An IoT Based Smart Farming System Using Machine Learning

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***Abstract*— Smart farming allows to analyze the growth of plants and to influence the parameters of our system in real time in order to optimize plant growth and support the farmer in his activity. Internet of Things (IoT) arrangements, based on the application particular sensors data measurements and intelligent processing, are bridging the holes between the cyber and physical worlds. In this paper, we propose the design and the experiment of a smart farming system based on an intelligent platform which enables prediction capabilities using artificial intelligence (AI) techniques. This system is based on the technology of wireless sensor networks and its implementation requires three main phases, i) data collection phase using sensors deployed in an agricultural field, ii) data cleaning and storage phase, and iii) predictive processing using some AI methods.**

Keywords—Smart farming; IoT; Machine learning; Sensing; Precision agriculture.

I. Introduction

Agriculture uses 85% of available freshwater resources worldwide, and this percentage will continue to be dominant in water consumption because of population growth and increased food demand. There is an urgent need to develop strategies based on the science and the technology [1]. The need of using IoT in agriculture applications becomes nowadays a reality after the success of theoretical research contributions in the previous decade [2,6]. IoT have recently motivated adoption of information technology solutions in crop fields within precision agriculture approaches which contribute for rational use of water, including technical, agronomic, managerial,…etc. Several research studies were conducted on irrigation systems to achieve water savings in diverse crops from basic ones to more technologically advanced ones [4,5,7,8,9 and 21]. To achieve water saving, irrigation system frameworks have been proposed based on various techniques, e.g., thermal imaging, Crop Water Stress Index (CWSI), direct soil water measurements, etc. Precision farming is a principle that aims to optimize yields and investments, while seeking to better take into account the variability of the environment. This concept appeared in the context of the race for progress in agricultural yields. It notably influenced: tillage, sowing, fertilization, irrigation, spraying of pesticides. Precision agriculture is essential to meet the challenges of agricultural production in terms of productivity, environmental impact, food security and sustainability as the world's population demands a significant increase in food production must be achieved while now availability and high nutritional quality worldwide [14,16 and 18]. Due to the recent advances in sensor technology for the implementation of irrigation systems in agriculture especially smart farming [13, 15 and 17] and the evolution of IoT technologies that can be applied in the development of these systems. IoT takes a major role in the revolutions of digital transformations, and today we will discuss the applications of 'IoT in Agriculture'. We anticipate the proposal of IoT-based intelligent irrigation architecture with a machine learning approach to predict soil moisture to reach more convincing conclusions. In this paper, we propose an IoT based smart farming architecture founded on new EDGE-Fog-IoT-Cloud platform. After giving the design of the overall architecture, we detail the implementation part (hardware and software components). The aim of this platform is to demonstrate the effectiveness of AI techniques to help in making effective irrigation decisions with optimum water usage in smart farming. The rest of the paper is organized as follows. Section II briefly surveys the related works. Section III presents our proposed smart farming platform in agriculture of precision specially irrigation. Section VI introduces and explains the tool developed and illustrates the use of AI techniques. Section V concludes the paper and outline directions of future work.

II. Related Works

We present in this section recent research work aimed at the implementation of irrigation systems in agriculture. Some of them have used AI techniques to enhance the prediction aspect. Researchers in [3] developed irrigation sensor based on smart phone. For sensing soil moisture, the digital camera of smart phone is used to process RGB to gray for estimation of ratio between wet and dry area of soil. The ratio of wetness and dryness is transmitted via gateway to water motor controller. A Mobile Application (APP) is developed to control sensor activity (like wakeup) and to set sensor in sleep mode. Majority of the earlier irrigation systems do not consider the weather forecasting information (e.g., precipitation) while making irrigation decisions. It leads to a wastage of fresh water, energy and loss of crop growth (due to

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excess water) when a rain is followed immediately by the watering of the crop.

