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Forecasting irrigation scheduling based on deep learning models using IoT

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Abstract*– Potatoes are one of the staple foods in Boyacá and play an important role in family nutrition and food security in Colombia. Therefore, timely and accurate information on the irrigation of this crop is relevant in agricultural decision-making, the sustainable development of its production and the reduction of unnecessary water consumption. This study estimated the irrigation prescription of a potato crop from crop meteorological information with the support of IoT technologies to solve the problem of inefficient water dosing in the crop. Two deep learning models were developed, a One-Dimensional Convolutional Neural Network (1D-CNN) and a short-term long-term memory neural network (LSTM). Training data was collected daily from a potato crop from 2018 to 2020 using two weather stations located in the UsoChicamocha irrigation district. To predict irrigation prescriptions, deep learning architectures were trained using Python® by selecting input climatic variables measured with a subsystem of sensors installed in the crop and an actuation subsystem with control of Latch-type solenoid valves, both remotely controlled wirelessly. The algorithms were validated by calculating precision metrics such as MSE and coefficient of determination. The results showed that the LSTM model surpassed the 1D-CNN model, obtaining training and validation errors less than 0.096 and presenting greater precision in the estimation of crop irrigation, giving a coefficient of determination R^2 between 0.881 and 0.919. Irrigation prediction algorithms using deep learning techniques achieved promising results and serve as a decision support tool for farmers to automatically decide when and how much water to irrigate.

Keywords-- Deep Learning, CNN, LSTM, Irrigation Prescription, IoT, Smart Farming.

I. Introduction

For the agricultural sector of the department of Boyacá in Colombia, it is necessary to develop irrigation methods based on precision agriculture. Specifically, potato crops require the use of irrigation forecast estimation technologies that contribute to increasing economic and productive yields, minimizing the environmental impact that these tasks can produce [1].

Precision farming is a strategy based on the use of new technologies, which allows the productivity of the land to be managed more efficiently, maximizes income and minimizes environmental impact [2]. With the advancement of new technologies in telemetry, remote sensing, communications, signal processing, internet connectivity and scientific-technical knowledge in these areas, it is possible to create crop ecosystems based on the Internet of Things (IoT) [3].

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IoT allows the connection and monitoring of objects located over long distances using WSN technologies and centralized data collection systems connected to the network [4, 5]. For precision irrigation systems, based on IoT, humidity sensors located in the crop are used, weather stations close to the planted area and actuator systems on solenoid valves that allow irrigation supported by technical approaches, which take into account the dynamic behavior of the crop [6, 7]. The irrigation prescription and application methods that are now available can be divided into five types:

- Through soil variables: where soil sensors are used to measure and process data on the Volumetric Water Content (VWC) or the Potential of the Soil Matrix (PCM) [8].
- Through climatological variables: which are based on calculations of missing water, through formulas of water balance and meteorological data, to calculate the Evapotranspiration (ET) [9].
- Using plant parameters: in this method, remote sensing tools are used (satellites, drones and Geographic Information Systems (GIS) for the management of irrigation in crops) and sensors connected directly to the plants [10].
- Using crop models: several models endorsed by international organizations such as FAO are used, which allow estimating the hydric status of the soil and the particular requirements in each cultivation stage [11].
- With the farmer's experience: it is based entirely on empirical data acquired by each farmer in his field and on his own experiences.

All of these methods can be integrated and automated through IoT-based technologies, cloud computing, and the use of machine learning algorithms. Additionally, Deep Learning (DL) techniques have been used in applications for agriculture, since agricultural processes are characterized by the biodiversity of products and the variability of crop conditions. DL extends its application in the estimation of sowing processes, crop yield, prediction of irrigation prescription, application of nutrients and fertilizers in the plots, collection of products, identification of diseases, climate and soil mapping, among others, processing information automatically [12-18].

This work explains the implementation and development of an irrigation prescription forecasting system in a potato crop using IoT technologies for the acquisition and transmission of crop data measured by a sensor network. The treatment of the cultivation variables is transmitted remotely, to enter an irrigation prescription estimation system based on deep learning.

Crop variables such as maximum, minimum and average temperature, soil moisture and rainfall were measured daily for three years. The Evapotranspiration of the crop was calculated, and together with the climatic and soil variables were entered as input data to the deep learning algorithms to make reactive and proactive decisions about the prescription of irrigation in the potato crop through an infrastructure of drip irrigation.

II. Materials and Methods

A. Studio Site Selection

This study was developed in potato crops from Finca San Carlos located in the municipality of Tibasosa, Boyacá, Colombia. The land belongs to large-scale Irrigation and Drainage District of Chicamocha (UsoChicamocha). The UsoChicamocha Irrigation Station has eleven irrigation units with one pumping station each as illustrated in Fig. 1.

