An Application with *Jetson Nano* for Plant Stress Detection and On-field Spray Decision

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Abstract: Increasing field productivity is not just a financial need, but also a social issue. Several technologies converge to promote food production and, in this context, the fog computing paradigm can support the development of solutions for precision agriculture. This paper proposes an application of the Jetson Nano device, embedded in an agricultural spraying implement. This device supports the decision on irrigation activity, based on data collected by sensors distributed in the field. The sensors read information about the plant's stress level from electrical signals and the Jetson Nano enables real-time analysis, through machine learning algorithms, to manage the product spray rate, according to the condition of the crop. Initial studies validated the proposed solution on an experimental basis, showing that the device can be an alternative for this purpose, since it can be used efficiently in machine learning tasks from data collected by the sensors. The experiment also highlighted some limitations of the proposed solution, such as the importance of observing the conditions of the system as a whole, its context and environment, in order to improve performance in spraying process.

1 INTRODUCTION

Agriculture is the fundamental basis for human survival, however, in recent years, some factors arising from the evolution and globalization of society are impacting agricultural production, restricting the development of the sector and worrying producers. As shown in (Zhou et al., 2011), the three main reasons for these concerns are: (i) the aging of the agricultural population, migration from rural to urban areas and, consequently, a reduction in rural labor; (ii) large constructions invading rural spaces and, therefore, reducing the production area; and (iii) increased climate change, such as temperature, rainfall and soil moisture, which affect crop growing conditions in unpredictable ways.

Internet of Things (IoT) and Artificial Intelligence (AI), among other innovative technologies, have been promoting major changes in the agricultural scenario (Misra et al., 2020). These technologies not only solve the problems related to the increased demand for food and environmental pollution caused by the use of pesticides without proper control, but also promote intensely the continuous development of agriculture. The increased use of IoT devices in agriculture has led to a huge growth in the use of sensors and the growing number of data to be processed. Allied to these technologies, the concepts of Edge Computing (Shi et al., 2016) and Fog Computing (Bonomi et al., 2012) emerge. These paradigms intend to meet application requirements, such as the need for greater reliability, hardware weight (size, location and number of machines), and network and power consumption (Byers, 2017). This model allows the investigation of data processing performance close to the place where they are produced and/or needed (Baller et al., 2021).

Since there is less processing power in edge and fog devices, applications in these contexts are instantiated in a specialized manner, dealing with a single problem. In recent years, one of the contexts in which research in edge and fog computing has increased was precision agriculture, due to the great impact caused by technology in the agricultural sector. The *Smart Farms* concept has been leveraged in recent years by IoT devices. Its use allows farmers to receive near real-time data about farm conditions. With the smart farm concept under construction, Artificial Intelligence (AI) strategies (Li et al., 2018) have been incorporated into the solutions. From the potential to reduce the need for human interference in field management processes, these strategies in general need some level of edge computing, so the devel-

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opment of solutions goes through the search for devices capable of performing these processes. Thus, the key is to identify edge devices that have hardware resources capable of processing AI techniques. Among the edge devices available on the market, we have the *Jetson Nano* (Nvidia, 2021) as a possible solution. This device is a embedded computing board from NVidia, which contains a low power system and hardware resources like GPU, designed for accelerating machine learning applications.

Therefore, this work investigates the feasibility of using the edge device *Jetson Nano* for the implementation of AI techniques, focusing on the identification of the stress level in bean plants. This paper extends previous results of (de Toledo, 2019) in which plant stress state classification techniques were successfully performed using neural networks and machine learning. The main contribution intended is to validate the use of the mentioned device for an application that measures the amount of agricultural inputs, water, fertilizers, pesticides, etc., in an agricultural implement. This is possible through the analysis of data collected by sensors spread across different regions of the crop, which serve as input to classification algorithms that indicate the stress level of plants in that region. So, based on that stress level, each region receives a specific amount of spray. From the experiments carried out, it was possible to validate an application model with the Jetson Nano device for the detection of stress in bean plants, which enables the use of this information for real-time decision-making in the spraying of agricultural products in the field.

