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Adding Machine-Learning Functionality to Real Equipment for Water Preservation: An Evaluation Case Study in Higher Education

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Abstract: Considering that the fusion of education and technology has delivered encouraging outcomes, things are becoming more challenging for higher education as students seek experiences that bridge the gap between theory and their future professional roles. Giving priority to the above issue, this study presents methods and results from activities assisting engineering students to utilize recent machine-learning techniques for tackling the challenge of water resource preservation. Cost-effective, innovative hardware and software components were incorporated for monitoring the proper operation of the corresponding agricultural equipment (such as electric pumps or water taps), and suitable educational activities were developed involving students of agricultural engineering. According to the evaluation part of the study being presented, the implementation of a machine-learning system with sufficient performance is feasible, while the outcomes derived from its educational application are significant, as they acquaint engineering students with emerging technologies entering the scene and improve their capacity for innovation and cooperation. The study demonstrates how emerging technologies, such as IoT, ML, and the newest edge-AI techniques can be utilized in the agricultural industry for the development of sustainable agricultural practices. This aims to preserve natural resources such as water, increase productivity, and create new jobs for technologically efficient personnel.

Keywords: internet of things; machine learning; smart sensors; fault detection; embedded systems; smart agriculture; water preservation; sustainability; educational practices; higher education

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1. Introduction

Nowadays, innovative technologies have been incorporated into the curricula of schools, delivering promising educational outcomes, particularly in the STEM (Science, Technology, Engineering, and Mathematics) framework. Although STEM education has many benefits for young students, the same courses and principles cannot apply to higher education without proper adaptation, as higher-education students, having already acquired several basic knowledge sets and skills, seek advanced learning experiences [1]. Quite a few innovative solutions are available that support laboratory-level trials and create interesting activities that encourage the students to take part in all stages of the development of real-world applications. Indeed, considerable work is done, involving microcontrollers, pairing electronics [2], and small-scale inexpensive systems (i.e., robotic devices), usually through applying PBL (Project Based Learning) approaches [3], in the context of K-12 education [4,5] and higher education [6]. The inclusion of the STEM model into today's educational methods is challenging for a variety of reasons [7]. In the case of university students, more effort should be made, as the students ask for more complex systems and learning experiences that are equal to real-world conditions.

There is apparently a gap between university and industry, regarding appropriate engineering capabilities [8,9], which is easier to bridge by developing pure software, using open platforms [10]. Additionally, software platforms are highly beneficial for facilitating the development of systems and programming controllers of industrial specifications [11–13], including the ones applied in the agricultural sector [14]. It is worth mentioning that, quite frequently, students are not being given the opportunity to experiment with the full set of diverse settings of actual equipment during the classes, which mainly operates as a "black box" system [15]. This situation, inherited by the secondary education, is experienced in the engineering university department and is further magnified due to the intensification of the students' technical curricula. Additionally, the outdated equipment being used on several occasions during the laboratory classes cannot always be computerized (i.e., with modern interfaces for communication, monitoring, and control) or it is merely computerized, solely with the assistance of properly trained personnel.

These facts indicate the necessity and the difficulty of incorporating advanced technologies into the universities' courses [16], not only in theory but also in practice, via enriching laboratory activities with practical experiences and, thus, aiming to train students so as to develop skills for tackling real-world problems. In this regard, the inclusion of innovative technologies and hands-on activities in higher education will prepare students to adapt easily to the continuously developing industry and to gain valuable knowledge and skills that will be utilized in the future to improve the planet. These actions need to be carried out taking into consideration the fostering of sustainable development in order to ensure environmental protection and preservation of natural resources [17].

Indeed, sustainability serves as a main pillar for the green transition, it entails fulfilling current needs while ensuring future generations can meet their own needs without compromises [18]. Hence, sustainable practices intend to decrease the negative impact of human activities on the environment, society, and the economy [19]. In this context, entrepreneurship should enable the development of new technologies and business models that provide fresh products, and services that create value by addressing sustainability challenges, while also contributing to economic growth and job creation [20]. Sustainability and education are intricately linked concepts that play a pivotal role in shaping a sustainable future for our planet. The idea of Sustainable Education (SE) involves seeking lasting solutions to environmental, social, and economic challenges through educational means [21]. This concept calls upon both formal and informal education sectors to engage proactively in developing programs that enhance quality of life, promote empowerment, and recognize the interconnectedness of economic, social, and environmental aspects [22,23]. On the other hand, Education for sustainability refers to the integration of sustainability principles into the curriculum and educational experiences. It focuses on teaching students about concepts, values, and skills related to sustainability, enabling them to understand and address complex global challenges, such as climate change, biodiversity depletion, and social inequality [24]. It emphasizes the content of education, incorporating topics related to environmental conservation, social justice, and economic viability into various subjects. Students are encouraged to explore real-world issues, develop critical thinking skills, and participate in projects that promote sustainable practices in society. The goal is to create environmentally and socially conscious citizens who can contribute to building a more sustainable future.

From the perspective of agriculture, dealing with the problem of water depletion, according to sustainable policies, is of particular concern since the agricultural sector is the main water consumer on Earth. In fact, water is an important input for agricultural production and holds significance in food security, as global irrigation for agricultural production comprises 70% of clean water use [25]. Water pumps and faucets play a vital role in irrigation operations, as they are primarily employed to transport substantial volumes of water from their respective sources to the fields. Furthermore, water pumps can undergo damage due to various factors, including insufficient provision of water from the origin, inefficient power, or the circulation of contaminated water. To avoid damage to the components of these pumps, it is crucial to observe their operational status and act in the event of a malfunction. The digitalization of agriculture appears to be a promising opportunity for monitoring and automating agricultural operations through cutting-edge technology, such as the internet of things (IoT) and machine learning (ML) [26,27].

For the aforementioned reasons, the case described in this paper focused on addressing water depletion issues and equipment maintenance. This approach aimed to familiarize students with the principles of sustainability, encouraging them to comprehend the intricate interplay between human activities, environmental concerns, and sustainable solutions. Above this, the contribution of this work is to emphasize the viability for integrating software and hardware components to provide, apart from technical outcomes, considerable educational outcomes regarding the issue of strengthening the benefits of real equipment for water preservation. These components, without being expensive, can assist in creating effective instruments for maximizing the educational benefits for the students, while they are called to tackle problems related to the water preservation purposes. The experiments carried out were dedicated to sustainability, emphasizing the preservation of water and the maintenance of equipment. This method strives to achieve dual advantages for participants: acquiring additional technical knowledge while also putting sustainable applications into practice. In this context, the experimental arrangements described herein are trying to highlight the potential benefits—from technical and educational perspectives, with more focus on the latter—of modern technological advancements like the ML and the IoT, aiming at the delivery of cheap devices capable of making smart in situ decisions and reporting the results to the interested parties accordingly, instead of relying upon complicated, non-cost-effective, centralized infrastructures.

In more detail, the first step of this research, in the direction of the on-device intelligence deployment technique [28], was the development of a classification model executed on a microcontroller attached to a commercial faucet along with a flow sensor so as to determine water-consumption profiles and alert the user about them [29]. To further benefit from this deployment technique, a machine-learning model was developed for classifying and diagnosing possible motor defects in a water pump, using vibration data from an accelerometer to achieve a more comprehensive and precise perspective on the factors influencing the system [30]. These preexisting works, apart from introducing technical innovations, provide fertile ground, from an educational perspective, for pedagogical setup descriptions, experimentation, and evaluation reports that are among the main subjects of the study being presented. Toward this direction, the applications' implementation process and overall utilization experience are also evaluated through questionnaires, suitable for the specific target groups of undergraduate and postgraduate university students. The results indicated that valuable hard skills and soft skills were acquired (and, thus, reported) by the students who participated, thereby making them better prepared for their roles in a rapidly changing era.

Subsequently to the introduction in Section 1, the paper is laid out as follows. Section 2 identifies the main motivations and challenges of this work. Section 3 provides an overview of the educational arrangements as well as some facts about the functionality and the selection of the components. In Section 4, the design of the system is presented and some interesting details regarding its implementation are highlighted. Section 5 concentrates on evaluation of the results and discussion of some insights derived from the findings of this work. Finally, Section 6 of the paper presents key conclusions derived from this work and outlines potential directions for future research.

