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Embedded Sensors Combined with Artificial Intelligence for Improved Agricultural Yield

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Abstract: Automation in agriculture is a big cause of concern and a hot subject all around the world. The world's population is rapidly growing, increasing the demand for food and jobs. Traditional farming practices were insufficient to meet these objectives. New automated procedures were created as a result. These innovative techniques met food demands while also offering employment opportunities for billions of people. Artificial intelligence (AI) has easily slipped into a range of monitoring and control applications, including agriculture. Attempts to build low-power sensing devices with fully functional AI, on the other hand, are still dispersed. In this work, we provide an AI-enhanced embedded system for studying and predicting plant leaf growth dynamics in real time. The embedded solution is based on a low-power embedded sensor device with a GPU capable of running neural network-based AI on the device. A Recurrent Neural Network (RNN) and a Long-Short Term Memory Network (LSTMN) are the foundations of our AI system. The recommended approach assures the system's autonomy for 180 days using a standard Li-ion battery. We use cutting-edge mobile graphics processors for smart analysis and administration of autonomous devices. This work paves the way for a variety of sophisticated monitoring applications, especially in agriculture.

***IndexTerms* - Embedded sensing, Smart sensing, Artificial intelligence, Precision agriculture, Sensing and control.**

I. INTRODUCTION

Food production and supply continue to be a concern in a lot of rural regions, as well as in developing countries. Indeed, social worries about environmental impact and food safety have sparked a surge in interest in cutting-edge technologies that are expected to aid in these areas [1]. Precision agriculture is a technology paradigm that attempts to improve the results of agricultural systems by automating the watching, measuring, and responding phases while keeping the system's overall control efficient in terms of resources. These technologies hold promise in terms of maintaining food safety, decreasing negative anthropogenic environmental effect, and, eventually, ensuring economic profit. Despite the significant advances achieved in precision agriculture in recent years, several problems persist. However, there is still a difficulty with automating greenhouses and monitoring plant development in remote places (especially in underdeveloped nations) [2]. The difficulties involved with the system's autonomous functioning and the transfer of gathered data to high-performance computers for additional processing might explain this.

The low energy storage and high-power consumption have been major concerns in terms of autonomous operation. In reality, obtaining all of the essential parameters for creating a high-quality prediction model to analyze plant growth dynamics via a bottom-up method is nearly difficult in distant locations. A distributed low-power embedded solution with AI on board is required to solve the aforesaid challenge. This approach adheres to the "edge computing" paradigm, which aims to process data using AI on the sensing device rather of relying on complex data transmission and processing in the cloud. Computer vision and machine learning-based methods have been shown to be beneficial in assessing fruit attributes [3]. The complex software used for picture analysis is a disadvantage of 2D imaging. The leaf overlap and concavity are a problem. When it comes to plant digitization, laser scanning is frequently a viable alternative. It has been effectively applied, for example, to statistical analysis of forestry and canopies [4]. Its use is restricted to the extraction of single plant characteristics due to computationally costly data processing [5]. The authors show how to integrate reconstructed 3D points and real pictures in an automated 3D imaging system for plant modeling. According to this study, the user will benefit from a more effective segmentation of data into individual leaves. A study [6] that is comparable to ours suggests a 2D/3D system supplemented with a number of sensors that can identify connections between leaf area and biomass. The presented method aids in forecasting the plant's growth rate and leaf area.

The construction of a low-power embedded system enhanced with AI based on RNN is described in this paper. The suggested system is capable of gathering essential agricultural data and conducting in-situ leaf growth dynamics prediction. This method uses an experimental test bed to evaluate the system's automatic operation.

II. METHODOLOGY

As shown in Figure 1, an experimental setup focused on a hydroponic method to plant development and connected with an imaging system was built and installed for the purpose of gathering image and conditions data characterizing plant growth. This technology allows tiny plants to be grown right now, with cameras automatically monitoring their progress. We divided a plant-growing tray into six distinct parts. The plants were fed with various feeding solutions in each of them. There were eight plants in each segment. They have been raised in a 0.65-liter mineral wool slab and were hand fed.

The tray was coated with foam plastic to make image post-processing easier. Six high-resolution cameras were positioned above each segment on a controlled platform in the imaging system. 150 Watt LEDs were used to give artificial lighting for the plants. 70 MicroTina [7] seeds were germinated in a tiny rock wool cartridge on a separate tray under LED light at the start of the experiment. For the germination of all seedlings, 1.3 litres of commercial nutrient solution were utilized. For each section, a unique sort of solution was created.