To handle such cases, WSNs based solutions can provide a better decision support for irrigation by utilizing weather forecasting information (e.g., precipitation) from the Network. Irrigated agriculture represents the bulk of the demand for water, being the first sector affected by water shortage, resulting in a decreased capacity to maintain per capita food production. Therefore, the efficient use of water in agriculture is one of the most important agricultural challenges that modern technologies are helping to resolve [11]. The objective of authors in [10] was to develop understanding on site-specific suitability of the Mid Elevation Spray Application (MESA) and Low Elevation Spray Application (LESA) sprinkler systems in irrigating corn crop and potential water as well as energy savings. The automated irrigation system put in place has proven to be feasible and cost-effective to optimize water resources for agricultural production [1,5 and 21]. Authors in [8] propose an intelligent irrigation architecture based on IoT as well as a hybrid approach based on deep learning to predict soil moisture. The proposed algorithm uses sensor data from the recent past and weather forecasts to predict soil moisture for the next few days. The disadvantage of these approaches [1,5] is that they set the maximum humidity and do not take into account the need for water exactly needed. They plan to save water. Unlike this state-of-the-art work, we propose in this paper an automated irrigation management platform using a WSN by making the following contributions: i) Design and implementation of a new EDGE-Fog-IoT-Cloud based architecture dedicated to the smart farming, and ii) We show clearly the interest of our system in saving water and preserving this natural resource by using AI techniques to predict soil moisture of the upcoming days.

III. Smart Farming System

The smart farming platform architecture (Fig. 2, Fig. 3) has been proposed to collect, transmit and process the physical parameters (Soil-Moisture, Air-Temperature, Air-Humidity, Water-level, Water-flow, Luminous intensity, Combustible Gas (vapors) for security of crops) of farming land along with the weather forecast information to manage the irrigation efficiently. The system architecture is designed in three layers: data layer which is depicted in Fig. 1, data processing layer and application layer. This distributed architecture is shown in Fig. 2 and Fig. 3 which represents a major extension of our previous works [20,21] on agriculture of precision where we calculated the useful reserve of water (RU) according to the texture of the soil (Clay, Limon, Sand, Organic Matter), and for the second method we used the (Rawls and Turq formulas) equations. The operational architecture shows information regarding soil moisture of the upcoming days, it also provides irrigation suggestions, based on the defined level of soil moisture and predicted precipitation, to save water and energy the generated information by algorithm and device is stored in MySQL database at the server (see Fig. 2). A web service based on NodeJS process data before sending them periodically to the cloud architecture. All streams of data are stored in Google drive before they are transmitted to Google Colab to execute artificial intelligence techniques (AI) used for training, testing and prediction. The EDGE is placed between IoT sensors Network and the Cloud as an intermediate layer. EDGE comprises three primary modules: data acquisition, prediction, and visualization. Data sent by sensors network by means of different transmission network protocols. Data is stored closely to the EDGE to provide quick access to data for farmer during interventions. Moreover, farming data remains available even if the internet connection is temporarily interrupted. Processing and validating data at EDGE level reduce the amount of data transmitted to the cloud and conserving global energy of the architecture and network bandwidth. Each sensor in our IoT system has a range of measurement which must be evaluated in the level of EDGE to serve as a baseline for the detection of abnormal behavior. For example, we have temperature measuring range -40 to +80 °C for the DHT22 sensor. These not clean data must also be corrected according to the behavior of each sensor and also take into account historical data to avoid triggering unnecessary alerts and adapt the frequency of collecting sensing data in order to obtain clean data.