2. Related Work and Rationale

In terms of agricultural engineering education, in most cases, universities primarily prioritize enhancing the performance of particular implementations from a technical standpoint, often without placing emphasis on the basis of educational practices or the social impact [31]. It is important to highlight that students in agricultural engineering show a clear preference for teaching methods based on experiential learning, which equips them with skills for innovation and creation [32,33]. The field of digital agriculture includes not only agriculture, but also engineering and computing, and, thus, it is challenging to find experts that are fully conversant with these aspects simultaneously [33]. Moreover, education for sustainable development [34] is not included in the activities of universities, although it is a key element in the Agenda for Sustainable Development, driving the fulfillment of all the Sustainable Development Goals (SDGs) [35]. The ESD stands for the inclusion of sustainability issues, i.e., protection and conservation of natural resources, climate change, and sustainable exploitation/consumption, in teaching and learning [34]. In this regard, preparing well-trained professionals should include equipping them with the knowledge, skills, and values that will empower them to contribute to the creation of a more sustainable world and enhance wellbeing as well as socio-economic growth, along with conserving natural resources. The importance of introducing the sustainability concept in higher education has been identified by researchers. As [36,37] indicate, in order to emerge as leaders and catalysts for change in sustainability, higher education institutions must prioritize understanding and addressing the needs of both present and future generations. This involves equipping professionals, well-versed in Sustainable Development (SD), to effectively educate individuals of all ages and guide them in transitioning to sustainable societal patterns. To achieve this goal, it is crucial for university leaders, faculty, and students to be empowered to introduce Sustainable Development into all aspects of their institutions, including courses, curricula, and various activities. Recognizing the importance of multidisciplinary and transdisciplinary approaches in teaching, research, and community outreach is essential for expediting the necessary societal transition toward sustainable development.

The literature also shows that the incorporation and utilization of technologies in education systems, overall, are not advancing as indicated by the digital and 2030 agendas [38] due to technological, pedagogical, and organizational inefficiencies. Many of the new technologies having a strong impact in modern life are not well incorporated yet into the higher education curricula, that remain more theoretical than practical, while flexibility and multidisciplinarity are required. A notable case of such technologies is the field of artificial intelligence (AI) known as machine learning (ML), that has many practical applications offering solutions to several critical problems, and, thus, could be making it a prime example motivating for integration into educational practices.

Apart from the more conventional educational approaches dealing with engineering with electromechanical [39,40] and basic IoT [41] solutions applied in modern industry and agriculture, various educational projects aim to improve individuals' AI literacy. According to recent research [42], preliminary courses on AI are offered at various educational levels, from elementary school [43] and secondary education [44,45] to higher education [46,47]. Nevertheless, most of these approaches are software-based paradigm and they are not well linked with real-world problem solutions that fully exploit the engineering spectrum. Unfortunately, it is hard to find research works combining education on machine learning with impact on sustainability and offering at the same time real-world performance applications experiences.

Some works may be found, dealing with sustainability or with machine learning, although not satisfactorily covering both issues. machine learning models possess the ability to learn and adjust according to the problem, whereas traditional programming alternatives are constrained since those implementing them are expected to already understand the intricacies of the system for which the solution is being customized [48]. In recent years, the accessibility of extensive volumes of data and information has enabled more fast and accurate ML models [49]. The swift growth in available data, facilitated by improved sensor inventions, has significantly elevated the significance of machine learning, transforming it into a potent instrument for numerous applications between various disciplines. Indeed, fresh hardware and software tools have recently appeared, allowing for fast deployment of applications in the area, and it is worth these tools to be efficiently and creatively utilized by higher education professionals.

This work initially aims to bridge the aforementioned gap and proceeds further to achieve mutual benefits from the educational and technological context. In greater detail, the combined goal of this work is to facilitate the communication of innovative technology practices to agricultural engineering university students, based on the development of a final product, in order to become more efficient in their careers, and simultaneously to make the students aware of critical sustainability issues. In this regard, the activities being proposed need to be oriented towards covering all these types of challenges. Traditionally, through technology, several solutions had to be found to tackle intense problems, such as the depletion of natural resources or the increased nutritional needs of humans, while modern disciplines like IoT, automation control, artificial intelligence, and networking were amongst the most promising instruments of the abovementioned efforts. Therefore, the emerging advance in the area is further increasing the need for well-trained students and future professionals involved in developing, parameterizing, and maintaining the relevant systems.

Going deeper, it emphasizes the feasibility of developing economical systems of realistic dimensions, which is achieved due to the presence of user-friendly programming software, which can be either textual or visual, streamlining the entire approach. Indeed, according to the study report of 2021 of the European Commission (EU) [50], the role of open-source software and hardware is paramount for facilitating the digital transformation and fostering the improvement of societies. Additionally, from an educational perspective, the proposed processes, which are mainly oriented (but not limited) to agricultural engineering students, are utilized for better delivering the essentials of machine-learning techniques and various hardware, software, and networking principles as well as to raise awareness of sustainability issues and ways to contribute to more sustainable agricultural production practices. The demanding collaboration needed for the completion of the suggested system also offers the essential setting to reinforce several cooperative and organizational skills. Apart from that, the exploitation of retired or remaining/unused components is a good option, as they are inexpensive for the creation of educational scenarios, and they align with the common guidelines for sustainability and circular economy that modern communities are encouraged to adhere to [51]. In greater detail, during laboratory lessons experiences, university students of little technological background, were assisted to clarify cutting-edge technologies, and to bridge the gap between small-sized educational constructions and real-size systems. The experiments conducted have a very clear technological description in order to be easily reproduced by other teams of researchers/educators, but they are also strongly oriented towards sustainability, as they are dealing with subjects that intrinsically exist in the sustainability context, such as water preservation and pump equipment maintenance challenges.

To that end, this paper takes into consideration the material provided by two studies that use machine learning techniques for developing detection systems in order to address typical irrigation network problems. The first one introduces a water-misuse alert system [29], while the second one utilizes a classification model to detect water pump malfunctions in agricultural premises [30]. This article, except from providing a brief technical overview, is trying to explain how the latter systems can be transformed into effective educational instruments, suitable for serving the priorities of an agricultural engineering laboratory. It is an attempt to delve deeper into the integration of ML in the field of engineering from a scientific and educational standpoint, providing university students with the opportunity to combine hands-on methods and create smart agriculture solutions, often called "the future of the digitalization of farming" and "the driver of sustainable development".

3. Methods and Materials

Section 3.1 delves into the field of education for agriculture, defining the pedagogical goals and framework for acquiring both technical (hard) as well as interpersonal (soft) skills. Section 3.2 offers a concise summary of the enhanced farming systems and the rationale behind their design, to aid the understanding of the article.

3.1. Pedagogical Approach

From a pedagogical point of view, it is considered that the development of real prototype systems, for example a smart-agriculture application, will function as a crucial tool for problem-solving and aid in the integration of various disciplinary domains. Note that an indicative review of the STEM educational directions along with the related trends, can be found in [52–54] and the references within them, whereas the advantages from the synergy of incorporating STEM practices with agricultural are shared and significant [55,56].

In this regard, aiming for a more effective education in agricultural engineering, a water usage alert system was developed, and a retired water pump was exploited in order to be transformed into educational instruments. Below, the fundamental goals of the suggested approach, concerning the acquisition of skills, are referred:

- Enhanced comprehension of machine learning basics,
- Enhanced comprehension of networking basics,
- Enhanced comprehension of embedded systems basics,
- Improved ability of students to model and solve real-world problems,
- Equipment of learners with knowledge, capabilities, and values that contribute to sustainable development.

Furthermore, to cultivate better pedagogical results of the students' training in this approach, one priority was the development of several soft skills, including:

- Enhancing the students' communication and team-working skills,
- Enhancing students' confidence of their professors' efficacy,
- Assisting students' self-confidence to accomplish a project based on given instructions.

According to the abovementioned analysis of the expected outcomes, it is anticipated that students participating in these activities will demonstrate enhanced learning potential, improved skill development, and improved learning capacity for innovative technologies fostering sustainability. To evaluate the influence of the suggested arrangements on the attitudes of the students were recorded anonymously and voluntarily using five-point Likert questionnaires.

Over the span of the 10-month duration of the core activities related to machine learning, the persons participating in were: agricultural engineering professors (normally, one professor or two for each lesson activity), students working on their final thesis, students undertaking internships, and students involved in the curricular lesson activities. The mix of courses that the students attended during the semesters were: "Applications of Informatics in Agriculture", "Measurements and Sensors", "Electronics and Microprocessors", "Automatic Control Processes", and "Applications of Artificial Intelligence in Agriculture". Most students were in the age range of 20 to 26 years old. A team formation scheme was essential, aiming to assemble each group with members that had different but complementary capabilities, to some extent in accordance with the principles outlined in [57].

Challenge-Based Learning (CBL) provides an efficient framework for learning while solving real-world challenges, as it is an innovative teaching methodology that engages students to resolve real-world challenges while applying the knowledge they acquired during their professional training. Participants are encouraged to develop increasing interest for the subjects to be studied motivated by the significance of the problems to be addressed and their impact on society and well-being. Indeed, the CBL model has been applied to a large extend in higher education for groups of undergraduate students [58–60], and postgraduate students [61] and the results were positive, showing that the participants came up with innovative ideas to resolve challenges and improved skills and competencies. The benefits of the PBL [3] and CL [62] approaches, in terms of practicality and methodology, can be combined [63] and reinforced by the CBL technique to maximize the educational outcomes. As stated by Sukacke et al. [64] the implementation of active learning methodologies in education, such as PBL and more recently CBL, has become the new norm, especially in engineering universities, preparing future engineers for their professional careers.

The above philosophy is followed by activities being discussed, during which the instructors had the role to encourage and inspire the participants and to supervise the entire process, while the students in their teams, shared ideas and collaborated seeking for necessary information, comprehended techniques, conducted experiments, and executed challenging tasks of progressive difficulty. The students with greater experience served as mentors for the less experienced ones [65], thus assisting their professors.