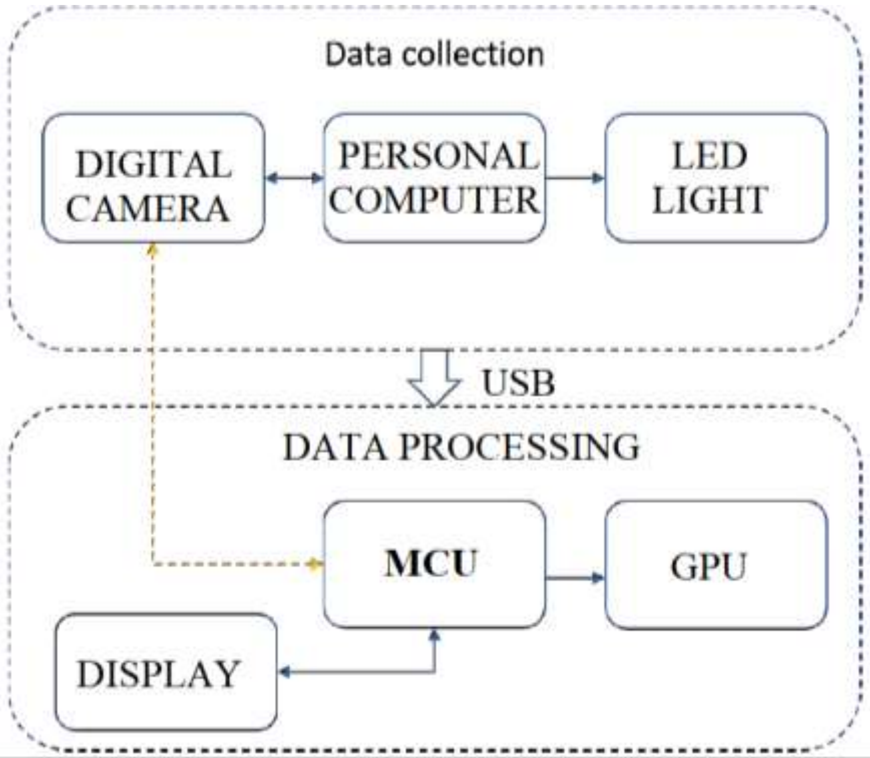

Fig 1. Block diagram of the proposed system for precision agriculture

For the estimation of plant development dynamics, we employ a Recurrent Neural Network (RNN) in this study. The RNN is a kind of ANN in which the nodes store information about their internal state and contain feedback responses. RNNs have the capacity to link prior knowledge with the current state, which is one of its most appealing characteristics. Using internal state knowledge, the RNN can analyze the data that is represented as time-dependent sequences. Long-term dependencies may be difficult for a conventional RNN to handle.

Long Short-Term Memory (LSTM) ANNs were presented as a unique architecture of RNN [8] capable of understanding long-term correlations to solve this problem. A cell state, which may be altered throughout the training process, is a fundamental component of LSTM. This characteristic is critical for simulating the dynamics of plant development. Many applications for the LSTM NN architecture have recently surfaced [9]. However, applying RNN for crop yield prediction or description of plant development dynamics based on environmental growth circumstances is a fresh research path for precision agriculture [10].

We use W to represent weight matrices (for example, W_{ix} is the matrix of weights from the input gate to the input), while W_{ic}, W_{fc}, and W_{oc} are diagonal weight matrices for peephole connections, as shown in Fig.2. B_i is the input gate bias vector, while vector b is a bias vector. I is the input gate, f is the forget gate, o is the output gate, and c is the cell activation vector, and function is the logistic Sigmoid function. The cell output activation vector m is the same size as functions I_f, o, and c. The cell input function is function g, while the cell output activation function is function h. In this neural network, $tanh$ and ϕ are the activation functions utilized.