The paper is organized as follows: Section 2 presents works related in precision agriculture; Section 3 presents the proposed application design for practical use and Section 4 the case study developed and initial experiments, as well as a discussion of the results. The conclusions and possibilities for future work are presented in Section 5.

2 RELATED WORK

The use of IoT devices has allowed a lot of achievements, since the intelligent objects connected to sensors allow their interaction with the physical and logical world without the need for human intervention. However, even if the Internet itself is not needed, some form of communication support for the edge/-fog devices must be available.

In (Saraf and Gawali, 2017), an intelligent agricultural irrigation system, monitored via an Android smartphone, is proposed. Field communication support is provided by the Zigbee protocol, which ensures communication between sensors and a base station. The system performs real-time readings that are presented in a web-based interface to the user. So, the user interaction can be through their smartphone, controlling the water distribution. In (Kamilaris et al., 2016), a framework capable of connecting and monitoring numerous sensors is presented. The collected data, as well as the decisions made by the sensors, are collected by a central database and then made available in a cloud. AgriSys (Abdullah et al., 2016), using Fuzzy logic, explores the cloud in the same way, but deals with the desert's challenge: dust, infertile sandy soil, constant wind, very low humidity and extreme variations in daytime and seasonal temperatures.

In the works cited, for its full functionality, the use of network resources is necessary, either for the collection of monitored information or for sending commands to perform actions on the field. However, providing access to network services in the agricultural context is expensive, mainly due to the use of energy for communication on farms with a large area to be covered. Considering these aspects, solutions that minimize network consumption have emerged in the context of precision agriculture.

As an alternative, WSN (Wireless Sensor Network) type network protocols and their low-power and/or long-range hardware resources were developed, such as the LoRA protocol. This protocol has been used in places where other networking technologies are not supported. However, the low bandwidth offered is a characteristic of the protocol, which must be considered when designing solutions. In (Gia et al., 2019) a case study is presented using LoRA to establish an edge layer connecting the sensors to each other and to a gateway. The gateway then regroups the information collected in its coverage region and forwards it, in a single message, to a concentrator.

In order to reduce the need for the use of network resources, recently, edge computing concepts have been introduced as an alternative to cloud computing and aim to maximize processing close to the data generation point. Thus, a new generation of applications for precision agriculture has been exploring the use of machine learning techniques embedded in edge devices, to distribute data processing across application layers and reduce the transmission of information between them.

Also, popular ML techniques (*Machine learning*) have been employed in systems. Such techniques include K-NN (*K-Nearest Neighbors*, SVM (*Support Vector Machines*), ANN (*Artificial Neural Networks*) among others, which have been shown to be of great value. Its effects and applicability are diverse, in (Kamilaris and Prenafeta-Boldú, 2018), they demonstrate the different algorithms that have been used in search of the best result in the agricultural environment. Applications are focused on tasks such as analyzing plant images for anomalies, fruit counting, weed detection and even fire outbreaks. Moreover, inadequate spraying tends to mistreat plants, pollute water near the harvest and below ground. In (Liakos et al., 2018), he demonstrates that it is possible to have even greater control over the amount of spraying required and the size of the sprayed area.

Few proposals provide more information about *hardware* or even propose one that can serve from small to large farms. In (Imran et al., 2020), the authors present a review of the main embedded devices found on the market with processors capable of running AI algorithms at the edge. In (Proietti et al., 2021), the authors present a study that aims to develop a system based on Deep Learning that will be applied in greenhouses in order to detect anomalies in plant growth. To develop the solution, embedded devices NVIDIA Jetson Nano and Raspberry Pi 4 Model B were used, capable of using a complete deep learning framework such as TensorFlow (Abadi et al., 2015). In (Kawai and Mineno, 2020), the validation of an automatic irrigation system in tomato plantations using edge AI and the embedded devices NVIDIA Jetson Nano and Raspberry Pi 3 Model B is performed.