Consequently, the primary challenges in implementing AI-based systems revolve around the absence of standardized programming practices and the insufficient multidisciplinary background knowledge of both trainers and trainees [66], thus selecting easy-to-use electronic parts as well as popular programming tools is needed. For the above reason, the activity being presented upgrades a water pump of convincing size and a faucet being used in real-world applications, while remaining plain and utilizing tools and components possessing these attributes.

3.2. Functionality Overview and Component Selection

This section provides, in brief, the overall functionality of both systems and the components selection for their development, while it additionally reports their role to be capable of executing important work related to water usage and pump functionality.

The aim of scenario A was the development of a system that can intercept and characterize water usage events. The water alert system included sensor nodes positioned at the place (edge points) where water is being consumed, along with appropriate sink/gateway node(s) to gather the reports transmitted by the peripheral nodes. The edge nodes, apart from collecting time series data corresponding to events that contained information about water usage, also possessed the intelligence to classify these events into categories of rational or irrational water consumption without depending on external entities. The user could monitor the operation of the entire system using portable devices (e.g., tablet, smartphone, or laptop) through traditional connectivity options.

In the case of the malfunction detection system installed on the water pump (scenario B), some common malfunctions were emulated for comparison with the normal operation of the water pump. Motion sensor data was recorded for four classes, which correspond to normal operation, and three cases of malfunction (inlet choke, outlet choke, and air intake) in addition to the fifth class of data with the engine switched off to simulate cases of inactivity. Therefore, a dataset containing five distinct classes was generated and a neural network model was developed that had the capability to identify each class. Additionally, a webpage was created to offer information to the user about the operation condition. More specifically, the hardware components being utilized were an AC centrifugal water pump (which was retired equipment), a water tank of a capacity of 50 lt, placed on a custom base and connected to the water pump via ¾ plastic hydraulic tubes interceded by plastic valves within each tube. These valves were quite significant components as they enabled the simulation of possible malfunctions. Moreover, readily available, well-documented, and cost-effective off-the-shelf hardware modules were employed.

Both systems incorporate an Arduino Nano 33 BLE Sense (Arduino, Turin, Italy) [67], which is a microcontroller board equipped with a robust processor that provides the ability to create bigger programs when compared to an Arduino Uno (Arduino, Turin, Italy) [68], with a 32 times bigger flash memory, and 128 times bigger RAM. In addition, a unit, based on the ESP8266 (Espressif Systems, Shanghai, China) [69] chip, for Wi-Fi connectivity options investigation, was used.

The Arduino Nano 33 BLE Sense device needed to be programmed in a way to:

- record and upload flow sensor data, specifically the interrupt signals corresponding to the pulses of the rotor rolling in the water flow sensor (scenario A),
- record and upload motion sensor data, specifically through its built-in accelerometer (scenario B),
- enable the essential networking connectivity (scenarios A & B),
- run the ML models (scenarios A & B),
- modular deployment with provision for implementations of diverse complexity.

The above prerequisites were fulfilled through the Arduino IDE (1.8.16) [70] programming environment, that was the most promising choice.

Regarding the machine learning part corresponding to both systems, training, and integration of each artificial neural network (ANN) [71] model into the software of the microcontroller was needed. Typically, the structure of an ANN model features a single input layer and some interconnected hidden layers, along with an output layer to provide the results. The Edge Impulse (EI) cloud environment was the platform chosen for the development of the ML models, as it is a straightforward and effective platform for developing ML models (encompassing training and extraction/compilation processes) tailored for edge devices [72]. EI accommodates a variety of development boards, including the Arduino Nano 33 BLE Sense, facilitating the immediate recording along with uploading the samples needed for the dataset. After the training, it also allows to directly deploy the model to the development board.

To make the procedures easily comprehensible for the students, the following deployment strategy was implemented:

- Installing a flow sensor on a typical water faucet (scenario A);
- Creating the basic water pump—water reservoir system plus the necessary valves emulating specific disturbances and installing an accelerometer sensor on it (scenario B);
- Connecting the sensors to a microcontroller so as to inspect and collect the readings of scenarios A and B;
- Training the ML model and installing it on an ML-capable microcontroller (e.g., the Arduino Nano Sense);
- Building an elementary networking functionality for easy inspecting the smart decision results.

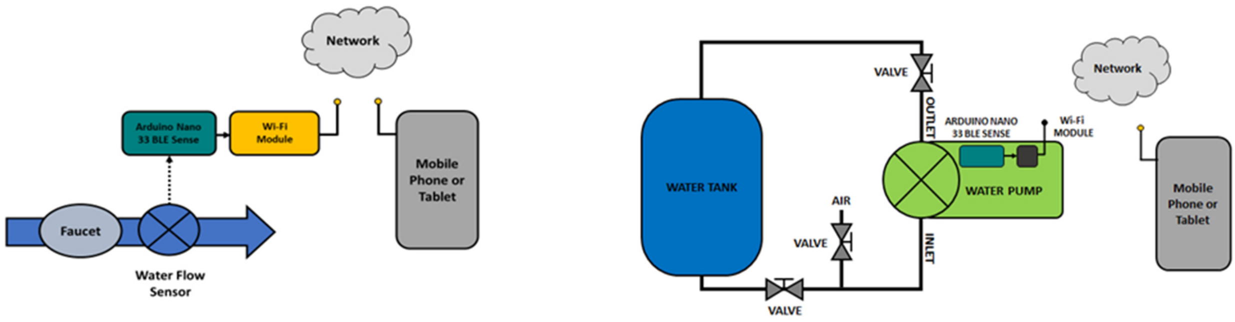
The design and execution of the project were purposely made modular to clearly define the specific functions of each component. This was aligned with the university curriculum and helped agricultural engineering students to better understand modern technologies. Despite using relatively simple components, a few challenges arose, triggering the interest of students, particularly due to the real-scale nature of the systems being proposed.

4. Design and Implementation Details

Section 4 is devoted to describing the crucial implementation details and challenges of the presented farm systems. In particular, Section 4.1 furnishes technical details pertaining to hardware and software issues while Section 4.2 covers information regarding neural network training. Section 4.3 specifies the details of on-device integration, and finally Section 4.4 outlines the hardware and software for the system at the end-user.

4.1. Description of the Basic System

The proposed implementation, regarding the water alert system, was built around an Arduino Nano BLE unit, being the coordinator of the main functions. For measuring the water flow, a Hall effect meter sensor (YF-S201 model) [73] was employed, capable of detecting changes in the flow of water as it passes through and rotates the rotor. This system is intended to be fixed close to a tap/faucet, so as the flow sensor to be connected in series with the water supply pipes, as depicted in the design overview of the system in Figure 1a. The second system that is being discussed involved a water pump that was designed to operate as a closed system, meaning that water was drawn from a 50-L tank and recycled back into the tank. Plastic tubes were used to connect the inlet and outlet of the water pump to the tank, intercepting by plastic valves to control the flow of water in each tube. An additional tube was attached vertically to the inlet tube of the water pump and had an open end that allowed air to enter based on the position of a valve. The Arduino Nano, equipped with an integrated accelerometer, was positioned on the side of the water pump to identify and differentiate the vibration patterns for each dataset. (Figure 1b).



(**a**) (**b**)

Figure 1. (**a**) Design overview of the water misuse system added in series to a standard faucet (system A); (**b**) Overview of the design of the malfunction detection system for water pump operation (system B).

During the implementation stage, to acquire the necessary data for training the model, a connection was established between the Arduino and a computer, via serial interface, thus enabling the straightforward recording, and uploading samples to the designated Edge Impulse project. This connection was also used for the compilation and uploading of the trained model to the Arduino Nano BLE, as well as to monitor the model's performance. Last but not least, the Arduino Nano BLE was connected to an ESP8266-based radio [74] to enable remote network connectivity, via a Wi-Fi link.

4.2. Neural Network Training

An artificial neural network (ANN) is a kind of machine learning model that is designed to emulate the configuration and functionality of the human brain, comprising interconnected nodes, or "neurons", responsible for processing and transmitting information [71]. The fundamental phases of a machine-learning model training and deployment can be summarized into 4 stages as shown in Figure 2. The initial phase involves acquiring data, a critical step that enables the training of an ANN model, which will impair the entire system with machine learning capabilities. This includes formatting the data, as well as splitting it into training and testing sets. The second and third steps detail the training process. During these stages, the suitable parameters are chosen to train the model by utilizing the prepared data and any required improvements are made, such as the learning rate and number of layers. Then using the testing data, the model evaluation is performed. This stage is crucial to determine whether the model requires modifications and to obtain an initial assessment of its accuracy. In the fourth step, the trained ANN model is integrated into the edge device (e.g., microcontroller) to enhance the system's functionality. The deployment of the optimized model to the edge device involves converting the model into an appropriate format and integrating it into the device's software or firmware. The deployed model should be tested to ensure its correct and accurate operation on the edge device.