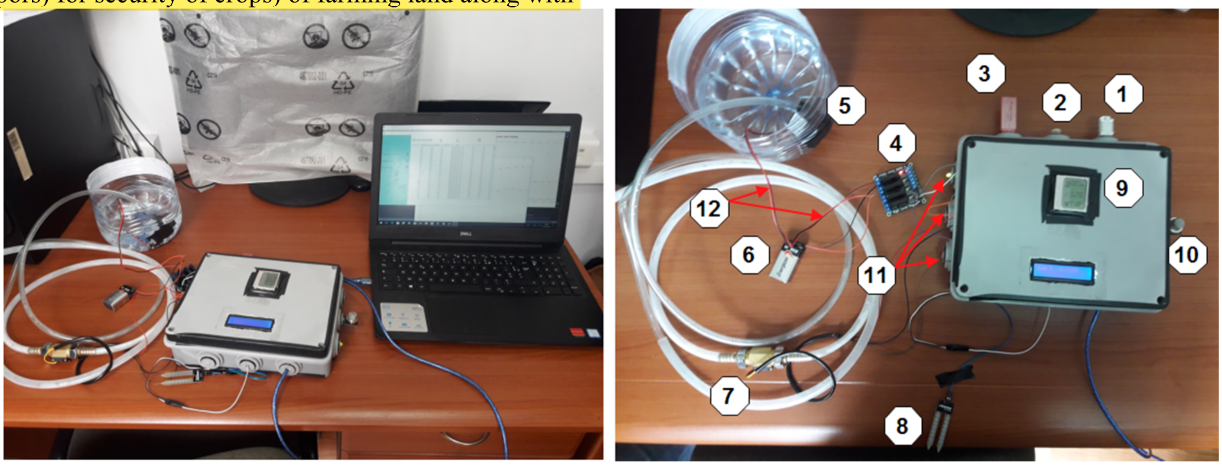


Fig. 1: Hardware components involved on the Field experiment. [Legends 1: DHT22 Sensor, 2: LDR Sensor, 3: Water level Sensor, 4: Relay Switch, 5: Water pump, 6: Power supply 9 V, 7: Water flow sensor, 8: Soil moisture sensor, 9: LCD display, 10: MQ2 sensor, 11: LEDs, 12: Jumpers]. The mega arduino card and NRF module are in the Box.