All these possibilities for the application of new technologies in agriculture are having promising results and enabling the growing use of IoT and AI edge technologies. Thus, our motivation in this work is to validate a solution for detecting the stress level in common bean, using edge devices for the execution of AI algorithms in model training and data classification tasks.

3 PROPOSED SOLUTION ARCHITECTURE

The proposed solution is based on the previous work documented in (de Toledo, 2019), which uses the black bean *BRS-Expedito* species for a laboratory experiment. Like any plant, beans are subject to multiple environmental variations, some of which generate stress, such as lack of water resources and soil salinity. These stressful situations lead to financial losses. However, the manifestation of stress can be observed by reactions involving changes in electrical activity in the plant (Maffei and Bossi, 2006).

In (de Toledo, 2019) experiments were carried out to monitor seedlings submitted to induction stress, with application of solutions that generate situations of lack of water and salinity. To induce stress in the plants, three solutions were used: *NaCl*, *Polyethylene glycol* and *NaCl+Polyethylene glycol*. For each type of stress, 30 experiments were performed. Each experiment monitored the electrical activity of 3 individuals for 4 consecutive hours, two hours before application of the solution and two hours after. The capture of electromas from the plants was carried out with electrodes inserted in the plant, with a reading rate of 62.5 Hz. The time series produced, for each two-hour range, has, therefore, 450,000 readings (electromas). These data were input to classification algorithms, using traditional computational resources. In the methodology used, each sequence of 30,000 points, equivalent to 8 minutes of monitoring, was represented by three values: average, maximum and minimum of the values captured in the period. The interval of 30 thousand points was adopted, according to the author, as it presents a better result in terms of accuracy. According to the discussion presented, the results showed a high success rate in recognizing the plant's stress situation.

Extending this idea to the field scenario, a solution is proposed for monitoring a crop, as well as collecting and processing data through the *Jetson Nano* device embedded in an agricultural implement. The base model of the designed application is shown in Figure 1, where, in a crop, a set of plants is selected for monitoring, in a distributed way, allowing each monitored point to represent the situation of the surrounding plants. In detail, the monitored plant and the monitoring device are presented. This device is capable of storing the time series that represents the evolution of the plant's electromagnetic signal. This device is also capable of responding, via a wifi network, to the request to send the collected data.

Eventually, this agricultural implement circulates over this plantation, spraying agricultural inputs such as fertilizer or pesticides, or even water. The amount of product to be sprayed in a given area can be identified in real time by rating the stress level of the individual monitored in that region. A device on this implement requests, via a wifi network, information from the plant being monitored in the different regions to calculate the amount of product needed in each region. Also, if available and depending on the application, meteorological data can be used in the decision-making process to complement the information available for analysis.

Among the small board options to meet the objectives of this work, the option chosen was to use the *NVIDIA Jetson Nano* coupled to the agricultural implement. The choice was based on the wide use of this device embedded in edge solutions for agriculture, according to related works, which motivated the acqui-

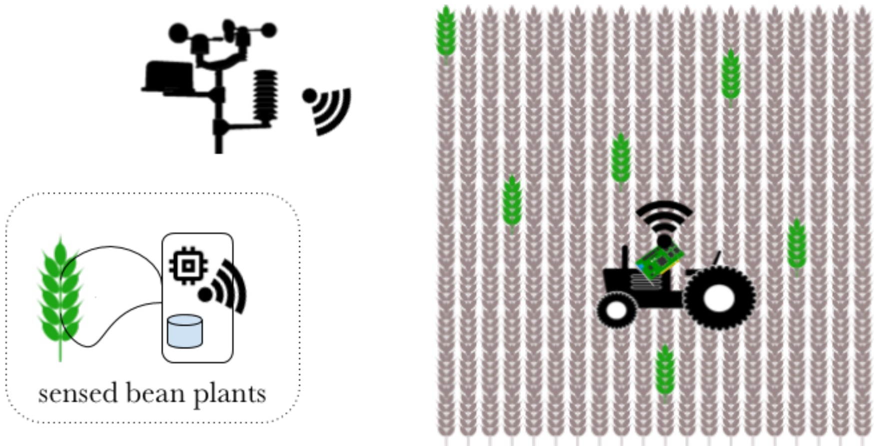

Figure 1: Proposed application model.

