Embedded system for real time analysis of thermal images for prevention of water stress on plants

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***Abstract**: Given the evolution of electronics technology and electronics equipment, their price has fallen, thus making them affordable for the use in new branches: industry, security, agriculture. In this paper we propose a complete integrated analysis system that can learn – through deep learning algorithm – several templates for one parameter (spatial temperature evolution) for the occurrence of water stress and can then recognize these preconditions in the real environment. The system can then generate alarms to farmers / researchers about the occurrence of water stress. The system uses a FLIR camera sensor and capture the spatial arrangement of temperature at plant level, make an local intelligent analysis and return different levels of alarm. Thus, instead of transmitting the image to the central station on a conventional channel, the system will perform an on-site analysis over a period, identify potential water stress by recognizing templates, and will only convey indications of the crop state.*

1. INTRODUCTION

The detection of water stress in agricultural crops is a maximum interest research topic, especially in terms of global warming and increasing demand for water consumption. A research direction is the use of FLIR thermal cameras to determine the prerequisites for water stress at plant level. Thus, by analyzing the thermal image in remote IR and by comparison with the image in the visible spectrum, stress conditions can be determined in plants before the effect is observed by the growers. So they can intervene before the effect is destructive for cultures. Equipment is built that can automatically acquire thermal imaging and can store or transmit it remotely. Several methods of acquiring images from different crop points are proposed either by an operator who makes ground-based measurements (thermal photography) [1] either automated by using aerial devices (drones) [2] or images from satellite [3]. Images are collected at a central station where their analysis takes place.

Autonomous automated image acquisition systems can determine water stress for fruit crops – as described in the example of olive groves [4] but also grain crops – e.g. monitoring the salinity impact of [5], fodders, industrial plants (for example plants for fabrics – cotton [6]) – to monitor the impact of drought, or an intelligent irrigation control system where irrigation systems are desirable. In addition to the determination of water stress, thermal monitoring of agricultural crops (fruit trees, for example) can also be used to treat crops of certain diseases or pests [7].

Such solutions have though a disadvantage. They allow for punctual analysis over time, only at the time of image acquisition (operator or drones), or they suppose the use of communication channels for broadband images sometimes inaccessible to crop fields. A more comprehensive analysis would be done over a period (e.g. days, weeks, etc.). This would be more accurately captured by the evolution of the thermal factors that can cause water stress in plants. For this reason, we propose, in this article, a complete integrated analysis system that can learn – through deep learning algorithm – several templates of conditions for the occurrence of water stress and can then recognize these preconditions in the real environment. The system can then generate alarms to farmers / researchers about the occurrence of water stress. Thus, instead of transmitting the image to the central station on a conventional video channel, the system will perform an on-site analysis over a period, identify potential prerequisites for water stress by recognizing templates, and will only convey indications of the crop state.

2. System Description

A block diagram of the system is shown in Figure 1.

As you can see, the system has two components: the acquisition modules and the central event server.

The system uses a 300×128 resolution FLIR sensor connected via an interface to an integrated ARM Cortex A7 based system. The system allows the running of a deep learning neural network for both learning and testing. Following testing, the values (outputs from neural network) are transmitted using 866 MHz (LoRa) free radio communication.

The main component of the input mode is the thermal camera. It makes inputs at a time interval of 1 minute to 10 minutes (obviously it may be even greater – experiments were performed with these intervals). The purchased images are stored in the system – a small storage on a 16 GB SD card will be used for this purpose. An image buffer will be stored for 20 days. The purpose of storing these images is to be downloadable for more detailed analysis – if desired.

