Hardware Accelerator for Ethanol Detection in Water Media based on Machine Learning Techniques

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***Abstract*—In the last years, the Industry 4.0 paradigm is gaining relevance in the agro-food industry, leading to Smart Farming. One of the applications in the Smart Farming domain is the advanced chemical analysis in process monitoring using distributed, low-cost embedded systems. Optical sensing technology is used in conjunction with machine learning techniques for this advanced analysis. From the embedded system perspective, it might be required to propose a method for the implementation of machine learning techniques in heterogeneous platforms. This paper focuses on implementing Machine Learning techniques in a System on Programmable Chip, based on an FPGA and ARM processors. As a use case, we mimic water pollution by ethanol. Thus, the application might determine the percentage of ethanol of the water during run-time. As a result, this paper provides a methodology for implementing a machine learning technique for ethanol prediction using an FPGA, and the study of its parameters as resource utilization and accelerator latency for the architecture proposed.**

***Index Terms*—Smart Farming, Optical Sensing, Machine Learning, Feature Extraction, SoPC.**

I. Introduction

Nowadays, productivity, efficiency, and automation are the pillars of the industry, whose improvement has strong relevance in this domain [1]. Furthermore, the integration of the Internet of Things (IoT) paradigm inside the industry environment led to the creation of Industry 4.0. One of the relevant objectives of Industry 4.0 is the development of advanced data analysis for optimizing resource usage, reducing the faults and the system downtimes [2].

The application of Industry 4.0 paradigm in the agro-food industry does not only search for the improvement of productivity but also sustainability, and it is also known as Smart Farming. Its purpose is to bring more sophisticated control of processing, farm, and logistics, increasing the food quality monitoring [3]. From the advanced data analysis perspective, food processing requires more advanced chemical detection for the identification of certain compounds in fluids during run-time, for instance, identifying pollutants in water.

Currently, advanced chemical analysis, such as compound detection, is done out of the monitoring process. Commonly, fluid samples are analyzed in specialized laboratories. Therefore, the system downtimes and time responses might not be suitable for certain processes. There are approaches based on measuring physicochemical properties during run-time, although they cannot be used for sophisticated chemical analysis, as compound detection in fluids [4]. For advanced chemical analysis, optical sensing has strong relevance due to the capabilities of spectroscopy. Nevertheless, it is done outside the monitoring process because of the complexity of the sensors, acquisition and processing systems. Advances in the optical sensing domain, such as micro-structure optical sensing systems, reduced the size and cost of photonic transducers. This development allows to integrate these transducers inside the embedded systems, generating a framework for advanced fluid monitoring at run-time.

Depending on the chemical composition, fluids might have different Refractive Index (RI) values. Changes in the RI might be used to determine fluid properties, for instance, the concentration of a particular molecule inside a fluid. Resonant Nano-Pillars (RNPs) transducers, based on nano-structures, are capable of measuring the RI changes of the fluid where they are dived. The signal of RNPs transducers consists of a frequency domain response, generating a high amount of variables to process in each measure. Hence, the generation of a mathematical model is a sophisticated task. Due to the complexity of the photonic signal processing, in spectroscopy domain, there is a trend based on applying machine learning techniques [5], [6] for compound detection. These techniques generate a model using a dataset from the application. As a result, machine learning models should fit better compared to traditional models.

In the continuum cloud-to-edge in the IoT, machine learning techniques are usually solved in the cloud layer due to its high computational capabilities. In [7] a smart farming approach is developed, whose machine learning and statistical techniques are computed in a server. This might increase the time response of the control and communication loads and might reduce the security of the system. In terms of machine learning for water quality, there is an intent for the use of machine learning techniques for processing this system [8], [9]. However, it is done outside the monitoring process. For improving these metrics, there is an effort of moving some machine learning techniques from the cloud to the edge. Furthermore, there is a current trend in smart farming for deploying intelligence inside the sensors [10]. Apart from the low-power and low-cost requirements, edge devices, which implement machine learning techniques, should also be flexible to be adapted to different application constraints, such as latency, energy consumption or changes in the machine learning model. Heterogeneous embedded platforms based on FPGA technology, such as System on Programmable Chip (SoPC), can achieve this flexibility, while accelerates the machine learning techniques in the FPGA side. Moreover, low-computational tasks might run in the ARM cores.