sition of this hardware in this research project. Basic technical specifications of the device can be found on the supplier's website (Nvidia, 2021). This device is focused on meeting the recent demands of handling data at the edges. With a GPU for processing, this device is capable of supporting the execution of programs with great processing needs, such as image processing, computer vision and deep learning, as is the case in this work, with low energy consumption (between 5 to 10 watts).

Furthermore, this type of device can be easily integrated into an agricultural implement since its reduced dimensions do not imply adjustments to the machinery structure. In fact, this equipment does not necessarily need to be permanently attached to an implement, which can enable the use of the same device in different implements. This can be specifically adjusted according to different aspects such as machine model and number of devices available.

Given its characteristics, the *Jetson Nano* meets the four major needs, mentioned above, related to the concept of edge computing, such as reliability, hardware weight and low energy consumption. The other items that make up the infrastructure shown in Figure 1 are not detailed in this article due to space limitations. This paper documents the evaluation of the *Jetson Nano* to determine if this device makes the proposed solution feasible within this scenario.

4 METHODOLOGY AND TECHNICAL FEASIBILITY

In general, the main objective of the work is to establish a proof of concept for the use of the Jetson Nano device in agricultural applications to processing data sensed by IoT devices. The data were stored in a time series format and used for decision-making in spraying tasks, through machine learning algorithms. Thus, it is intended to identify the feasibility of using an equipment embedded in an agricultural implement to, during its operation, in real time, identify the stress level of bean plants and make a decision regarding the spraying of inputs on the field.

To validate the proposed solution, a bench situation was simulated, using real data from a previous agricultural experiment, seeking to observe the performance of the Jetson Nano device for the available data set, as well as designing a real application through use that device. Next, the observed performance of the Jetson Nano as an option for on-board equipment is presented, as well as a discussion of the impacts of this solution. All data considered in the present study are those collected in the experiment documented in (de Toledo, 2019).

4.1 Implementation of Classification Algorithms

The time series that represent the data collected from the plants are stored in a text file, with one sample per line, and preprocessed, transformed into triples, as mentioned above, to reduce the data volume. The result obtained is a lower processing demand for the classification algorithms, with no loss in result quality. These values are stored in a spreadsheet in *.csv* format, where each line represents a measurement range, with the first three columns corresponding to the minimum, average and maximum values of the range. In model training, the fourth column informs if the plant has any stress (1 means stress and 0 no stress).

The collected data were used in the training of classifier models to identify the substances. The algorithms used were *K-NN, SVM* and *ANN*. The choice was made based on the investigation of solutions typically used for these scenarios, and, for the purpose of this article, for performance analysis, all algorithms were used based on default parameters. The implementations were in *Python*, using two machine learning libraries: *Scikit-learn* (Pedregosa et al., 2011) in the first two and *TensorFlow* (Abadi et al., 2015) for the other.

To measure the classification accuracy, the input data set (around 15,000 entries) was divided: 70% of the data were used in the model training and 30% for the accuracy test. With regard to classification accuracy, the results obtained with *K-NN* and *SVM* showed the best results, reaching 70% and 60%, respectively, of accuracy, while the *ANN* had 54%. In this step, all the algorithms were used with the standard parameters of the mentioned libraries, that is, in this first moment, the algorithms were not tuned, since the initial results were considered interesting. The focus here is to analyze the performance of the algorithms in terms of execution time for training models and for classifying a new input.