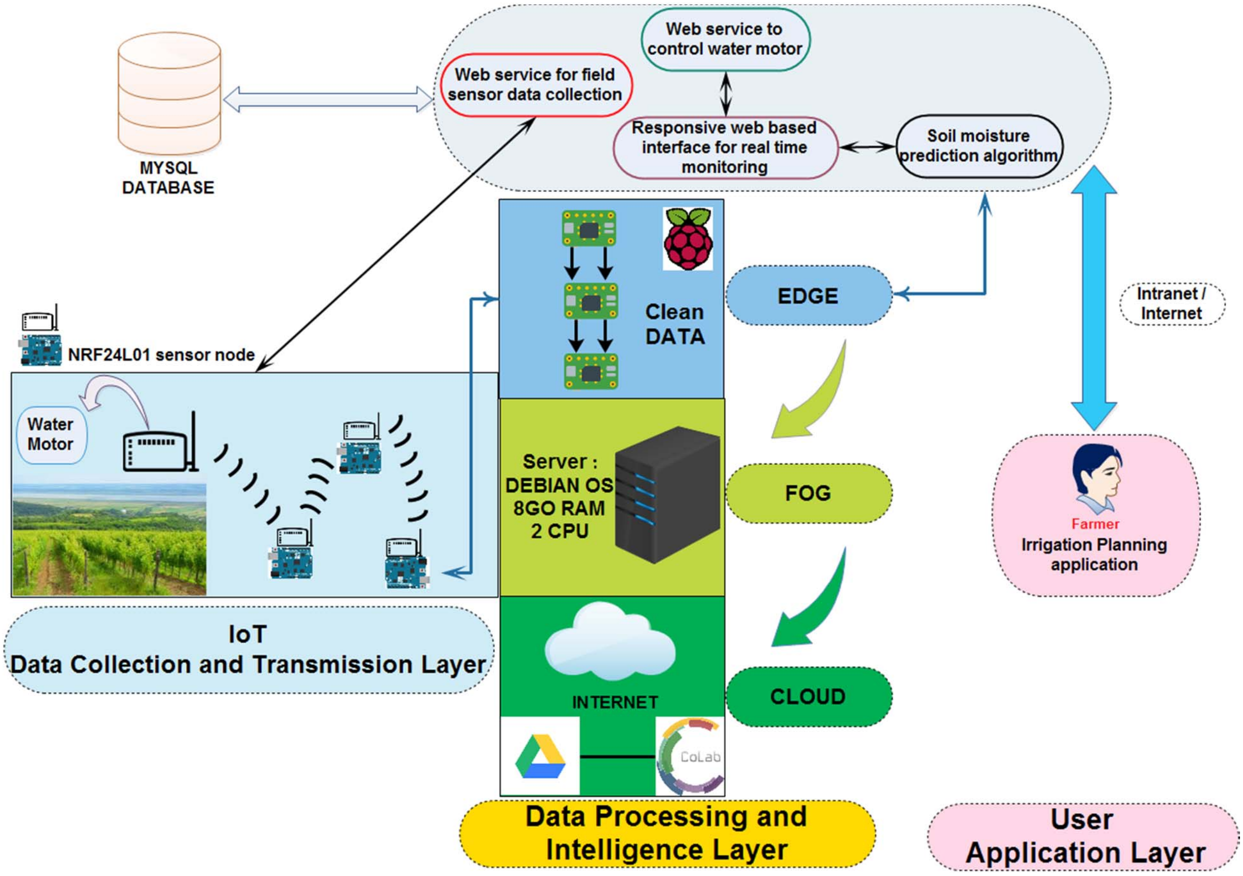


Fig. 2: Global View of our proposed operational architecture.

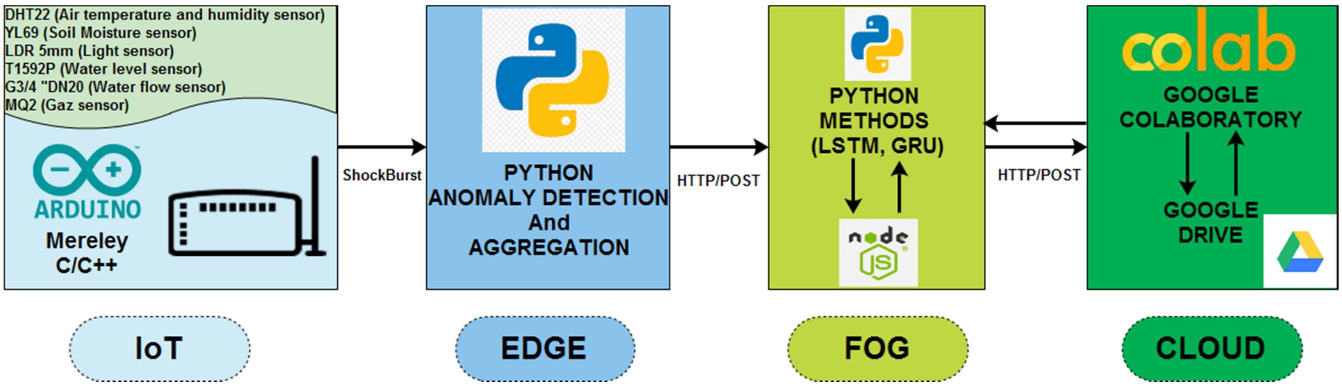


Fig. 3: Proposed layered architecture of smart farming with the technical choices of implementation.

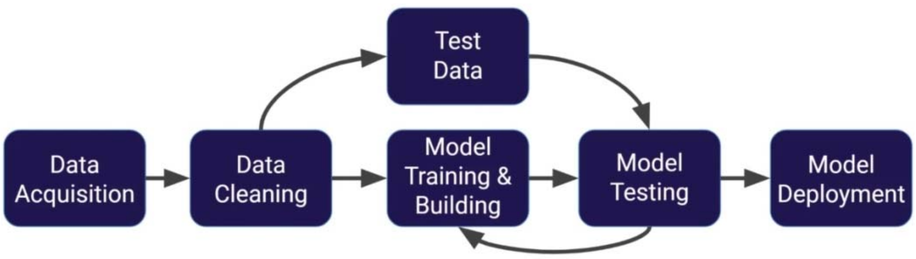


Fig. 4: Main steps in the proposed architecture based on IA techniques.