To adapt machine learning approaches to edge devices, we focus on the following Machine Learning structure: Feature Extraction and Machine Learning Model (see Figure 1). The feature extraction reduces the number of input variables which are going to feed the model. Then, the reduced set of variables will be applied to the model, whose output is the value of the desired monitoring property, for instance, the percentage of a compound in a fluid.

According to the water pollutants, we propose to identify the percentage of a compound which is not commonly present in water. In particular, the use case consists of detecting the percentage of ethanol in water media, mimicking contamination during a chemical process.

Based on this, the purpose of this paper is to present a hardware-accelerated implementation for fluid characterization inside SoPCs, based on machine learning techniques and RNPs transducer signals. To this end, the paper follows a methodology for implementing machine learning algorithms in resource-aware platforms. Moreover, the use case provides a framework for evaluating not only the machine learning system but the performance of the machine learning system inside the heterogeneous device. As an expected contribution, this paper presents a hardware architecture for predicting the amount of ethanol in water media, using a hardware accelerator controlled by a processor. This accelerator integrates the machine learning technique for the ethanol prediction.

The remainder of this paper is structured as follows. Section II describes the methodology followed and the hardware architecture. Section III includes the dataset from the use case and the evaluation of the machine learning system and the hardware architecture. Section IV comprises the final remarks and future work of the research.

II. Methodology and System Architecture

In this section, we present the sensors technology, the design of the machine learning system, the feature extraction method, the heterogeneous system architecture inside the SoPC, and the hardware architecture of the machine learning approach.

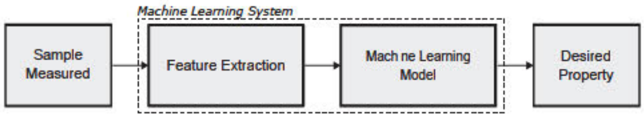

Fig. 1: Embedded Machine Learning System

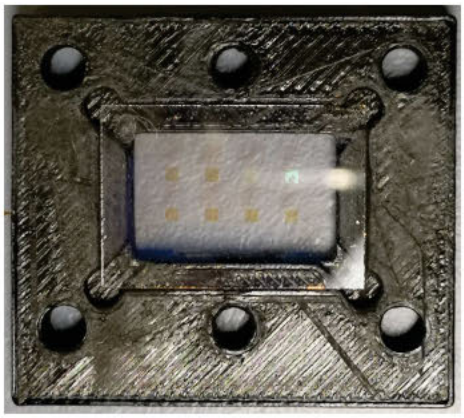

Fig. 2: RNP Photonic Sensor [11]

A. RNPs transducer

The sensor is manufactured as a chip with a layer of the quartz substrate. In this layer, 8 square cells of $1mm^2$ of nano-pillars arrays are distributed (see Fig. 2). Each cell of nano-pillars is considered as an RNPs transducer. Each Resonant Nano-pillar consists of 10 pairs of Bragg Reflectors with a central cavity of $200nm$. The diameter of the pillars is close to $200nm$, and the height is approximately $2000nm$.

These photonic transducers are passive devices, and it is required to use an external light source to stimulate the transducer and acquire the light, reflected by the RNPs transducer, with a spectrometer. This light has an interference pattern that depends on the RI of the surrounding media. A response from the RNPs transducer can be seen in Figure 3, which has a Photonic Band Gap with a resonant mode in the center. Additionally, each point of this signal corresponds to the intensity value of a particular wavelength, being the number of points in the range of thousand points.

B. Machine Learning System Design

As it is shown in Figure 1, our embedded system receives the response of the RNPs transducer from the acquisition system. The input data consists of an spectral response from the RNPs transducers, which has 3648 points. The points are the number of input variables the system has. From the machine learning point of view, this is a high-dimensional problem. Therefore, our machine learning approach is composed of two stages: Feature Extraction and the Machine Learning Model (see Figure 1). The Feature Extraction technique consists of a dimensionality reduction method. Thus, the feature extraction