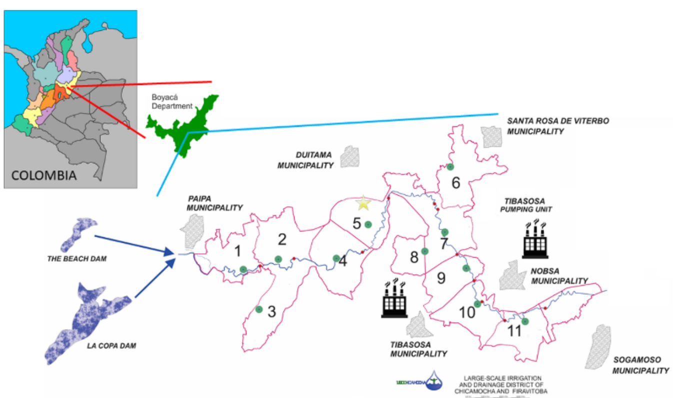

Fig. 1. Location of the study field in the UsoChicamocha Irrigation District and Irrigation Unit (9) of Tibasosa.

The water source for crop irrigation is the *La Copa* dam, and the water is distributed along the Chicamocha riverbed. The potato crop is located in the Irrigation Unit of Tibasosa (9 in Fig. 1). The Tibasosa irrigation unit supplies water from the potato crops on the San Carlos farm through a pumping station. Four lots were used, with an approximate total area of 100 m2, which are located with central coordinates at 5.76534 ° N, - 72.98283 ° W.

Cultivation lots have an average elevation of 2575 m.a.s.l. and it has a dry-cold climate. The lots have a bimodal regime and a water deficit during most of the year, the winters are short, cool and humid with a concentration of rains between April and May in the first semester and between October and November in the second semester, according to with data collected over 10 years [19]. Temperature does not drop below 7 °C or rise above 21 °C, where the average annual temperature is 14.05 °C. The average annual brightness in the Irrigation unit Tibasosa is 1853, with a high qualification for the sowing of agricultural species [20].

B. IoT Based Architecture

Each intelligent system houses the trained deep learning model implemented on a RaspBerry Pi platform that is connected to a Davis Vantage Pro2 Series weather station, allowing it to access data on ambient temperature, soil moisture, precipitation, and evapotranspiration [21].

Potato crop was divided into four lots of 25 m2. Each crop is supervised and managed by four intelligent systems that have a sensor subsystem in the center of the crop and an actuation subsystem with control of a Latch-type solenoid electrovalve at the entrance to the irrigation supply. A water supply with constant outlet pressure is guaranteed for each crop, so that there is a linear relationship between the opening time of the solenoid valve and the amount of resource applied.

Access to meteorological data allows the Smart system to make irrigation decisions according to the water balance equation of the crop expressed in (1).

$$WC_t = WC_{t-1} + I_{RR} + R_{AIN} - ET_C - DP \quad (mm) \qquad (1)$$

Where WC_t is the water content in the soil in the current day (*mm*), WC_{t-1} is the water content in the soil of the previous day (*mm*), I_{RR} and R_{AIN} are the irrigation applied and the rainfall that fell last day (*mm*) respectively, ET_C is the accumulated evapotranspiration of the previous day (*mm*) and *DP* the deep percolation (*mm*) [22]. With the data acquired in the field and from the meteorological station strategically located near the crop, the amount of irrigation to be applied was determined by calculating the difference in the volumetric water content and through changes that the farmer can make from the mobile application, the schedules of when to carry out the watering process.

The IoT based architecture showed in Fig. 2 has been proposed to collect, transmit and process the climatic and soil variables of the potato crop (air temperature, soil moisture, and precipitation) of farming land along with the weather forecast information to manage the irrigation efficiently.

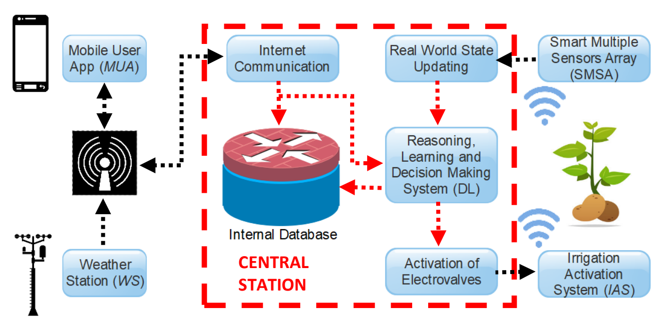

Fig. 2. IoT based arquitecture for Prescription Irrication Prediction using Deep Learning (DL).