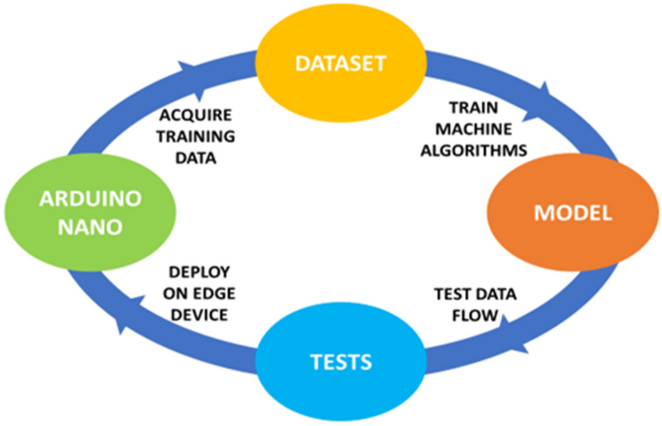


Figure 2. The necessary stages for the machine-learning training of the systems described and deployment on an edge device.

Firstly, in order to train a neural-network model, it is necessary to gather an adequate quantity of data for each specific class. The dataset for the water-pump malfunction-detection system included 5 classes: one for data corresponding to normal operation, three for simulated failures, and another for data categorized as noise. The length of the sample was five minutes or more, which is sufficient for this work, given its primary educational purpose. The gathered data must be divided into a training dataset, employed for training the neural network, and remaining data should be set aside to test the model's efficiency. When the data collected is automatically uploaded to the training set, it is recommended to allocate approximately 20% of them to the testing dataset. Nevertheless, this percentage can differ slightly since the total number of samples may not be divided accordingly. For these models, the split was conducted at a ratio of 78% to 22%, which did not have an impact on the model's overall accuracy or effectiveness.

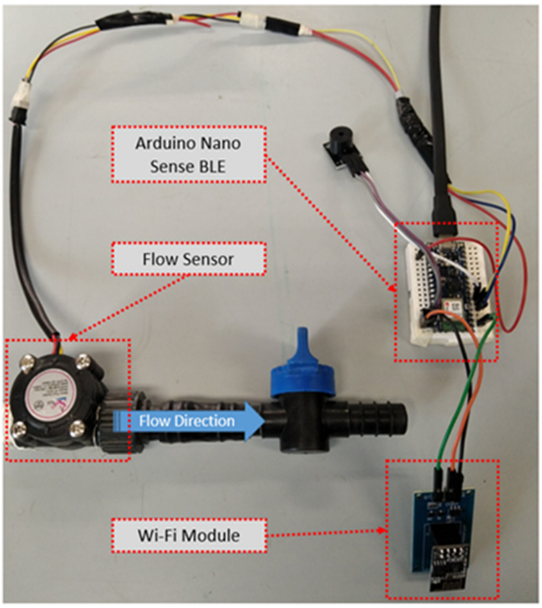
Once the requisite data has been collected and segmented, the subsequent step involves designing and training the model. This phase entails the incorporation of a processing block to modify the data and of a learning block that facilitates the selection of the specific neural network to be trained. The information was gathered using the built-in accelerometer of an Arduino Nano. To process this type of data, the appropriate block, "Spectral Analysis", was chosen since it can analyze continuous motion, such as accelerometer data, and extract the signal's frequency and power characteristics over time. In the learning block, we utilized a classification neural network library implemented with Keras. This library is equipped to learn patterns from input data and implement them to new data. This library is particularly well-suited for recognizing audio or categorizing movement, with the latter being the primary focus of this experiment. Moreover, the window size was configured to be 2000 ms (equivalent to 2 s), in accordance with the profiles input into the training system, taking into account the duration of the phenomenon. Similarly, the window increment was established at 80 ms, and the frequency was set at 100 Hz.

Yet for the water pump malfunction detection system, the processing block produced 33 features, which are then imported as the input layer in the training procedure. The intermediate layers comprised 10 and 5 neurons, respectively. Thirty training cycles were set, and the output layer encompassed the 5 classes. Following the training process, Edge Impulse can store the best performing model in the Quantized (int8) version, suitable for the Arduino hardware platform.

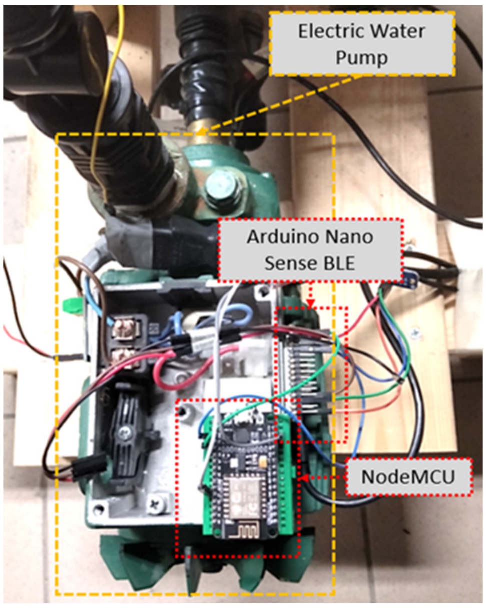
The same approach was followed for the development of the ANN model for the water usage alert system. The data related to water flow was transferred to the Edge Impulse cloud platform and then manually labeled before being automatically divided into training and testing data. To train the ANN model, a window size of 200 s was set based on how long someone uses a faucet, with a window increase of 1 s and a frequency of 1 Hz. Moreover, the "Raw Data" was chosen as the suitable processing block, along with "Classification (Keras)" as the learning block for the ANN. This allows for the original data to be used without any additional processing, retaining as many attributes of the original data as feasible. Thus, the neural network had an input layer with 200 features, two hidden layers with 20 and 10 neurons, respectively, and an output layer with three classes, namely NU, WL, and WW. The model was saved in the quantized version, that occupies 1.9 KB of RAM and 22.5 KB of flash memory, allowing it to be uploaded to the Arduino and run in real time. Indeed, the Edge Impulse platform allows to efficiently experiment with different settings in order to keep the best-performing model. The latter model can then be downloaded, as code, from the Edge Impulse platform that encompasses the library and sketches to be compiled and uploaded to the microcontroller using the Arduino IDE environment.

4.3. On device Integration Details

In the smart faucet case, the flow sensor and the ESP-01 radio module are powered from the Arduino Nano Sense BLE unit. On the latter device, interrupt signals are enabled so as to intercept the flow pulses, while the communication with the radio module is established through its hardware serial interface. Figure 3a depicts details of the prototype smart faucet system, while Figure 3b highlights the main electronic components of the water-pump malfunction-detection system.



(**a**)

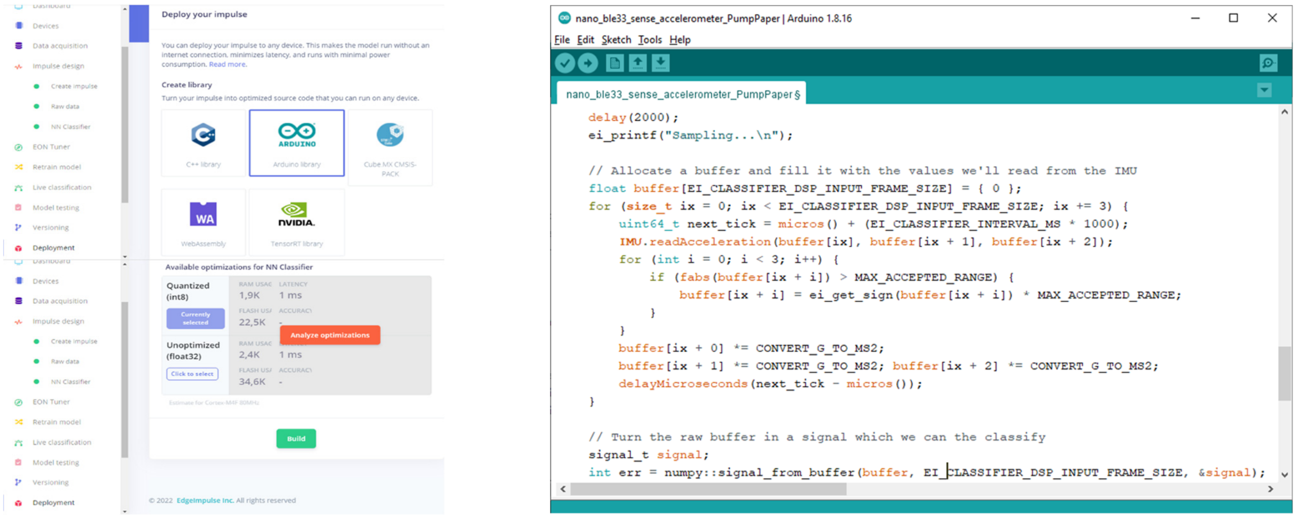


(**b**)

Figure 3. (**a**) Details of the prototype smart faucet system; (**b**) Details of the prototype water-pump operation malfunction-detection system.

In both systems, for simplicity and safety reasons, the power supply is done via the USB port of Arduino. Nevertheless, the flexible powering options of the main microcontroller were exploited to familiarize the students with battery-based variants, offering improved autonomy using a Li-ion battery of 18,650 type.