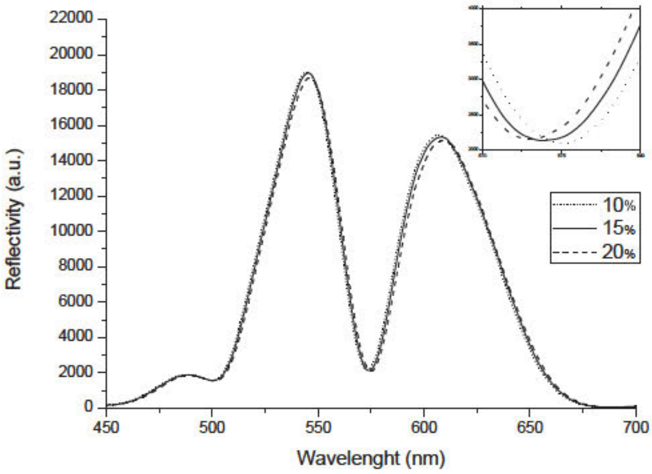

Fig. 3: Response of RNPs transducer in the ethanol detection

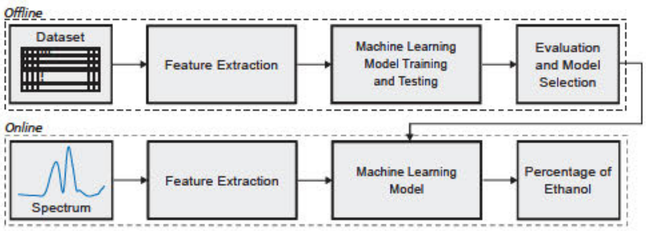

Fig. 4: Development of a Machine Learning Approach for Embedded Systems

methods reduce the input variables space (m) to a lower one (n), being $m >> n$. This set of n variables is used for the model to infer the desired property.

As introduced before, the machine learning model has to identify the percentage of ethanol. In this regard, it is necessary to provide labels to the machine learning approach for model generation. The type of machine learning which uses labeled dataset is called supervised learning [12]. In this case, the label corresponds to the theoretical percentage value of ethanol. High computational capabilities are necessary to create a machine learning model, therefore, this task is done offline. Offline tasks are executed out of the embedded system, for instance, on a computer or a server. On the other hand, online tasks correspond to the tasks deployed in the embedded system for inferring the percentage of ethanol (see Figure 4). In both, offline and online tasks, the feature extraction method is required.

For offline tasks, the first step is to develop a labeled dataset. This dataset comprises the measures from the RNPs transducers, called instances. Each instance is composed of the value of the input variables and the label. The model generation has two phases: training and testing. In this regard, 10-fold cross-validation is proposed for training and testing. Before the training phase, we select the machine learning models. In the training phase, the parameters of the selected models are calculated. Once this phase is finished, in the testing phase the machine learning models are evaluated according to particular performance metrics.

The percentage of ethanol of a fluid is a continuous variable, thus, the machine learning approach which might be followed is regression learning. Moreover, in [13] it is demonstrated that there is a linear correlation between the RI of the media, measured by the RNPs transducer, and the compound detection. Therefore, we propose to explore four well-known regression learning models: Linear Regression, Interactions Linear, Robust Linear, and Stepwise Linear. The performance metrics used for evaluating these models are: Root Mean Square Error ($RMSE$), Mean Absolute Error (MAE) and coefficient of determination (R^2) [14], [15].

After the training and the testing, a designer should select which model has to be deployed in the embedded system regarding the performance metrics. Thus, we developed a hardware accelerator which implements the feature extraction and the selected model. This model is also called inference. Moreover, an architecture is created for controlling this accelerator and for testing the accelerator behavior.

C. Feature Extraction: WSRM method

As introduced before, feature extraction methods might be used in order to enhance the model generation based on machine learning techniques. The objective is to reduce the model complexity and its computational load. Moreover, the reduction of the number of features might lead to a reduction of the noise fed into the model.

There are multiple feature extraction approaches, however, in this paper, we focus on the Wavelength Shift of the Resonant Mode (WSRM) method. The WSRM method is commonly used in the literature for RNPs signal characterization [16], [17], [18], [19]. According to the response of the RNPs transducers (see Figure 3), there is a minimum local point between the two local maximum points, this minimum local point is called the resonant gap point. In [19] a correlation between the Refractive Index of the fluid inside the transducers and the resonant mode displacement is presented. Hence, the displacement of the resonant mode might depend on the ethanol concentration.

Therefore, this domain-expert method searches a single point from the whole signal of the response of the RNPs transducers, the resonant gap point. Hence, this method reduces the number of input variables, the response signal ($m = 3648$), to one variable, the resonant gap position ($n = 1$). As a result, it gives the wavelength where this particular point is placed.

