughout the schedule (Figure 18b,c). This work approach, clearly identified in the literature [51,52] was the subject of various contractual documents: functional specifications, technical specifications of requirements, modelling using standard tools (Structured Analysis Design Technique, algorithms, diagrams, functional blocks, etc.). Three criteria were also considered: cost, lead time and performance. Figure 19 summarizes the technical progress of the project in a few photos.

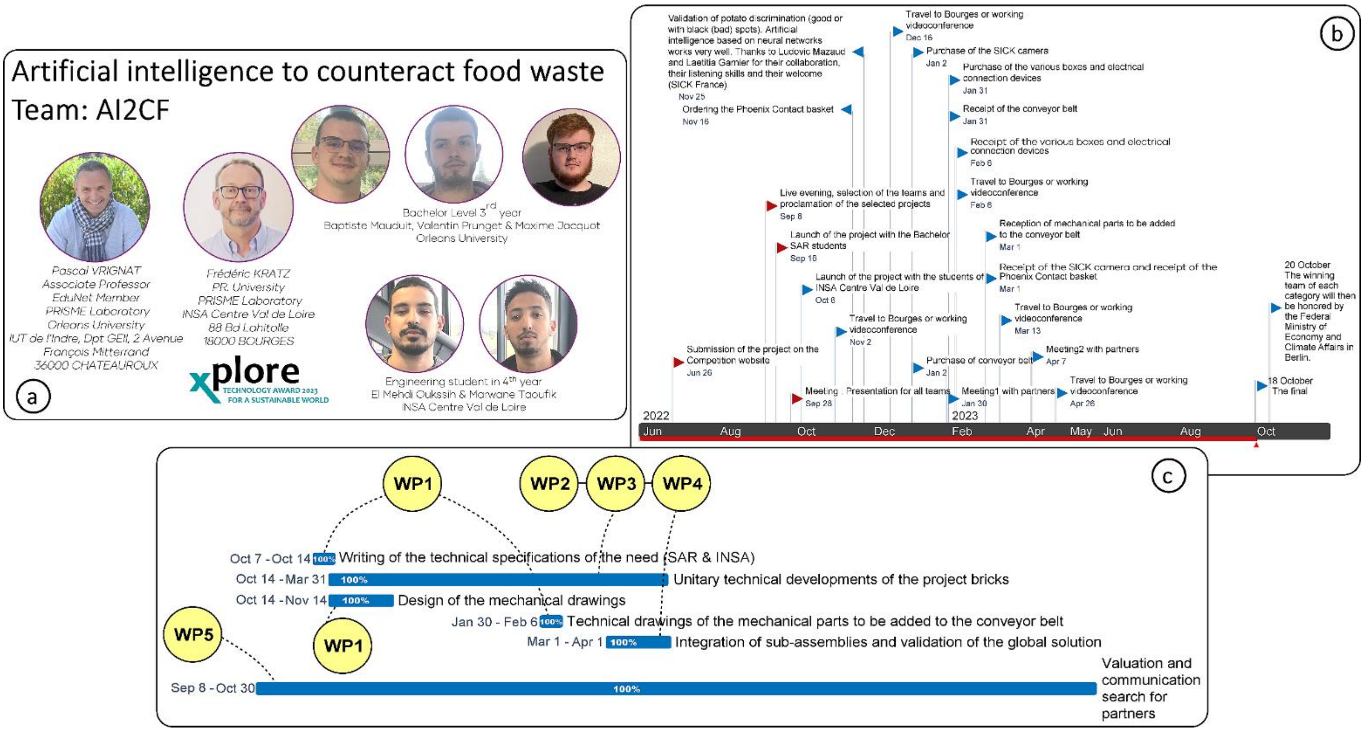

Figure 18. Project organization, team calendar with WPx.

Figure 19. A selection of photos.

RESULTS

Control and Measurement

Figure 20a shows part of the man-machine interface developed to be hosted on a Smartphone or tablet (connected to the WIFI of the RaspberryPI (Figure 13)). This result concerns the various developments described in Figure 14. The elements shown in Figure 20b,c enable different items of information about the system to be consulted on the computer dedicated to reporting (Figure 13). This live consultation reproduces current needs which, for example, enable a production line manager to have access to essential information (synthetic yield rate, quantity of products manufactured, production stoppage, etc.). On-demand report generation in .pdf format is also available.