To enable real-time alert generation reflecting either pump malfunction or water misuse event classification, the Edge Impulse platform generated code in the form of an Arduino library as indicatively shown in Figure 4a, which could be used with the Arduino Nano 33 BLE Sense board. This flexible option helps to integrate the native machine-learning model with supplementary algorithms. Figure 4b depicts a screenshot of the Arduino IDE environment throughout the time of programming.



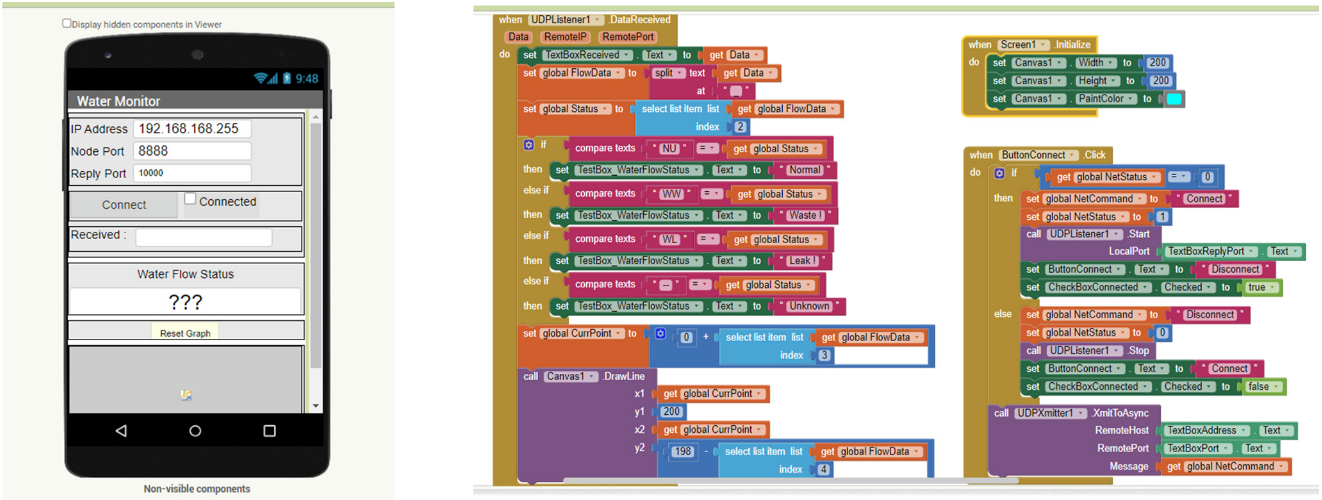
(**a**) (**b**)

Figure 4. (**a**) Indicative neural-network model deployment options via the Edge Impulse platform; (**b**) Indicative code including the trained model and the necessary modifications for fluent operation onto the microcontroller, using the Arduino IDE environment.

The classification outcomes were subsequently accessible to the user through TCP/IP connection offered by the ESP8266 core of the radio module. Indeed, two separate hardware variants were used in the experiments, utilizing the ESP8266 chip. For the smart faucet (i.e., the water alert) case, a minimal ESP-01 board (Espressif Systems, Shanghai, China) was connected to the Arduino microcontroller, while for the water pump malfunction detection case, the NodeMCU board (Espressif Systems, Shanghai, China) was the preferable option. The ESP-01 comes with preinstalled firmware that offers modem-like communication commands. This fact makes its connection with the Arduino Nano 33 BLE Sense more complex, and thus the original code was substituted by a version that supports direct Wi-Fi and TCP/IP client/server functionality, via the ESP8266WiFi library. The lack of a USB port on the ESP-01 module requires an additional module for (re)programming it. For this reason, on the water pump system, the NodeMCU variant of the ESP8266 chip was used, which is more user-friendly. The NodeMCU board was primarily set up as a small web server hosting a straightforward HTML page with dynamic content reflecting the operational status of the water pump. Although more advanced networking methods were available, they were beyond the objectives of this study.

4.4. Monitoring Arrangements

To receive and inspect remote alerts through Wi-Fi, a basic monitoring application was created utilizing the MIT App Inventor environment [75]. This application utilized visual blocks and was designed to be run on an Android smartphone (or other Android device, e.g., tablet), which are commonly used by modern and especially young users [76]. Various algorithmic flavors utilizing TCP, UDP and HTTP messaging mechanisms were implemented and tested with the participation of the students [69]. Figure 5a depicts the smart phone interface design details using the MIT App Inventor environment, while Figure 5b presents indicative code blocks defining the smart phone application behavior. Initial experiments involved direct communication between the in situ sensors and the mobile device of the user. In this case, either the sensor node or the smart phone was acting as a Wi-Fi access point while the other device was set as a wireless client. At the next level, a dedicated access point was utilized, i.e., a TP-LINK TL-WR841N device (TP-LINK, Shenzhen, China). The last set of experiments involved a separate gateway/sink node, developed using a Raspberry Pi 3 Model B+, to tackle multiple sensors delivering misuse/malfunction alerts. This node intercepts data statements from the other sensor nodes and stores them into files, making them accessible through a TCP/IP-based service. This task is performed using Python and Linux shell scripts, techniques using IP sockets [77], and the activation of preexisting on the Raspberry Pi applications like the Apache web server [78]. Further networking optimization might require services and security/privacy settings that were beyond the scope of this work.



(**a**) (**b**)

Figure 5. (**a**) Indicative smart phone interface design details using the MIT App Inventor environment; (**b**) Indicative code blocks defining the smart phone application behavior, using the MIT App Inventor Environment.

5. Results and Evaluation

The people getting involved into the corresponding evaluation study belonged to one or more of the following potential categories: students that participated in the construction, programming and training process of the two systems, students that were implementing small curricular projects of similar character, students that were explained how the pilot systems work, students that verified the functionality of the two systems by creating disturbance events (i.e., water waste or leak events or repositioning the valves of the pumping system) and by inspecting the corresponding results on their mobile phone screens. After finishing the above activities, the participants were asked to complete assessment forms and to provide potential remarks about the role of the proposed experimental systems incorporating machine learning techniques. In Section 5.1, technical details of these evaluation activities are highlighted, while Section 5.2 focuses on the educational counterpart.

5.1. Technical Aspect

Initially, the students assisted the process of data collection for both systems, that needed to be transferred to the edge impulse platform for the training of the machine learning models. Figure 6a,b depict the labeled raw data as shown from the environment of edge impulse during the features' generation process.

Following the training process, the confusion matrix of the model is generated automatically by the EI platform and the overall percentage accuracy is computed, as well as the testing accuracy of the model by utilizing data specifically reserved for this purpose is produced. Accuracy is the most used metric for evaluating classification models, often accompanied by a table in statistics known as the confusion matrix. Accuracy is the measure of the extent to which a model's predictions align with the actual reality, typically expressed as a percentage. In the realm of predictive analytics, the confusion matrix is a 2×2 table, providing information on the counts of true positives, false negatives, false positives, and true negatives [79–83].

Figure 6. (**a**) Water flow sample data used for training the smart faucet system model; (**b**) Accelerometric sample data used for training the water-pump malfunction-detection system model.

In the case of the water-misuse neural-network model, according to the EI cloud environment, the NU category was correctly classified with an accuracy of 77.8%, the WW categories attained a 100% success rate and similarly the WL category reached 100% accuracy. These results led to a final model with an expected accuracy of 96.59% utilizing the testing data set as depicted in Figure 7a. In the next stage, the system was tested with actual episodes of water consumption (i.e., NU, WW, or WL) by appropriately rotating the tap head to allow the machine learning engine to classify the flow data gathered in segments of 200 consecutive values. The analysis of the collected data showed that the accuracy of the water-consumption prediction model was 91% when tested utilizing user-generated profiles with the recommended smart water metering system. It is noteworthy that the model was able to accurately identify unwanted WL profiles, with accuracy rates of up to 100%. However, some incorrect predictions were made, with the ML model confusing an actual WW situation as NU or WL.