D. Heterogeneous System Architecture

For the development of the heterogeneous system architecture, we propose the utilization of an SoPC. This type of platform adds flexibility to the system design and development, providing control and communications capabilities. According to the heterogeneous systems, there are multiple platforms depending on the computational requirements. However, we decide to focus on low-cost platforms from Xilinx, the XC7Z010 platform, to minimize the deployment cost. The

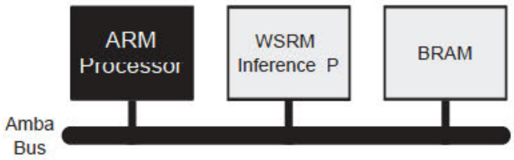

Fig. 5: Heterogeneous System Architecture

architecture developed in the SoPC for this application consists of an ARM Cortex-A9 processor, a WSRM-Inference IP, and the RAM are connected by an AMBA bus (see Figure 5).

In this processor, a Linux OS is deployed to manage the external communications of the embedded device, the hardware accelerator control and the write operation of the RAM. The use of Linux OS not only permits to update the software layer during run-time but to modify the hardware architecture of the FPGA part. Therefore, Dynamic Partial Reconfiguration techniques might be applied to update the model during run-time without stopping the embedded system.

From the dataflow perspective, a software program receives a complete measure from the RNPs transducer, then, it loads the BRAM of the FPGA and starts the IP core. The IP core receives the start order, from the ARM, and applies the WSRM method and the model, called WSRM-Inference IP core. Once it finishes the operation, it saves the result, the percentage of ethanol, in a register and sets a flag to indicate to the processor that the operation is done.

From the hardware architecture point of view, instead of using an external RAM, we use a Block RAM (BRAM) integrated into the SoPC for saving the measurement from the RNPs transducers. The objective is to gather all the resources inside the FPGA. The flexibility permits to add other IPs, BRAMs or the external RAM, whenever the system requires it. The architecture was developed using the Vivado tool from Xilinx, which permits to manage communication and RAM parameters. The development of the device tree is made using the Vivado SDK tool, and the SW application was directly made on the Linux OS.

E. WRSM-Inference Accelerator

After developing the software prototype and its verification, the next step is to create the hardware architecture of the IP core. The tool used for developing the IP core hardware architecture was Vivado High-Level Synthesis (Vivado HLS). High-Level Synthesis tools permit to describe the architecture by means of High-level languages, instead of hardware description languages, leading to a reduction of development time.

On the one hand, the WSRM method has access to the BRAM. It fetches, sequentially, the measured values to identify the resonant gap. Once the resonant gap is found, the value is passed to the model. The constants used by the WSRM method and the Inference model are written in particular registers by the processor, during the hardware programming of the FPGA. Moreover, this approach can adapt the model during run-time only modifying the values of the registers. As in the SW design of the system core, the 32-floating point is used in the IP in order to maintain the same level of accuracy. Moreover, in HLS there are pragmas which permit the designers to modify the architecture. In this case, we use the Unroll pragma which tries to increase the parallelization of the accelerator. As the WSRM is a search algorithm, the Pipeline cannot be used due to the fact in this strategy there are dependencies between the current value analysed and the previous values.

III. Experiments and Results

In this section, we present the datasets used for training and testing the machine learning system, the parameters selected to define the experiments and the results obtained.

A. Dataset

The machine learning techniques proposed in this paper are based on supervised learning approaches. Therefore, it is necessary to provide a labeled dataset for training and testing (see Section II-B. Furthermore, this dataset is used for testing the resulting machine learning application implemented in the SoPC. The dataset generation consists of adding pure ethanol to a water media from 1% to 20%, applying steps of 1%. In each step, 200 measurements were done, thus, the dataset has 4000 instances.

The use case consists of inferring the concentration of ethanol in the fluid, thus, we have to label each instance with the amount of ethanol which the water media contains.

The variables of the dataset correspond to the intensity values of the wavelengths interrogated in each measurement. This transducer operates in the visible waveband. Due to the sensitivity of the spectrometer, 3648 variables were obtained. As a result, we obtained a dataset of 4000 samples, with 3648 input variables and its corresponding label.

B. System Evaluation

In this section, we train and test the machine learning approach proposed in Section II-B. Moreover, a trade-off might be established between different regression learning techniques attending the performance metrics. The objective is to provide a machine learning approach before the architecture application.