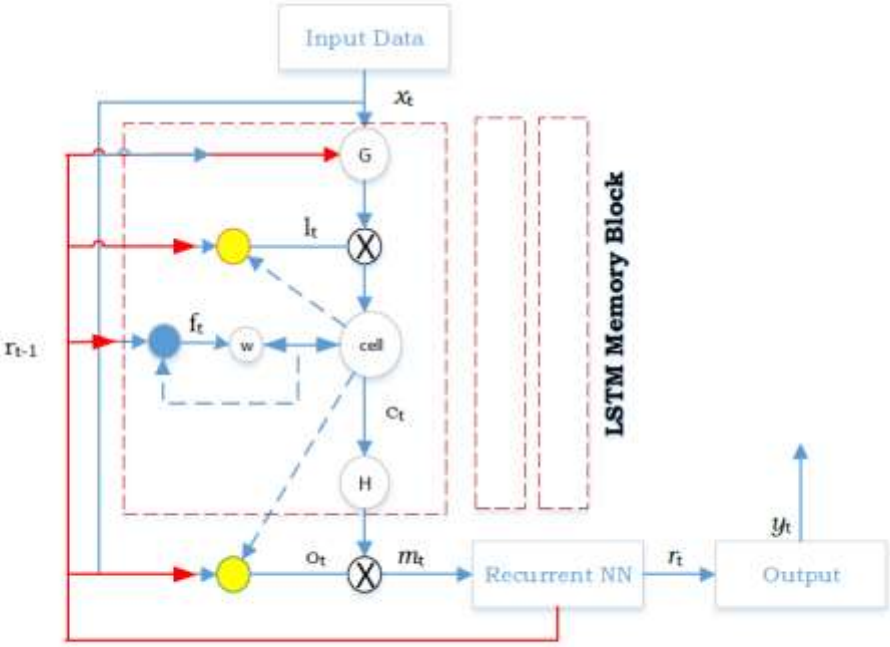

Fig 2. RNN-LSTM Architecture

In this architecture, each memory block had an input gate (G) and an output gate (H). The flow of input activation (X_t) into the memory cell is controlled by the input gate (G). The output gate controls the cell activation output flow (C_i) into the remainder of the network; the next phase is the memory block addition by the forget gate (w). The forget gate (w) adaptively forgets or resets the cell's memory by scaling the internal state of the cell before adding it as input to the cell through the cell's self-recurrent link. The output sequence *y* is calculated from the input sequence *x* using the LSTM based RNN. The activation functions for the time interval 1 to T are given below.

$$i_t = \sigma\left(W_{ix}x_t + W_{im}m_{t-1} + W_{ic}c_{t-1} + b_i\right) \tag{1}$$

$$f_t = \sigma\left(W_{fx}x_t + W_{fm}m_{t-1} + W_{fc}c_{t-1} + b_f\right) \tag{2}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g\left(W_{cx}x_t + W_{cm}m_{t-1} + b_c\right) \tag{3}$$

$$o_t = \sigma\left(W_{ox}x_t + W_{om}m_{t-1} + W_{oc}c_t + b_o\right) \tag{4}$$

$$m_t = o_t \odot h\left(c_t\right) \tag{5}$$

$$y_t = \phi\left(W_{ym}m_t + b_y\right) \tag{6}$$

As shown in Fig. 3, we connect the multimeter to the Raspberry Pi's power rode through a 100 m 1% shunt, which receives the volt-ampere (VA) characteristics and delivers the digital data to the RPi's COM-port. We collected cognitive and power utilization related data. Timestamp, test and train scores, VA, power consumption, CPU, and RAM utilization are some of these parameters used for the analysis.

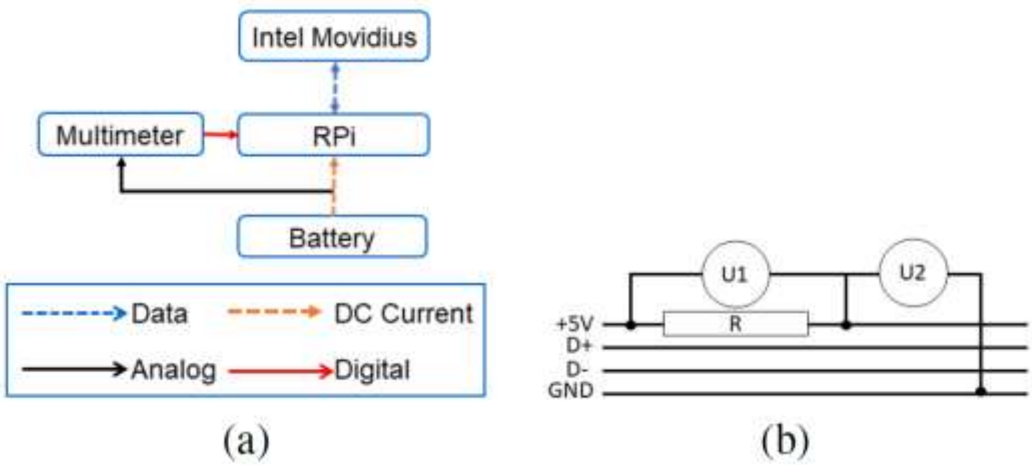

Fig. 3 (a) Block diagram of the experimental testbed (b) Connection of the multimeter probes to the Raspberry Pi power rode

Power consumption is calculated from the measured voltage (U_2) on the power rode, voltage on the shunt (U_1) and shunt resistance (R).

$$P = \frac{U_1 * U_2}{R} \tag{7}$$

III. Experimental results

Fig. 4 depicts the average leaf area for each plant in each sector, allowing us to determine which addition to the basic solution is the most effective. Phosphorus additives, among other things, have the best impact in our situation. It's critical that we can use basic cameras to quantitatively evaluate the effects of various variables on plant development dynamics.