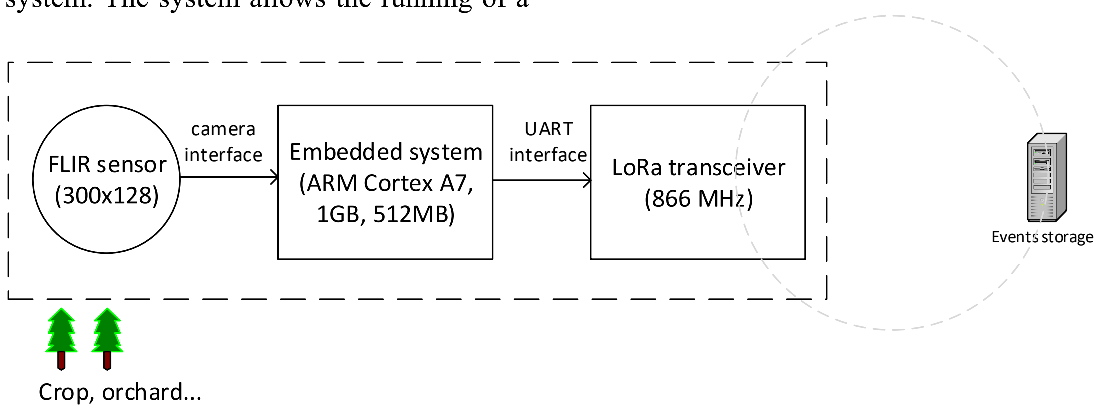


Fig. 1. System block diagram.

The captured image reaches the processor where it is analyzed and classified – the deep learning neural network is used as shown below. It also stores the image on the card. If, after the intelligent analysis, the detection of some prerequisites for the occurrence of water stress takes place – thus generating an event – then this condition will be associated with the name of the stored image. If desired, the image can be downloaded from the card (offline) and can then be associated with the event.

In the end, the events are transmitted through the LoRa communication interface to the server.

The element that distinguishes our monitoring solution from other solutions is given by the implementation of the deep learning algorithm on the acquisition module. Thus, as it has been shown, the local analyze of the images is available, but also their classification and recognition of certain events that are related to the prerequisites for the occurrence of water stress. So, instead of transmitting the image, only useful information related to that image is transmitted with the resulting implications – the use of a small bandwidth channel, which may for example be a LoRa communication with the resulting advantages: transmission on a relatively large distance (20 km) using low power equipment, using of free band of frequencies (866 MHz).

2.1. Server

The central component of our system is the event processing and storage server. The server engine is based on the use of a Complex Event Processing - WSO2 Data Analytics Server. A block diagram is shown in the figure below.

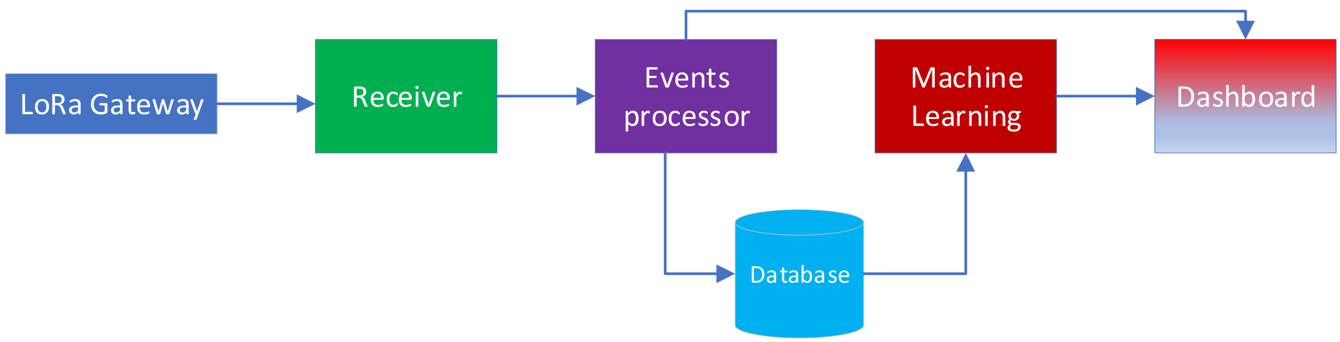


Fig. 2. Server block diagram.

It allows both managing events, analyzing them and reporting them – displaying in the dashboard.

Events can be retrieved via receivers. The server has a gateway that takes radio data from the monitoring modules and sends them to the receiver. The receiver knows how to interpret this data and convert it into the format of input streams which can be further processed.

The event processor takes input streams and applies real-time processing: determines the event type and stores it in a local database. There is also an analysis of the history – the events stored in the database are processed by a prediction algorithm based on Machine Learning.

So, on the one hand, we have the smart recognition of a water stress pattern by analyzing the thermal image acquired with the IR camera. This occurs at the input module level. On the other hand, we analyze the evolution over time of a set of events taking place at the central server level. From this analysis, one can make predictions on the future evolution of culture.