After measuring the performance in terms of accuracy, we focused on identifying the feasibility of the solution in relation to the time needed to classify a new sample. In this implementation, using the *Time* library, two timestamps were set, marking the start and the end of the execution. The time difference between the two points then corresponds to the time needed for classification. To manipulate the data sets, *Pandas* data analysis and manipulation tool (Pandas Development Team, 2020), one of the most popular open source library in this domain for Python, was used. Algorithm 1 presents the code used to measure the time spent in classifying a new entry by a model trained with the K-NN algorithm. The *text1.csv* file (line 6) contains the collected data.

Within the measured time (between lines 5 and 14), the following tasks are considered: data import (line 6), model training (lines 10 and 11) and classification of a new point (line 12). Now, 100% of the available inputs are used for training, and only one point is predicted (line 15). The implementation with the SVM algorithm follows the same logic and code structure. For the implementation of the ANN was used also the same code structure, but adding the library *Keras* (Chollet et al., 2015) to the aforementioned libraries. In short, the ANN was composed of three layers, with 3, 5 and 5 neurons each, *relu* activation method, Stochastic Gradient Descent (SGD) optimizer and trained in 100 epochs. Due to space limitations, the complete codes are not presented in this paper, but can be made available by contacting the research group.

Algorithm 1: K-NN measurement.

```
 1 import pandas as pd
 2 from sklearn.neighbors import
       KNeighborsClassifier
 3 import time
 4
 5 start = time.time()
 6 dataset = pd.read_csv('test1.csv')
 7 data = dataset.iloc[:, 0:3].values
 8 clas = dataset.iloc[:,  3]
 9
10 knn = KNeighborsClassifier(
11                 n_neighbors=5,
12                 metric='minkowski',
13                 n_jobs= 2)
14 knn.fit(data, clas)
15 knn.predict
       ([[-363464.0,-23718.2,126343.0]])
16
17 end = time.time()
18
19 print("time:")
20 print(end - start)
```

Table 1 presents the times taken by the classification algorithms, both on a desktop computer and on the *Jetson Nano*. The times correspond to an average of 30 runs, where the distribution of samples corresponds to normal. After the executions, the system was always restarted, in order to guarantee a standard execution situation, avoiding that the consequences of a execution, such as the temperature of the components, could influence the other executions and, consequently, cause differences in performance. The desktop processing was done entirely in CPU, while the *Jetson Nano* used the GPU. The desktop times (*Intel i5, 2/4 colors/threads, 8 GB RAM*) are presented illustratively, aiming to identify the distance of the processing times obtained with the Jetson Nano to a standard desktop computer configuration.

4.2 Performance Analysis and Discussion

Regarding classification accuracy, K-NN and SVM presented better classification of the stimuli to which the bean plants were submitted in the bench experiments. ANN, on the other hand, had lower accuracy indices. A more in-depth study of the parameters applied to classification algorithms is considered necessary in order, in a *tunning* process, to identify the best configuration for the application in question. However, considering neural networks, it is a fact that a greater amount of data in the training stage may re-

Table 1: Average time of algorithm executions (in seconds).

Device	**Desktop**			**Jetson Nano**		
Algorithms	***ANN***	***K-NN***	***SVM***	***ANN***	***K-NN***	***SVM***
NaCl	0.14	0.11	0.05	2.90	0.15	0.20
Polietilenoglicol	0.13	0.11	0.06	3.00	0.14	0.19
NaCl+Polietilenoglicol	0.14	0.12	0.20	3.00	0.16	0.70

flect better classification success rates. This aspect is relevant, because the K-NN and SVM algorithms need the training data to be available, and to be manipulated, at each new classification. Thus, can be considered valid to perform the prediction time analysis in the ANN algorithm, since for this network it is not necessary to access the training base to perform a new prediction. The consequence is a smaller amount of memory needed on a device in the fog, a desirable requirement in this type of application.