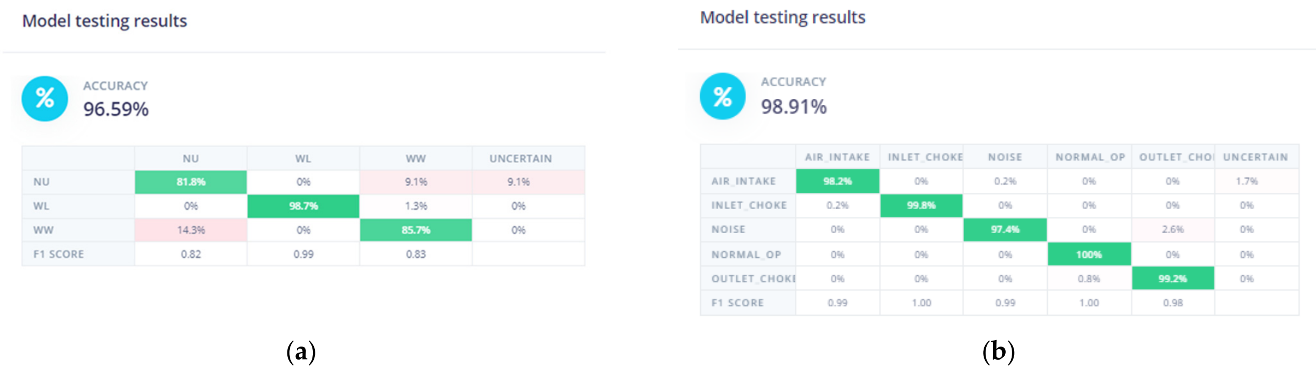
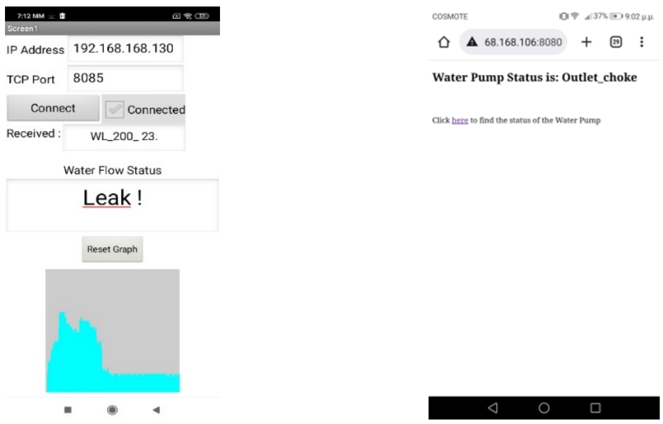


Figure 7. (**a**) Estimated performance of the machine-learning model for the smart faucet system; (**b**) Equivalent results for the water-pump malfunction-detection model.

Similarly, the accuracy of the system detecting water-pump malfunctions was evaluated by analyzing the platform results and conducting experiments with data that was not used in the training process. The overall accuracy percentage, as reported by the Edge Impulse, was 98.5%. The system achieved 100% accuracy for the normal operation category, while the accuracy rate for the air intake category was 97.2%, the accuracy rate for the inlet choke category was 99.8%, and for the outlet choke category, it was 96.7%, all according to the EI environment. These resulted to a total model accuracy score of 98.91% based on the testing dataset as shown in Figure 7b. Furthermore, a secondary assessment was conducted in order for the model to be tested on the actual system after classifying 1056 episodes. The analysis of the collected data showed that the overall accuracy reached 93.02% when the model was tested for malfunctions created by the students when manipulating the valves integrated into the system's design.

The inspection of the systems' performance was achieved through web interfaces and applications, as depicted in Figure 8a,b. The students used their smartphones in order to examine whether the model expected accuracy was reflected to the actual operation of each system. More specifically, students verified the functionality of the two systems by creating water misuse events (Figure 9a) via repositioning the valves of the pumping system (Figure 9b), and monitoring the corresponding results on their mobile phone screens. The recorded results indicated that 9 over 10 predictions were correct, which is in line with the performance of each machine-learning system, as explained in [29,30].



(**a**) (**b**)

Figure 8. (**a**) Indicative smartphone screenshot during the students' inspection process, detecting a water leak event; (**b**) Equivalent smartphone screenshot reflecting the water-pump status during the in situ experiments.

(**a**) (**b**)

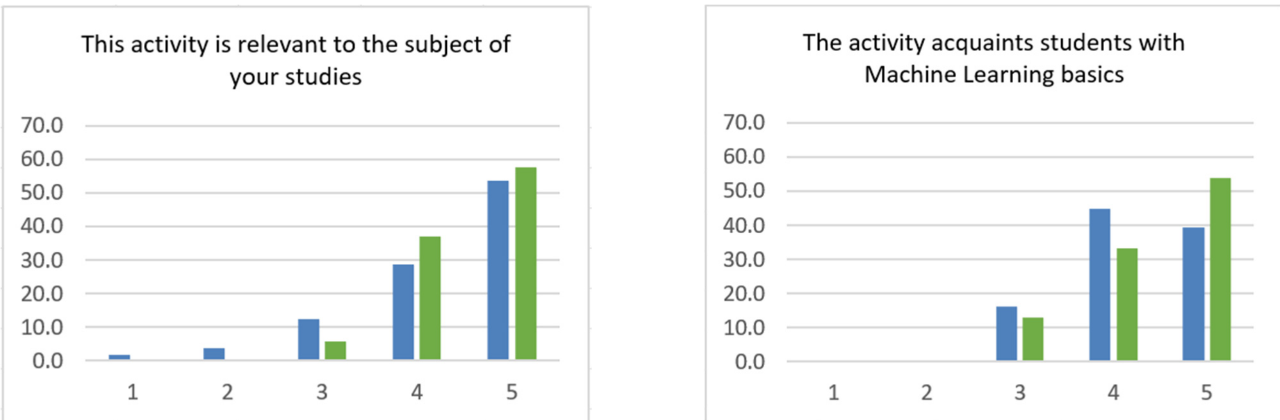
Figure 9. (**a**) Students inspecting the operation of the prototype smart faucet system during the in-situ experiments; (**b**) Students were repositioning the valves of the smart pump system emulating malfunction events.

Finally, the students verified the actual performance also in terms of power efficiency using an accurate amperemeter connected in series with the electronic components of the sensor node. Each of the two detection systems consumed a few tenths of mA during its activity. According to experiments performed inside the university campus, the Wi-Fi radios were offering a range coverage of 100–150 m, at line-of-sight conditions. More specifically, the perceived signal strength of the ESP8266 radio was reported to the user and the connection link could sufficiently transfer data up to the −90 dBm border. Data rate of a few packets per second was enough to sustain the notification messages from the in-situ device toward the user. Although the focus of this study is more put on the machine learning functionality aspect of the proposed malfunction/misuse detection systems, these performance data is also necessary to be mentioned, as they are essential for understanding any IoT approach.

5.2. Educational Aspect

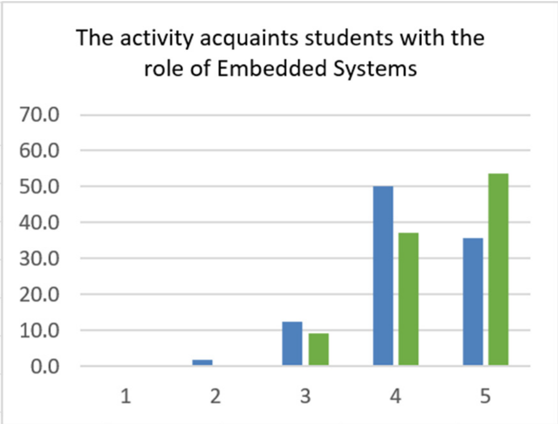
University students (both undergraduate and postgraduate) took part in all the stages of the development of the proposed systems, from the initial planning and design to the implementation, and final evaluation. The students engaged in those activities (55 participants in total), ranged from beginners (63.6% of them) to more experienced (36.4% of them), depending on their involvement in STEM activities, whether as part of their curriculum or extracurricular pursuits during the ten-month period of study. These participants were anonymously and consensually interviewed, through electronic forms [84] in Likert scale [85] questions to evaluate the entire process. An illustrative set of initial results, which are being collected and processed, is depicted in Figures 10–16. In the following charts, the bar height (vertical axis) illustrates the proportion of individuals with a particular level of agreement regarding the statement depicted above the chart. Blue bars refer to the water alert module and green bars pertain to the water pump fault detection system. The horizontal axis represents the characterization of opinion groups by a numerical scale ranging from 1 to 5, where the numbers 1 represent "Strongly Disagree", 2 stands for "Disagree", 3 denotes "Neutral", 4 indicates "Agree", and 5 signifies "Strongly Agree".

In all instances, the configuration was kept as open and inexpensive as possible to demonstrate high modularity and reusability of the units. This approach enables various educationally meaningful experimentation activities [63]. The survey results suggest that involvement in the entire activity was helpful for comprehending fundamental hardware and software topics, as well as for understanding the role of embedded systems (Figure 11a), and the proposed activities exhibit to be highly relevant to their courses at the university (Figure 10a). More specifically, most of the participants expressed that the activities acquaint them with machine learning and networking basics (Figures 10b and 11b, respectively), which are of great importance for giving intelligence to common systems.

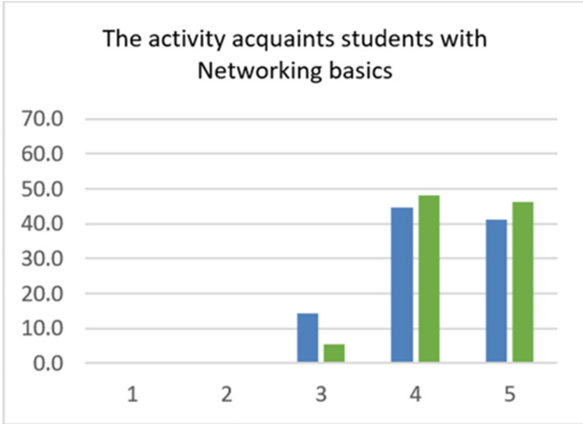


(**a**) (**b**)

Figure 10. Participants' opinion about: (**a**) whether these activities are relevant to the subject of their studies; (**b**) the impact of the proposed activities on understanding machine-learning concepts.