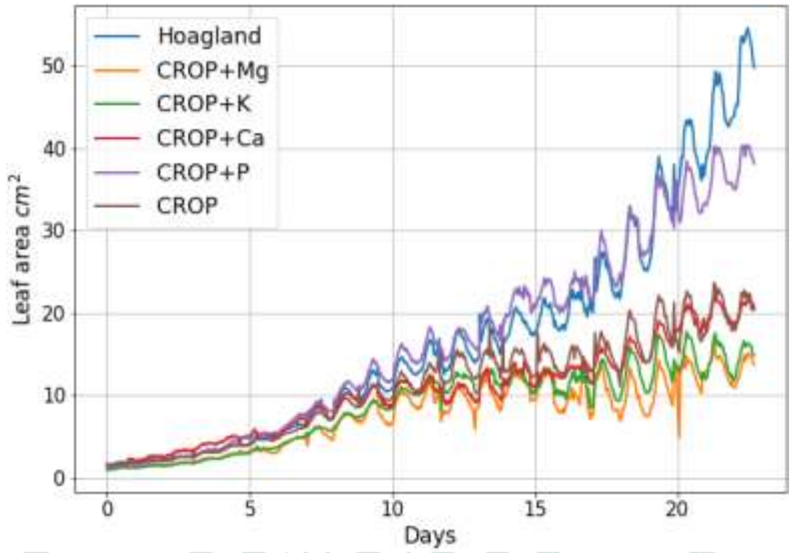

Fig. 4. Variation in leaves area with respect to feeding solution

This experiment is carried out on a desktop and a suggested low-power embedded device, both of which are defined by the parameters shown in Table 1. The model and the test dataset were updated after each run. The Root Mean Squared Error (RMSE) and the time spent on a single prediction were assessed during the research. The difference between the final and start times of a single run of the prediction algorithm was used to calculate the prediction time. While evaluating the Raspberry Pi and computer, the RMSE remains consistent throughout all iterations. We used a 2550 mAh battery bank to evaluate the proposed embedded AI system's long-term operation and looped the load model - load test set - make prediction sequence. We assessed the power usage over the iterations in this experiment, as shown in Fig. 5.

Table 1. Performance comparison between various experimental setup

Parameter	PC	Prototype
Minimum Prediction Time (s)	0.48	1.80
Maximum Prediction Time (s)	1.25	7.81
Average Prediction Time (s)	0.54	2.97
RMSE	8.29	8.29

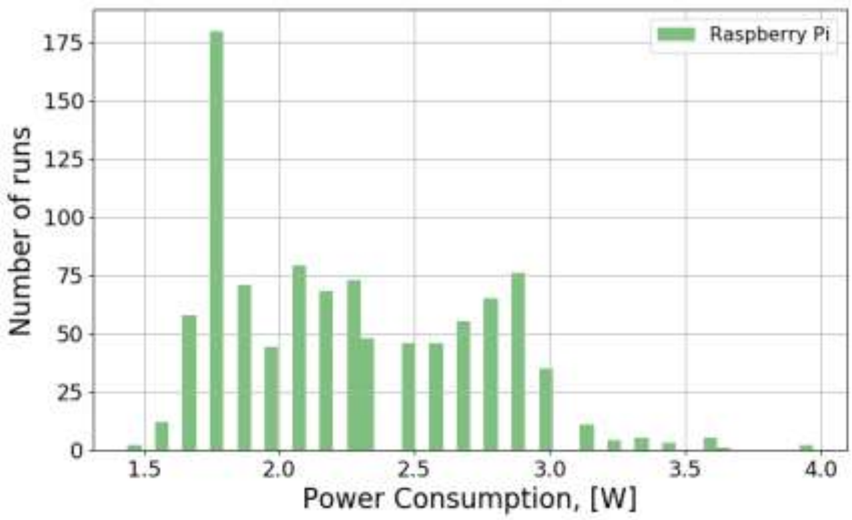

Fig.5. Power consumption of the prototype over iterations

IV. Conclusion

We proposed a general low-power embedded architecture with AI on board for analyzing and forecasting plant growth patterns in this paper. The suggested solution's performance test revealed that the created AI architecture, which is based on a Recurrent Neural Network (RNN) dubbed the Long-Short Term Memory network (LSTM), has adequate precision for prediction horizon. The suggested method may be utilized as a self-contained instrument for observing plant growth patterns in real time. The proposed technique, when combined with an actuation capability, has the potential to provide an easy-to-deploy, general, and robust optimization tool for precision agriculture. It may be used to build and verify novel machine learning algorithms in a range of computer vision applications. On the experimental setup, we employed a hydroponic method to achieve the growth stage. It ensures effective plant nutrition management and the ability to "push" the system in a preferred direction.

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