Regarding the practical application of the proposed solution, it is necessary to analyze the impact of classification execution times in the real world, since the average speed of an agricultural implement in the field is less than 15 km/h, or 4 m/s. It is observed that the average execution times of the algorithms on the *Jetson Nano* are, in most cases, less than 0.2 seconds, which is equivalent to a displacement of 0.8 m. Thus, these results validate the use of the device for the purpose, as it is capable of dealing specifically with the classification task in almost real time.

However, a significant problem was perceived in the task of collecting and preprocessing the data, which took a considerable time slice of 54 seconds, considering a data entry of 450,000 samples, at intervals of 30,000 samples, as detailed above. In terms of displacement, the agricultural implement would have traveled more than 200 m, moving away from the region where the measurement was taken. In addition, the communication times between the sensor and the device embedded in the implement must also be added to the times presented.

Regarding communication, let's consider a *LoRa* (Long Range) (Alliance, 2015) network, quite popular as network infrastructure in smart farm applications, with an average range of 15 km in open areas and transmission rate between 0.3 to 50 Kbps. Therefore, from the technical specifications of this network model, it is possible to observe that, even with the high volume of transmitted data, the proposed solution is valid. If we consider a median value for the transmission rate of 25 Kbps, the time to send data (6 MB) is around 240 seconds, which represents a displacement of less than 1 km, that is, the implement will still be within the network's coverage area. In this way, the machinery could start data collection and classification when it is at least that distance from the spray application point.

As the proposed scenario has an experimental character, it is possible that we have variations in the field area that each sensor will cover. However, given the long-range coverage of the Lora network, there is good scope for a project to deploy sensors within a significant coverage radius.

Furthermore, seeking to overcome these observed limitations, improvements can be investigated in the sense of: reducing the speed of the implement; decrease the volume of data transmitted (preprocessing); or still, use an extra device, in the field, as a gateway, for data preprocessing, before the implement action.

The first and possibly the simplest alternative to ensure that the proposed solution works is a deceleration of the agricultural implement, to increase the time available for data reception, training and classification. For this, however, it is necessary to analyze, together with experts in the agricultural area, what is the impact of this lower speed on the cost of the activity, in terms of fuel consumption and autonomy, given a consequent increase in time to cover large areas of farming.

Regarding the reduction of data volume, the following possibilities can be investigated: data compression, through algorithms that are supported in edge devices; or even the decrease in the frequency of data collection. For the first, the main challenge is to find information compression techniques that do not affect the efficiency of classification models, trained from compressed data. Previous studies (de Toledo, 2019) and (Pereira et al., 2018) indicate good classification indices, by neural networks, using compressed representations of the time series. In this case study, where the database provided corresponds to 450,000 samples (6 MB), the compact representation has only 15 triples of numerical data, totaling 180 bytes. The indication, therefore, is that the device coupled to the sensor in the bean plant has enough intelligence to compose this compact representation of the time series. As a positive aspect of this solution, the need for storage on this device is reduced. For the second, there is the same concern regarding the impact of training models with a smaller data set. As the frequency is reduced, less information will be available, so it must be observed whether the classification will not be harmed by this situation.

Within the scope of our group's research, advances are also being sought in terms of data volume reduction. Recently, the work published in (Oliveira Jr et al., 2021) presented contributions in the search for time series approximation techniques. This work carried out in parallel contributed not only with applicable approximation techniques, but also with the investigation of which approximation techniques can be used in combination with classification algorithms, without loss of data quality due to volume reduction.

Another possible solution is to use a central (gateway), installed in the field as well. This central would be in charge of processing the data and passing on to the agricultural machinery only the amount of input to be applied and in which area it should be applied. However, this may imply the use of a system with GPS to control the areas, which has become quite common in newer equipment. As the data packets to be sent to this gateway, and from the gateway to the implement, are small, it would not have much impact on transmission time. A single gateway can receive data from thousands of devices and forward it to the network server. Depending on the topology conditions of the deployed network, a single gateway can cover a radius of kilometers away.