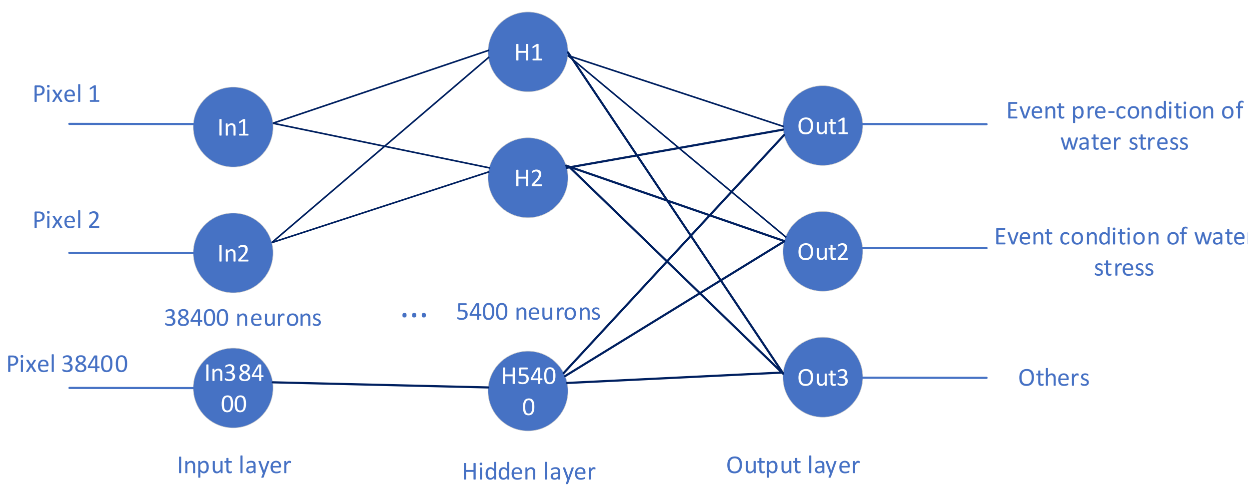


Fig. 3. Deep learning neural network used in embedded system

3. Experiments

The system can run both for supervised training and testing a Tensor Flow deep learning neural network configured by using the Keras API. The network features are as follows: input layer 38400, hidden layer 5400, output layer 3 classes (normal, prerequisites for hydric stress and water stress). For the input layer and the hidden layer, the RELU activation function and the sigmoid output layer were chosen. A figure of the neural network is presented above (figure 3).

The optimization method used is RMS prop. Through these configurations it is allowed the running of a small number of training periods. For a sample of 50,000 images, of which 10,000 are for testing during learning, 20 periods (each lasting about 2.5 seconds) were sufficient to achieve learning. The accuracy of the test response was 97.8% as it can be seen in the listing.

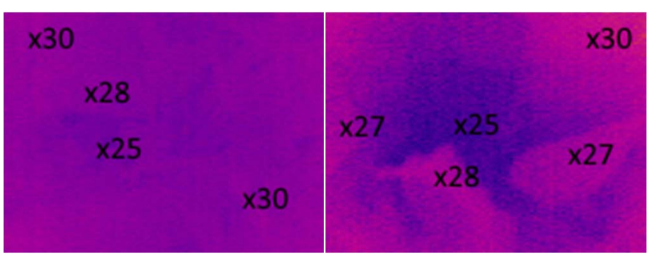
Listing 1. Results from ANN training.

```
Epoch 20/20
48000/48000 [==============================] - 2s 36us/step
val_acc: 0.9785
10000/10000 [==============================] - 0s 28us/step
Test score 0.09552692916354735
Test accuracy 0.9775

- 2s 36us/step - loss: 0.0727 - acc: 0.9788 - val_loss: 0.1001 -

- 0s 28us/step
```

The table below shows the timing for the input module. As you can see, the learning process consumes about 1 minute while the response in the test phase (basically the normal operating phase) is about 0.05 second. In other words, after learning, the monitoring system can identify thermal images that show signs of water stress on the plant.

Table 1. Timing for embedded system. Training is performed once. After that, the network just identifies the classes for the pictures provided from FLIR camera. Identification time is very short (28 ms). Time is deduced using debugging tools (console and time evaluation function)

Operation	Time (ms)
Training (once)	52 000
Response – identification (each time)	28



a) b)

Fig. 4. Two thermal images captured by FLIR camera and identified by ANN: a) image with a normal plant which is exposed to different temperature gradients b) a plant with preconditions of water stress: there are exposed leaves (30 degree) but dry leaves (27, 28 degree).