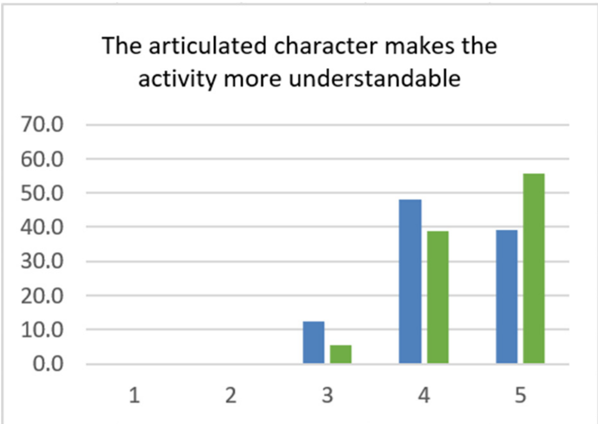


(**a**)

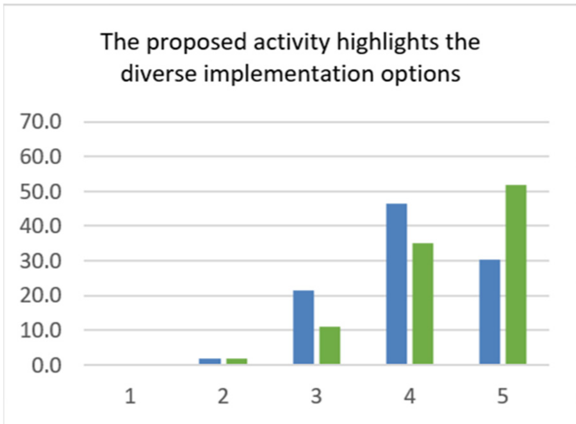


(**b**)

Figure 11. Participants' opinion about the impact of the presented activities to understanding: (**a**) the role of embedded systems; (**b**) networking basics.

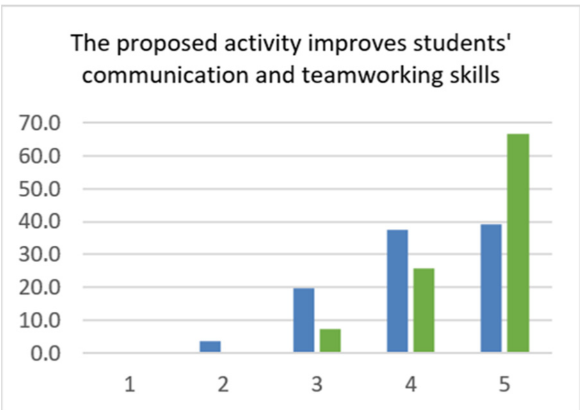


(**a**)

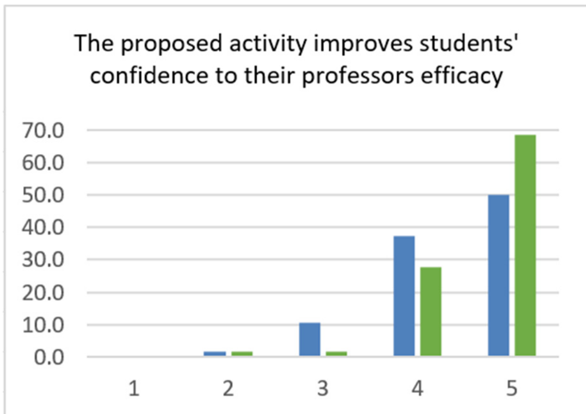


(**b**)

Figure 12. The views of the participants regarding the extent to which: (**a**) the articulated character makes the activities more understandable; (**b**) the proposed activities highlight the diverse implementation options.

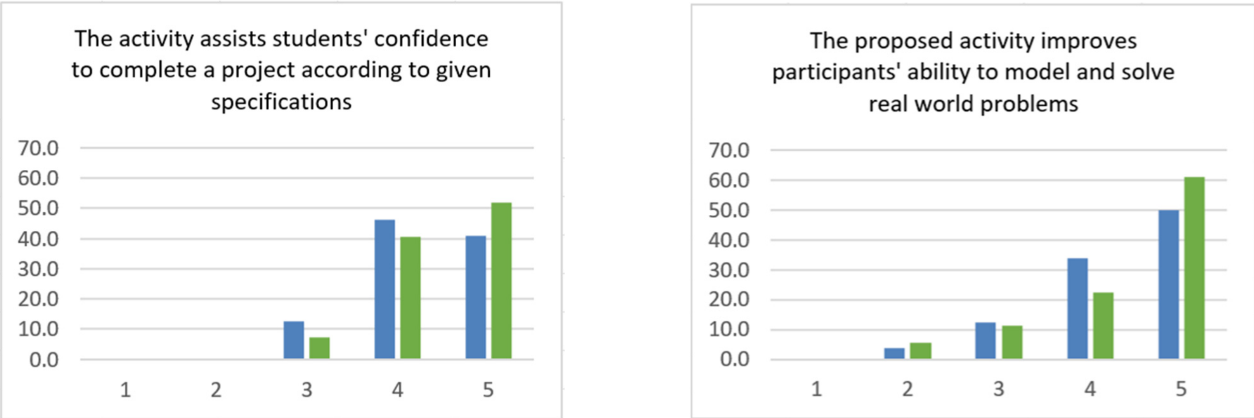


(**a**)



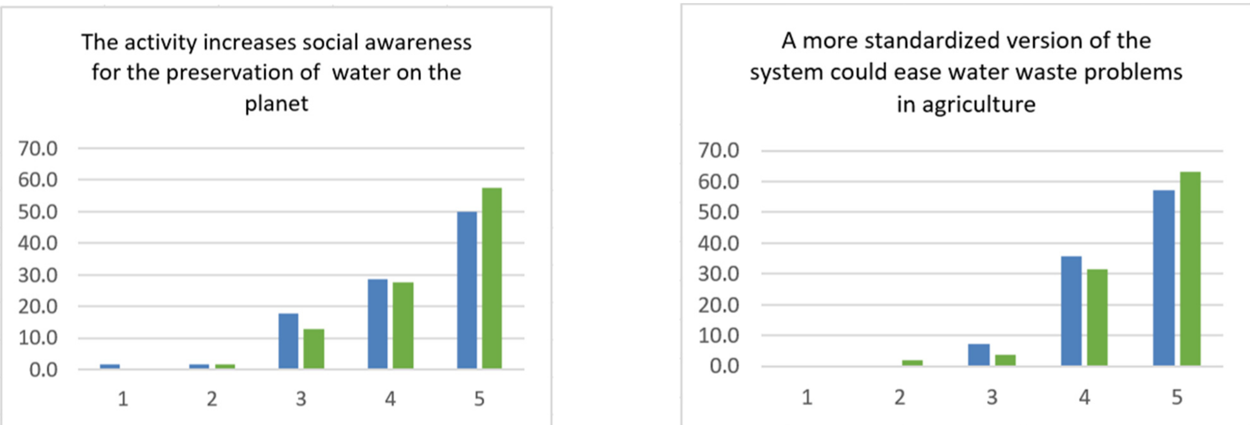
(**b**)

Figure 13. Participants' perspectives on the extent to which the presented activities improve: (**a**) students' communication and collaboration skills; (**b**) students' confidence in their professors' efficacy.



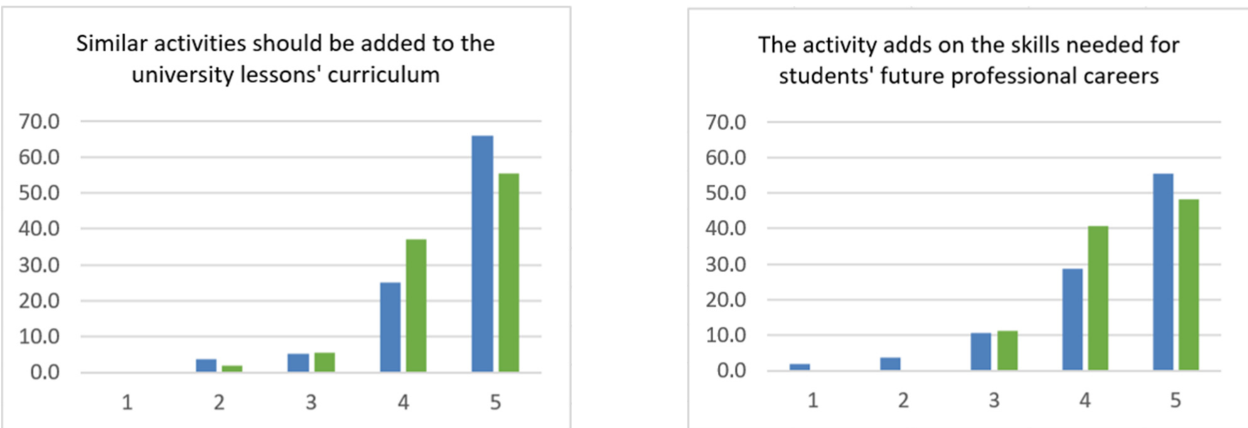
(**a**) (**b**)

Figure 14. Viewpoint on the degree to which the presented activities: (**a**) Assist students' confidence to successfully finish a project based on provided specifications; (**b**) improve participants' ability to model and solve real-world problems.