Finally, it is important to remember that inside the laboratory, where the experiments were carried out, it is a controlled environment where the plants are in a favorable environment for their well-being and development. Stresses are applied at controlled intervals so that we can know exactly where the stresses have occurred. In the field, the plant undergoes constant stresses, such as climate, soil, pests, which can lead to the need for other related information, such as the duration interval of each stress and weather conditions. Improvements in this aspect can also contribute to increased plant stress detection efficiency.

The work described in this paper was carried out in a bench test. A second experiment, which data is currently being compiled, was carried out in the field, and, in fact, was subject to several practical problems, which will be discussed in an upcoming paper. Infrastructure implementation aspects (battery, energy consumption, system autonomy, sensors, communication, robustness) are also addressed in another work front of the group.

5 CONCLUSION AND FUTURE WORK

Computing in Fog, thanks to the technological evolution of recent years and the consequent variety of devices, has the potential to promote the development of applications in the most different sectors of society. New uses of computing have thus emerged and, particularly in the context of this work, applying techniques that bring intelligence to processing.

In this work, the technical feasibility of using the NVIDIA Jetson Nano edge device in an agricultural spray application was studied. In the device, time series classification algorithms were executed in the field, and the initial results, in an experimental nature, showed that this type of device can be successfully used for the specific purpose. Furthermore, the experiment allowed the identification of limitations of the proposed solution, highlighting aspects to be observed and necessary improvements for the implementation of the solution in a real scenario. The issue of data volume represented by a time series presents a set of difficulties that must be addressed to enable the successful implementation of the proposed scenario.

Given the nature of time series, the number of samples can grow significantly due to the time period and frequency with which data are collected, which will imply time series of large volumes. This characteristic must be considered in the analysis of application costs, both with regard to storage and processing of this information. Previous studies indicated that there is no loss in classification quality in the studied algorithms with reduced representations, however, the processing time to obtain these triples for representing periods of the time series is quite expressive. Also considering the volume of data, whose communication times are quite high, there is a clear indication that an alternative should be sought for this task.

Future works aim to enable the proposed precision agriculture scenario. Objectively, focusing on the problem of data volume, alternative techniques are being studied for the compression of time series already in the device coupled to the sensor, minimizing the storage, communication and processing requirements in the device responsible for the classification. This activity also involves determining which alternative time series compression techniques provide suitable results for classification. Furthermore, an investigation about hyper parameter tuning in classification algorithms is also desired, in order to improve the performance for this task. Regarding communication, issues related to range and security (prevention of malicious access to the network) are being considered, as well as considering data collection by sensors of other natures, such as unmanned aerial vehicles.

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REFERENCES

Abadi, M. et al. (2015). TensorFlow: Large-scale machine learning on heterogeneous systems. Software available from tensorflow.org.

Abdullah, A., Al Enazi, S., and Damaj, I. (2016). Agrisys: A smart and ubiquitous controlled-environment agriculture system. In *2016 3rd MEC International Conference on Big Data and Smart City (ICBDSC)*, pages 1–6. IEEE.

Alliance, L. (2015). What is LoRaWAN - A technical overview of Lora and LoRaWAN. https://lora-alliance.org/resource\textunderscorehub/what-is-lorawan/. Acessed in 25/07/2021.

Baller, S. P., Jindal, A., Chadha, M., and Gerndt, M. (2021). DeepEdgeBench: Benchmarking deep neural networks on edge devices. *CoRR*, abs/2108.09457.

Bonomi, F., Milito, R., Zhu, J., and Addepalli, S. (2012). Fog computing and its role in the internet of things. In *Proceedings of the First Edition of the MCC Workshop on Mobile Cloud Computing*, MCC '12, pages 13–16, New York, NY, USA. ACM.