The designed platform is based on the ideas proposed by [1, 5, 8 and 19] with modifications made for our application. As we can see in Fig. 2, Fig. 3, the devices of our platform in the first layer aim to collect field data and transmit them using NRFL01 radio module. These data can be stored in private database so that the user (farmer) has a possibility to analyze them and monitor the crops in real time. In order to start irrigation planning we need to calculate the UR parameter in mm.

IV. Experimentation

This section presents the implementation of the new EDGE-Fog-IoT-Cloud based architecture dedicated to smart farming and the analysis of the obtained results.

A. Implementation and results analysis

The main objective of these experiments is to show how to create our own wireless network under Arduino environment to transmit data from one or more sensors at any time of the day. Along with weather forecast information for developing an algorithm for prediction of soil moisture of the upcoming days. The system was first tested in our laboratory and we plan to test it in a farm of vine near to El-Malah city, located in western Algeria. Figure 3 shows schematic of ML sub-process blocks for the execution of the models. An operational architecture has been developed (see Fig. 2) within the level of EDGE to predict the soil moisture based on field sensors data, and also weather forecasting data using LSTM-based models and GRU-based models.

In this paper, two different sources of information are considered, each of them featuring complementary and characteristic features useful to design and test LSTM and GRU approaches: Historical hourly weather data 2012-2017 [24]: the data have been collected from 30 US and Canadian Cities, as well as 6 Palestine cities. The dataset contains ~5 years of high temporal resolution (hourly measurements) data of various weather attributes, such as temperature, humidity what concerns us of our study. Detailed hydro meteorological data from the mountain rain-to-snow transition zone are present for water years 2004 through 2014 [23]: we interested only to the soil moisture measurements. This version of the data set fixes errors in all data files and supersedes the earlier datasets. In this study, the LSTM cell architecture described by Zaremba *et al.* [22] implemented in TensorFlow 2.0 has been used for the experiments. Many factors may contribute to speeding up the training time, including the dataset size, the development platform (e.g., Tensorflow, Pytorch, Keras, Caffe, MXNet), the hard-ware platform (e.g., CPU, GPU, TPU) and the AI/ML model's hyper-parameters (e.g., the number of hidden layers, the number of neurons in each layer, the learning rate, the batch size, the number of epochs). Google Colab (GC) is an awesome place provided by Google for training models. We was training our model but the Google Colab keeps disconnecting after 2 hours automatically if we do not respond the data is lost.

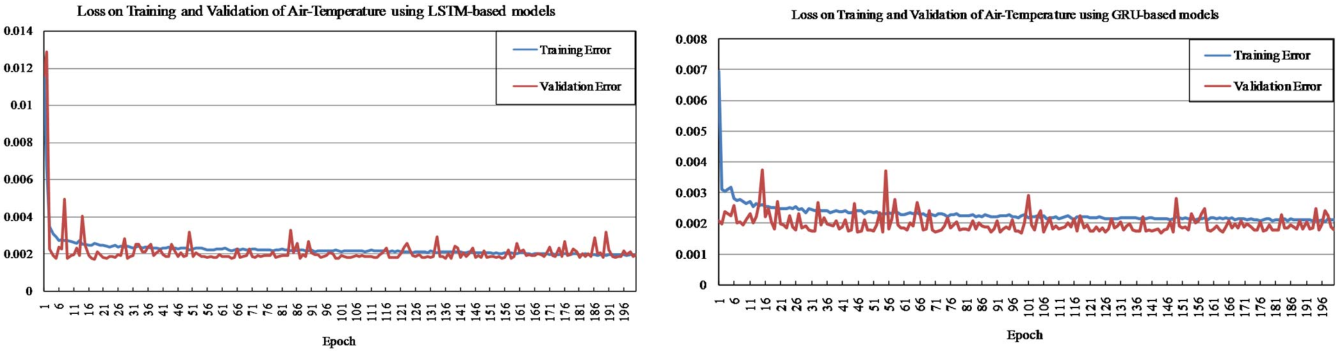
In time of prevent GC from disconnecting that's why in all the experiments, we use a Laptop (Laptop PC) with processor: Intel Core i5-6300U @ 2.40GHz, Memory: 8GO RAM, Disk: 256 GO SSD.