(**a**) (**b**)

Figure 15. Viewpoint regarding the degree to which: (**a**) the proposed activities raise awareness in society about the importance of preserving water on the planet; (**b**) more standardized versions of the systems could ease water-waste problems in agriculture.



(**a**) (**b**)

Figure 16. Opinion about: (**a**) whether comparable activities should be incorporated into the university curriculum; (**b**) the influence of the suggested activities on students' acquisition of skills for their professional careers.

Moreover, the respondents found that the articulated character of the systems was more understandable (Figure 12a), while at the same time, the diverse implementation options were emphasized (Figure 12b). Similarly, participants' viewpoints regarding the contribution of the presented activity to their soft skills acquisition were very positive. The involvement in the proposed activities improved students' communication and team working skills (Figure 13a) and enhanced students' confidence in their educators' efficacy (Figure 13b).

It is noteworthy that the detailed hardware and software configurations of the project served as lens, highlighting the challenges in the ongoing upgrade process. Based on the feedback from the respondents, the overall activities boosted their confidence in completing a task according to given specifications (Figure 14a), while improving their ability to model and solve real-world problems (Figure 14b). Significantly for these benefits, besides the Arduino programming community and the user-friendly Edge Impulse platform, was the facilitation of the MIT App Inventor cloud-based environment, enabling code sharing and rapid prototyping, along with the raspberry pi, which supports various programming sessions and allows for examining the behavior of the embedded system.

As explained, in Figure 15a, participants believe that this initiative enhances social awareness regarding the conservation of water worldwide, and a better standardized variant of the system could alleviate water wastage issues in agriculture. (Figure 15b), which are of great importance, as explained in the previous sections. Finally, it is worth highlighting that most participants believed that similar topics should be included in the university courses curricula (Figure 16a), while they also believe that the proposed activities triggered students' interests and were pertinent to the skills required for their future professional careers. (Figure 16b).

The suggested approach was adjusted to introduce and foster communication among students about the fundamentals of machine learning, which is an essential process for many agricultural operations and are connected with other contemporary technological methods of the digital era, such as networking. It must be noted that, based on the literature review and the current state of agricultural management, it can be inferred that there are limited specialized educational courses addressing these concerns [41]. The findings presented align with and build upon previous educational discoveries in the field [63,66,86], as they fulfill the objectives of agri-food professionals involved in the shift towards sustainable agriculture. Indeed, according to the study presented in [87], upcoming professionals require skills that foster an attitude based on diversity and the inclusion of various information, methods, and experiences, along with the ability to respond and proactively engage in a dynamic world.

5.3. Further Discussion

Throughout the activities presented, the instructors maintained a supportive and unobtrusive role, offering guidance and advice when requested. During the laboratory lessons, professors aimed to capture students' interests by gradually introducing topics in terms of complexity and rewarding students' daily improvement. The fact that the more experienced students, serving as mentors, was also of paramount significance. The optimistic attitude towards the different technical challenges in the process of upgrading water equipment proved to be the most effective paradigm, fostering further creativity and improvement.

Some non-machine-learning critical parts should be programmed and optimized independently and the entire program (sketch) for the Arduino Nano 33 BLE Sense unit should be kept as straightforward as possible. This is because compiling sketches for the Arduino Nano 33 BLE Sense unit requires extra time than those intended for the standard Arduino Uno platform. Furthermore, considering the implementation of the artificial neural network (ANN) model generated by Edge Impulse, the compilation duration variability was extended, i.e., to sometimes exceed a 15-min period. For these reasons, the decision being taken to utilize a second, inexpensive, and faster-to-program Arduino-based device (such as the NodeMCU board), to accomplish the auxiliary tasks with minimal interaction with the Arduino Nano 33 BLE Sense unit, facilitated the experiments.

Furthermore, favoring a slight overfitting of the neural-network models aimed the students to understand the connection between the data used for training and the final behavior. Additionally, the simplified models aided the students in comprehending the entire training process and the individual stages being necessary. These settings allowed them to experiment with diverse features and generate more than one machine-learning model variants to select the most suitable one, in reasonable time and processing cost from an educational approach perspective. In general, as the possibility of experiencing failures in either the educational or the technical settings of the activities being discussed is always present, the overall approach should be kept as simple as possible.

Moreover, a challenge in this rapidly evolving area is the capability of using and being familiar with new technologies. For this reason, potential educators getting involved should be able to proceed beyond the narrow limits of their specialty, in order to organize and assist student teams, and to provide advice for solving the difficulties that arise. Added to this, they should be able to keep meticulous records and documentation of the overall process, a practice that fosters the reproducibility of the good practices being experienced. The latter attitude is also helpful for not losing valuable educational and technical resources typically acquired from the cloud, which are frequently liable to drastic changes due to their innovative character.

The selection of components was not as optimal as possible from a commercial production perspective, i.e., trying to find a good compromise between cost minimization, decent system performance, and educational friendliness. The latter (and most important) objective was favoring well-documented components with high modularity and reusability potential and comparatively easy assembling. In this regard, the utilization of the Arduino Nano 33 BLE Sense, the Edge Impulse platform, the MIT App Inventor and the Arduino IDE environment was fully justified.

In this regard, incorporating Wi-Fi technologies and smart phones was a good practice from the educational point of view, as young people tend to adore these devices and are familiar with the corresponding wireless network settings. Nevertheless, for the future, realistic IoT experiences would require the engagement of more optimized technologies, such as LoRaWAN radios (LoRa) [88], and the implementation of sleeping/waking-up functionality on the sensor nodes, along with a more fluent monitoring software, providing access beyond the limits of the university laboratory wireless local area network (WLAN).

It is worth mentioning that extremely useful feedback, referring to the systems being investigated, was provided by the students that are traditionally being more capable for unbiased thoughts, compared to their professors. More specifically, some participants proposed the system to incorporate functions that stop the pump from working, through a relay, on malfunction detection, or to close the water supply to the faucet via an electric valve, on water waste or leak events. The subject of efficiently powering the smart systems being installed in situ, was also a fruitful field for inquiries, as students proposed solutions utilizing the water flow itself (via a micro turbine) for generating the necessary current for the smart faucet system, or solar panels solution for both systems and even for their actuating part (i.e., for the pump, the relays, and the valves).

By harnessing the capabilities of machine learning and artificial intelligence, we can not only monitor water preservation more effectively but also significantly improve the availability of pertinent information. These advanced technologies will enable us to analyze vast datasets in real-time, identify patterns, and make predictions related to water usage and conservation practices. This enhanced level of data-driven insights can empower decision makers, researchers, and environmentalists to devise more informed strategies for sustainable water management. Ultimately, the integration of machine learning and AI systems in monitoring water preservation not only increases efficiency but also lays the foundation for smarter, more adaptive water-resource management in the face of evolving environmental challenges.

The directions for implementing an affordable water usage alert system and water pump fault detection system, despite being in their early stages, can be beneficial for various real-world scenarios in both urban and rural areas, which is an encouraging outcome of the research conducted. To expand the scope of the research, the proposed systems and methodology will be further optimized and evaluated from both technical and educational perspectives. This will provide a more comprehensive set of results and practical solutions for various real-world applications. In this direction, the development of a commercial standards version for the discussed water alert module is being considered and pump's fault detection system will be a significant priority. Plans involve additional system enhancements, utilizing similar cost-effective components, and/or implementing other structures following a similar upgrading approach. The motivation is to enable the students of today and professionals of the future to experiment with a plethora of real-world challenges that they will face in their careers and contribute to a more sustainable future.

6. Conclusions

In this paper, two systems are demonstrated aiming to orchestrate educationally meaningful activities, for higher education, focused on water preservation and sustainability. In greater detail, a retired water pump for agricultural premises and a faucet were utilized and transformed into smart IoT systems, with the assistance of machine learning and embedded low-cost microcontrollers with networking capabilities, graphical user interfaces and smartphone devices. The greatest challenge was to form the necessary paradigm without sacrificing the real-world application suitability potential that these systems have and simultaneously to keep implementation reproducibility and cost at reasonable levels. Widely available hardware and software components were selected exhibiting easy-to-use character and fluent documentation.

According to the initial survey findings, the case being presented suggest that the approach is effective in achieving the increase of social awareness about water conservation while enhancing students' understanding of IoT and ML matters that are crucial for their future careers. The proposed approach assisted the participants in the educational activities to acquire multidisciplinary benefits, i.e., gaining more technical knowledge while simultaneously implementing applications that contribute to sustainability objectives. University students of little technological background were assisted to demystify cutting-edge technologies, and to bridge the gap between small-sized educational constructions and real-size systems. According to the survey findings, similar activities should be incorporated into the curricula of educational institutions and foster the future professional careers of the participants.

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Informed Consent Statement: Students' consent was waived due to not involving identifiable personal nor sensitive data.

Data Availability Statement: The data presented in this study are available upon request from the corresponding author.

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Conflicts of Interest: The authors declare no conflicts of interest.

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