For training and testing the machine learning techniques, the Statistical and Machine Learning Toolbox of Matlab is used. In this regard, the supervised regression learning techniques selected are Linear Regression, Interactions Linear, Robust Linear, and Stepwise Linear.

From the dataset point of view, first, we update the dataset applying the WSRM method. Instead of having the input variables for training and testing the model, the dataset will provide the resonant position gap value and its label. As a result, we reduce the number of features from 3468 variables to 1 variable (see Section II-C).

Table I shows the values of the performance metrics for each regression learning technique. The robust linear technique

TABLE I: Machine Learning Algorithm Evaluation.

Machine Learning techniques	RMSE (%)	R^2 (%)	MAE (%)
Linear Regression	1.1219	0.96	0.9502
Interactions Linear	1.1219	0.96	0.9502
Robust Linear	1.2445	0.95	0.9317
Stepwise Linear	1.1219	0.96	0.9502

presents the largest RMSE value, having the largest error and indicates that, compared to the others, it is the most sensitive to outliers. Furthermore, it has the lowest R^2 value, thus, the model fits the data worse. Therefore, this regression technique is not selected. Attending to the other techniques, the results obtained in terms of performance metrics are equal. Thus, we decide to select the Linear regression technique due to its simplicity for the online inference in the SoPC. The equation of the online inference is given by,

$$Inference(\%) = -1.1466 * 10^3 + 0.7414 * rpg, \quad (1)$$

where rpg is the resonant position gap of the spectrum. Analysing the results of this method, it could be generalized to other compounds which have a correlation between the RI and percentage changes.

According to the heterogeneous platform, we select the XC7Z010 device, from the Zynq-7000 Xilinx family, as the low-cost SoPC for developing the application. We analyze the resources utilized by the IP core using the Vivado HLS tool. We study the parallelization of the system applying the Unroll pragma. This pragma indicates the number of times a bunch of code is parallelized.

Table II shows the resources utilized and the latency obtained for a particular value of the Unroll pragma. As this pragma increases the value, it also increases the system parallelization and, therefore, it might decrease the latency. However, the latency starts to increase from the Unroll value equal to 4. In the system, there is a bottleneck related to the search algorithm of the WSRM. The WSRM compares consecutive values, thus, the limiting factor comprises the time of accessing the BRAM for a wavelength intensity value. According to this solution, the minimum latency achieved is in Unroll pragma equals 4. From a resource perspective, only solutions from Unroll pragma from 0 to 4 are relevant because, for the same latency, they use fewer resources. As we increase the number of Unroll values, it is shown that in Unroll equals to 20 the number of DSP is reduced. As the algorithm can not improve its performance in terms of execution time, the increment of logic generated (FFs and LUTs) is used to reduce the number of DSPs. Moreover, the system clock for the synthesis and the implementation is 100 MHz.

TABLE II: WRSM-Inference Performance for XC7Z010 platform for different unroll values.

Unroll	DSP Usage (%)	FF Usage (%)	LUT Usage (%)	Latency (μs)
0	5	5	17	220
2	5	7	24	200
4	5	12	37	190
6	5	19	54	200
20	2	21	66	240

IV. Conclusion

In the Industry 4.0 domain, there is an effort for implementing advanced data analysis inside the process. Particularly, in the Smart Farming field, advanced chemical analysis during run-time is being required for enhancing the monitoring. The optical sensing technology, such as RNPs transducers, is able to provide advanced chemical analysis using machine learning methods. To integrate this technology inside the process, it requires to deploy this data processing inside low-cost, low-energy and resource-aware systems, such as heterogeneous embedded devices. This paper proposes a methodology for embedding machine learning methods inside SoPCs, particularly FPGAs. Moreover, a hardware accelerator is developed which executes a feature extraction method and the inference for ethanol detection application. According to the flexibility of the platform, a trade-off is established between the latency of the WSRM-Inference accelerator and the resources utilized. The designers can choose a minimum latency of 190 μs, using 37% of LUTs, or minimum resource utilization, using 17% of LUTs, with a latency of 200 μs for this application.

For future work, the integration of the acquisition system directly to the FPGA might be a system improvement. Furthermore, from the edge layer domain, it would be useful to add a power consumption analysis as an application performance metric. Moreover, the search algorithm of the WSRM method might be improved to avoid current bottlenecks. Also, a device might be created to testing this system in an industrial environment.

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