Fig. 5. Embedded system (top) and FLIR camera (bottom). Display is used only for debugging purpose. Embedded system has attached video camera which is used to provide complementary information

Figure 5 shows a picture of the monitoring module (PICO i.MX7 Dev. Board) and the IR camera that was used. Examples of images captured with the FLIR camera and identified by embedded ANN are shown in figures 4a and 4b for two plant species in the laboratory.

It is possible to observe the temperature difference according to the illuminated areas. Thermal exposure leads to the first signs of water stress. Clearly, no such observations can be made in the visible spectrum.

In the listing below, we present the features of our system (prototype):

- **Integrated thermal camera – 300×128 FLIR resolution.** Thermal images show the preconditions of water stress in plants – which cannot be determined in the visible spectrum. The use of other sensors, e.g. a point thermal sensor, is not sufficient to determine the thermal profile of the entire canopy (whether it is trees) or plant leaves.

- **ARM Cortex A7 Micro-system (embedded system) for automatic image acquisition, local storage and analysis – 1 to 10 minutes acquisition/input rate. The storage buffer is minimum 20 days**. An essential condition is automatic image acquisition input for a certain amount of time. Thus, the evolution of the thermal profile of the monitored plant can be determined.

- **Thermal imaging algorithm based on deep learning neural networks to recognize the prerequisites for water stress. The analysis is done locally at the micro-system level. The parameters of the neural network that we have implemented in our prototype system are the following: input layer 38400, hidden layer 5400, output layer 3 classes (normal, prerequisites for hydric stress and water stress).** Why deep learning? Because it is the most modern and appropriate method for classifying images. Why is "learning" necessary and not just "comparing and identifying" as a method of analyzing images? Because the diversity of images is very large. We can have lots of different images to show the same state. For this reason, we must have a learning of the image characteristics that show the conditions for the occurrence of water stress. Why local learning is required and not just local testing? It was possible to learn some patterns on a computer and to download the weighting configurations into the embedded-system where the network was used only for prediction and classification. However, the thermal images defining the conditions of the occurrence of water stress differ from one plant to another (as it can be seen in the figures). For this reason, it is necessary to learn some in situ, which is why we provided both learning and testing (prediction, classification) for the deep learning neural network.

- **LoRa radio communications for identified events based on image analysis – 866 MHz EU bandwidth, 0.1 W, 25 km coverage.** By extracting events from images and transmitting events instead of images significantly decreases the amount of information to be transmitted to the server and the bandwidth. For this reason, the means of transmission of information will be through low-power European LoRa communication. On the one hand, it is a free, available communications solution, and it allows for longer distances (20−25 km).

- **Complex event processing server – can receive and handle up to 5,000 events per minute, allows real-time analysis of events and batch analysis, and allows machine learning integration for batch analysis.** The system designed by us intends to be widely applied in orchards and agricultural and textile crops. That's why the server was sized to support the reception of multiple events. In this regard, we used a specialized middleware for complex event processing. Alongside with the event reception, the server also performs a real-time analysis for classification (makes storage of the events on the three classes and their aggregation with time so that at any time they can generate reports like: the hydric stress precondition event appeared 3 times on 16/04/2018 at 16:00). On the other hand, we also have a batch analysis to determine how events evolve over time.

- **Dashboard for display of results: distribution of events on the surface, evolution of events over time. There will be two types of widgets: the map type showing spatial events and scatter events (points) that show the evolution of events over time for a particular surface. Web application with user account access. Client Response Interface (same interface for computer and mobile equipment).** Customers: Farmers, agricultural science researchers can visualize the evolution of events and their spatial distribution. For this they will connect through a browser – no application is required.

3. Conclusions

The article presents a complete system (implemented at the prototype level) to monitor the occurrence conditions of water stress in plant crops. The system is part of a wider project that aims to determine hydric and bio stress in plant crops before its effect is felt by crop damage. The use of FLIR thermal cameras in agriculture is currently possible due to technological progress that has led to a significant price drop of such equipment. In this case, an image with the space distribution at the canopy level of the temperature peaks is more relevant than the point input acquisition of the temperature values.

Also, local analysis instead of centralized image analysis provides the advantage of communicating a much smaller data package. This has become possible thanks to technological developments in micro-systems production and intelligent recognition algorithms. Central analysis of events and their publication to users in the form of a dashboard is possible using highly performing and modern methods of complex event processing tools.

As we have seen, the system has been implemented at prototype level and tested on plants under laboratory conditions. Future development directions would be related to the implementation of the system under real test conditions. The input acquired results and the paths that are learned will certainly be improved.

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