Byers, C. C. (2017). Architectural imperatives for fog computing: Use cases, requirements, and architectural techniques for fog-enabled iot networks. *IEEE Communications Magazine*, 55(8):14–20.

Chollet, F. et al. (2015). Keras. https://github.com/fchollet/keras.

de Toledo, G. R. A. (2019). *Electrophysiological characterization of beans (*Phaseolus vulgaris L.*) cv. BRS-Expedit under different water availabilities (In Portuguese)*. PhD thesis, UFPel, Pelotas.

Gia, T. N., Qingqing, L., Queralta, J. P., Zou, Z., Tenhunen, H., and Westerlund, T. (2019). Edge AI in smart farming IoT: CNNs at the edge and fog computing with LoRa. *IEEE AFRICON-2019*.

Imran, H. A., Mujahid, U., Wazir, S., Latif, U., and Mehmood, K. (2020). Embedded development boards for Edge-AI: A comprehensive report.

Kamilaris, A., Gao, F., Prenafeta-Boldu, F. X., and Ali, M. I. (2016). Agri-IoT: A semantic framework for internet of things-enabled smart farming applications. In *2016 IEEE 3rd World Forum on Internet of Things (WF-IoT)*, pages 442–447. IEEE.

Kamilaris, A. and Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and electronics in agriculture*, 147:70–90.

Kawai, T. and Mineno, H. (2020). Evaluation environment using edge computing for artificial intelligence-based irrigation system. In *2020 16th International Conference on Mobility, Sensing and Networking (MSN)*, pages 214–219.

Li, H., Ota, K., and Dong, M. (2018). Learning iot in edge: Deep learning for the internet of things with edge computing. *IEEE Network*, 32(1):96–101.

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., and Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, 18(8):2674.

Maffei, M. and Bossi, S. (2006). Electrophysiology and plant responses to biotic stress. In *Plant Electrophysiology*, pages 461–481. Springer.

Misra, N. N., Dixit, Y., Al-Mallahi, A., Bhullar, M. S., Upadhyay, R., and Martynenko, A. (2020). IoT, big data and artificial intelligence in agriculture and food industry. *IEEE Internet of Things Journal*, pages 1–1.

Nvidia, C. (2021). Jetson Nano. https://www.nvidia.com/jetson-nano. Acessed in 16/07/2021.

Oliveira Jr, M. A. d., Sedrez, G., Monteiro, A., Puntel, F. E., and Cavalheiro, G. G. H. (2021). Effects of agrosensor time series approximation on plant stress detection: An experimental study. In *2021 XIII Brazilian Congress on Agroinformatics (SBIAGRO)*.

Pandas Development Team, T. (2020). pandas-dev/pandas: Pandas.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., and Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830.

Pereira, D. R., Papa, J. P., Saraiva, G. F. R., and Souza, G. M. (2018). Automatic classification of plant electrophysiological responses to environmental stimuli using machine learning and interval arithmetic. *Computers and Electronics in Agriculture*, 145:35–42.

Proietti, M., Bianchi, F., Marini, A., Menculini, L., Termite, L., Garinei, A., Biondi, L., and Marconi, M. (2021). Edge intelligence with deep learning in greenhouse management. In *Proceedings of the 10th International Conference on Smart Cities and Green ICT Systems - Volume 1: SMARTGREENS,*, pages 180–187. INSTICC, SciTePress.

Saraf, S. B. and Gawali, D. H. (2017). IoT based smart irrigation monitoring and controlling system. In *2017 2nd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT)*, pages 815–819. IEEE.

Shi, W., Cao, J., Zhang, Q., Li, Y., and Xu, L. (2016). Edge computing: Vision and challenges. *IEEE Internet of Things Journal*, 3(5):637–646.

Zhou, G.-X., Li, P.-q., and Zhou, X.-d. (2011). Global climate warming on climate and agriculture in western liaoning impact. In *2011 International Conference on Remote Sensing, Environment and Transportation Engineering*, pages 2200–2203.