B. Discussion and Results

In addition, the comparison between the performances of the LSTM-based models and GRU-based models over the two test sets together is depicted in figures 5, 6 and 7, by comparing results on both training and validation datasets, respectively. The analysis of the obtained results has revealed the following key insights: (1) the training time can be shortened by reducing the model size and increasing the batch size; (2) CPU outperforms GPU in speeding-up the training time of small-sized models. This is explained by the fact that with small models, the CPU-GPU data transfer overhead exceeds the computation acceleration benefit; (3) LSTM-based models exhibit long training time compared to GRU-based models.

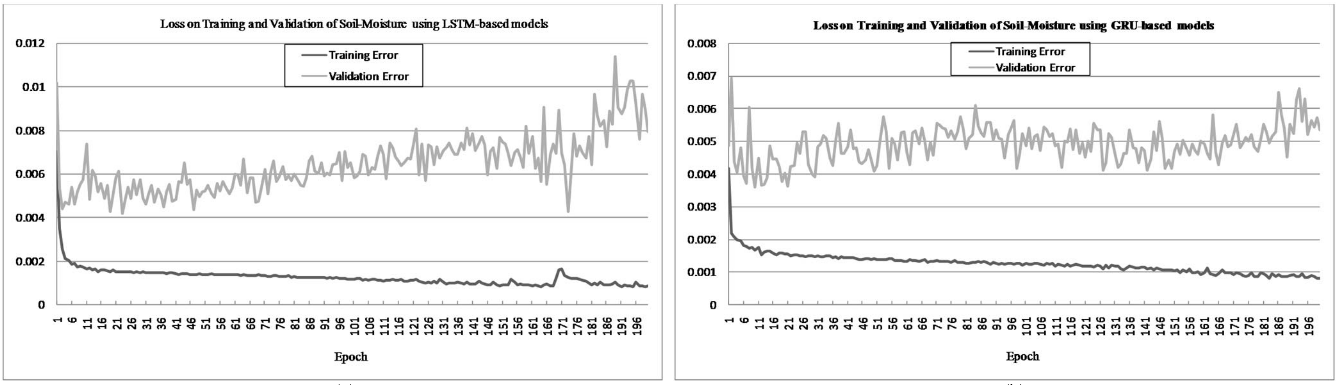
Even LSTM (Long Short-Term Memory Recurrent Networks) and GRU involve 1 input layer and 2 hidden layers with 128 neurons for the first and 64 neurons for the second. From the plot of loss, we can see that the model has comparable performance on both training and validation datasets. If these parallel plots start to depart consistently, it might be a sign to stop training at an earlier epoch (See figures 5, 6 and 7). We discovered also the importance of collecting and reviewing metrics during the training of our deep learning models. Indeed, we observe that the training time for each epoch with LSTM-based models is 200 sec, however it is about 300 sec with GRU-based models. According to the recent research results, it even surpasses LSTM-based models in many applications. The experiments were conducted for the prediction of the (Air-Temperature, Air-Humidity and Soil-Moisture) to predict these parameters of the upcoming days. Figures 5(a) and 5(b) illustrate that the model has comparable performance for Air-temperature and gives best results on both training and validation especially with LSTM-based models even the Mean Squared Error (MSE) is higher compared to GRU-based models. Figures 6(a) and 6(b) depict that the model with GRU-based models outperforms slightly LSTM-based models. Figures 7(a) and 7(b) show that the parallel plots start to depart consistently after 10 epochs approximately at the start of 60th epoch, it might be a sign to stop training at an earlier epoch.