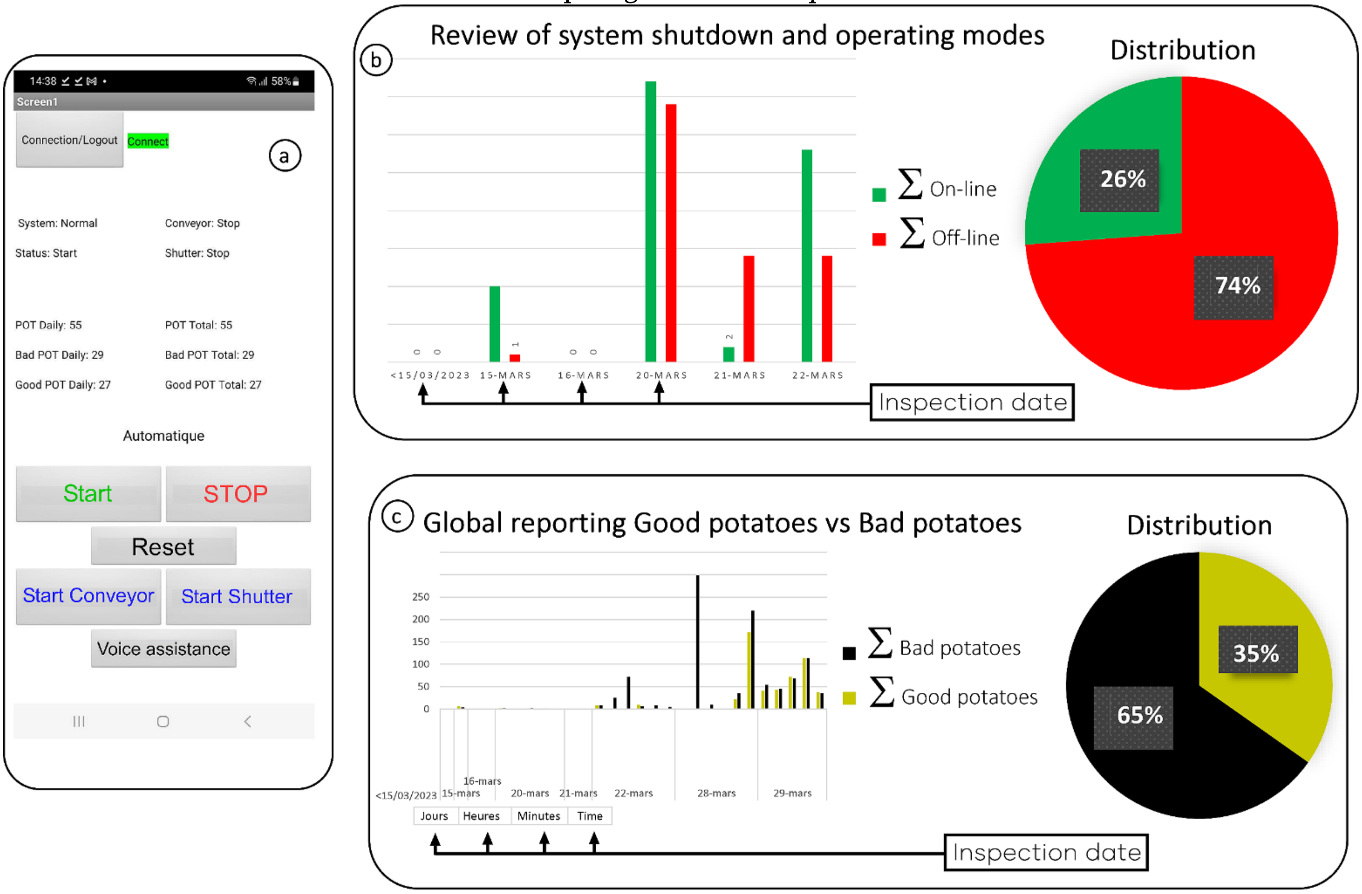

Figure 20. HMI solution, control and measurement, some results.