Despite all this, the model well mannered on both training and validation datasets knowing that the scale of the graph is too small. To avoid local minima problems in neural networks using ReLU as the inner activation function, the experiments are repeated 5 times and the median Mean Absolute Error (MAE), the (MSE) and Root Mean Squared Error (RMSE) on both test sets are presented in Table 1. According to the results, GRU-based models can result better performance for Soil-Moisture and Air-Temperature predictions. However, LSTM-based model outperforms GRU-based models for Air-Humidity predictions.



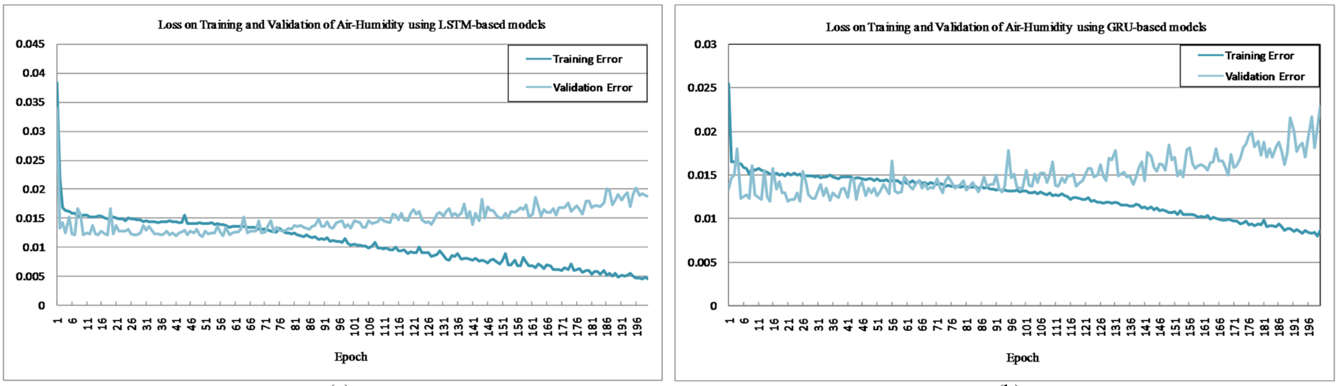
(a) (b)

Fig. 5: (a) Plot of Model Loss on Training and Validation of Air-Temperature using LSTM-based models. (b) Plot of Model Loss on Training and Validation of Air-Temperature using GRU-based models.



(a) (b)

Fig. 6: (a) Plot of Model Loss on Training and Validation of Soil-Moisture using LSTM-based models. (b) Plot of Model Loss on Training and Validation of Soil-Moisture using GRU-based models.



(a) (b)

Fig. 7: (a) Plot of Model Loss on Training and Validation of Air-Humidity using LSTM-based models. (b) Plot of Model Loss on Training and Validation of Air-Humidity using GRU-based models.

Table. 1: RMSE, MSE, MAE of the LSTM and GRU based models for (Air-Temperature, Soil-Moisture, Air-Humidity) Training and Validation.

Parameters	LSTM			GRU		
	RMSE	MSE	MAE	RMSE	MSE	MAE
Soil-Moisture	0.0268	0,00072	0.0114	0.0220	0,00048	0.0101
Air-Humidity	11.7550	138,18	8.1946	12.9778	168.4255	8.4585
Air-Temperature	1.4090	1.9855	1.0777	1.3331	1.7771	1.0167

V. CONCLUSION AND PERSPECTIVES

The implemented smart farming system was found to be feasible and cost effective for optimizing water resources for agriculture of precision. The main objective of this paper was to design a new EDGE-Fog-IoT-Cloud based architecture dedicated to the smart farming. We showed that AI techniques play a pivotal role in agriculture of precision by using machine learning and open sources technologies. One of future research directions related to experiments is to collect the physical parameters of our own farming system in order to collect our dataset and the use of these sensors data along with weather forecast information for developing an algorithm for prediction of soil moisture of the upcoming days. There is also the need to measure the hardware performance at the server level when ingesting data. Meanwhile, we spotlighted the limitations of AI techniques especially in training speed and accuracy balance that may hamper the integration of ML. Thus, more research efforts in this direction are required to fulfil the potential of transfer learning.

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