Final at Bad Pyrmont (German)

Six teams in the "environment" category were invited to take part in the final in Germany (Bad Pyrmont): Smart Aquaponics Systems—Heriot Watt University, Dubai (United Arab Emirates); Holus—Automated Hydroponic Cultivation Module—Universidad Technologica Nacional Facultad Regional Rafael (Argentina); Ketran Agrobot V2—Duoc UC, Santiago de Chilie, (Chile); RADiSH—Fully Automated Agricultural System—Purdue University, (Indiana) ; AI2CF—Artificial Intelligence to Counteract Food Waste—Orleans University, INSA Centre Val de Loire, PRISME Laboratory (France); H2HU Aquaponics Automation—Waste Treatment—Harrisburg University of Science and Technology (USA).

The final took place from 16 to 21 October 2023. After setting up in the various showroom-style rooms, an entire morning was devoted to presenting the 25 projects in the 5 categories (Smart Technology, Social & Health, Environment, Education, Smart Energy and Smart Technology). In the amphitheater of the Phoenix Contact factory in Bad Pyrmont, all the teams had 5 min to present their project orally to the jury and all the participants (Figure 21). The presentation had to be both highly effective on different communication themes and highly educational. Then, in the showrooms, the jury went from project to project on 2 occasions for the technical and detailed demonstrations (2×5 min, Figure 20). The organization was perfectly calibrated; everything had to work smoothly without falling into the 'demonstrator syndrome' (everything works perfectly until a bug occurs before the official delivery). Some teams unfortunately experienced this syndrome. At the end of Day 3, during the gala evening, the results were announced in a wonderful atmosphere (Figure 22). Use the link in Figure 21 to watch the video presentation of our project [53].

Figure 21. Twenty-five teams for the final.

Figure 22. Demonstrations in the showroom, general presentation in the amphitheater, podium.

PROMOTION, COMMUNICATION, AND SPIN-OFF

This part of the work was activated in September 2022. Communication was a key factor in attracting partners and funding, and in promoting our project to a wide range of audiences (institutions, industry, young schoolchildren, adults wanting to find out more about today's science and technology, etc.). We used several channels to do this, including a special Web page to keep track of our work as it progressed, articles in the regional press and regular posts on LinkedIn [54].

CONCLUSIONS

Giving meaning to scientific and technical activities, research and development and student training is a real challenge. Students and their wishes are evolving, just as generations evolve at the same pace as our societies. Traditional teaching methods (formal lectures in an amphitheater, tutorials, practical work, etc.) have shown their limitations and lack of effectiveness for several years now. In engineering and science courses at university, the core knowledge taught (mathematics, physics, automation, computing, electronics, project management, etc.) must be combined with teaching strategies in which the students are the real players. The work presented in this paper has shown that Project-Based Learning is an incredibly effective teaching strategy. However, this effectiveness is the result of hard work and quality in project management. This project benefited from a very interesting complementarity with students who came from different backgrounds. A great deal of work to support this project enabled us to bring together many partners, both private and public (Figure 22). This support was undoubtedly a key factor in the success of the project. This paper has shown that the use of artificial intelligence can also be applied to counteracting food waste. It is abundantly clear that the national or international challenges organized for students and teaching teams are real gateways to professional integration. The students in our team were placed in an international, English-speaking environment and benefited from a particularly enriching experience for this topic. The technical solutions validated and presented in this article will likely be updated in the coming years. Applications for the industry of the future are evolving rapidly. It is also worth noting, for example, that some manufacturers, such as SICK, do not provide full access to the various details of the algorithms used. The solutions are sometimes too blackboxed. AI is ultimately a spin-off of mathematics, much like computer science and statistics. This mathematical foundation permeates all AI products and will continue to shape their future.

CONFLITS OF INTEREST

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors on request.

IMAGE RIGHTS AND IMAGE USE

Informed consent for participation was obtained from all subjects involved in the study. Image rights and image use for various communications and promotional media were granted by the students who took part in this work.

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