The Smart Multiple Sensors Array (SMSA) is the *Measurement Station* that allows the acquisition of field information. *Central Station* is considered the brain of the prescription irrigation system where the crop information is stored and analyzed, as well as being the direct connection to the database located in the Firebase computer services.

Irrigation Station is the system in charge of acting on the solenoid valves of the system. *Weather Station* is responsible for acquiring data from the environment around the crop and a communication system with the farmer based on a mobile user application (MUA) for management irrigation system.

C. Dataset Collection

The set of daily climatic data for the potato crop were collected through one weather station located in the field *El Clan* that belongs to the Tibasosa irrigation unit (9 in Fig. 1), during the period of time from June 2018 to June 2021. This dataset provided selected climatic variables based on daily historical data that include rain, maximum, minimum and mean temperature, reference crop evapotranspiration and water content in soil (Table I).

TABLE I
WEATHER AND SOIL INFORMATION FOR TRAINING.

Data Source	Feature Name	Unit	Description
Climatic Data	T_{AVG}	°C	Daily Average Air Temperature.
	T_{MIN}	°C	Daily Minimum Air Temperature.
	T_{MAX}	°C	Daily Maximum Air Temperature.
	R_{AIN}	mm / day	Daily Cumulative Rainfall
	WC_1	%	Water Content in Soil at 20 cm.
	WC_2	%	Water Content in Soil at 40 cm.
	R_N	H	Daily Hours of Solar Radiation

Deep learning models require a large volume of data to train. Furthermore, recording crop yields based on different irrigation schedules is too slow and sometimes impossible. Evapotranspiration (*ET*) is the amount of water that evaporates from the soil and the soil water content (*SWC*) is the volume of water per unit volume of soil. ET_C was calculated and used as input for the water balance equation. ET_C was estimated from meteorological data using the FAO-56 Penman-Monteith Equation (2) [9]:

$$ET_C = \frac{\Delta \cdot (R_N - G) + \gamma\left(\frac{900}{T_{AVG} + 271}\right) \cdot WS \cdot p}{\Delta + \gamma(1 + 0.34 \cdot WS)} \quad (mm) \qquad (2)$$

Where R_N is the net solar radiation, G is the heat flux from the ground, p is the pressure deficit, γ is the psychometric constant, WS is the wind speed and T_{AVG} is the mean daily temperature. With the amount of rainfall measured, *ET* was calculated in an hourly time interval over a 24-hour period and summarized in a daily time interval. The advantage of using deep learning models is that it does not require manual adjustments once the model is trained and can be used automatically. These models can be used to create a decision support system for irrigation scheduling.

D. Data Pre-Processing

In the preprocessing phase, the data set was prepared so that the characteristic extraction phase was more efficient. The climatic data set for the period from June 2018 to February 2020 (60%) was reserved for model training, the data set from March 2020 to October 2020 (20%) was used for validation and the dataset for the period November 2021 to June 2021 (20%) were used to test the models, respectively. In time series modeling, the estimation becomes less accurate gradually, so it is more advantageous to train the models with real data when available.

During the training phase, the dataset was used to update the parameters of the networks. The validation dataset was used during the training phase to monitor the process and detect overfitting [23]. Finally, the trained models were tested with the test dataset characterized as new and unexamined (Fig. 3).

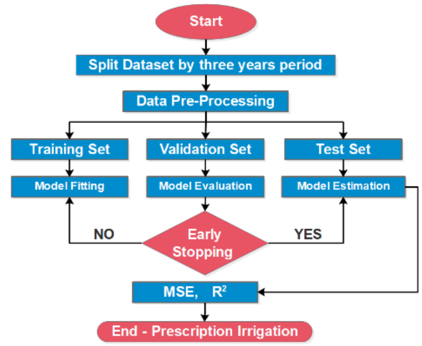

Fig. 3. Scheme of the Data Preprocessing for predict the irrigation prescription.

The training, validation and test data consisted of time series spaced every hour. The variables were normalized to ensure that they remain on the same scale. This preprocessing guarantees a stable convergence of parameters in the model. The standardization formula used in the studied data set was a Min-Max normalization model. For each variable in the data set, the minimum value of that variable is converted to 0, the maximum value is converted to 1, and all other values are converted to a decimal number between 0 and 1 using (3):

$$x^j_{i_{new}} = \frac{x^j_i - \min(x^j)}{\max(x^j) - \min(x^j)} \qquad (3)$$

Where xi represents the data in the i_{-th} of variable j, $\min(x_j)$ is the minimum value of x in variable j and $\max(x_j)$ is the maximum value of x in variable j, for $j = 1, 2, ..., 6$.

E. Developed Models

1) Architecture and parameters of the One-Dimensional Convolutional Neural Network (1-DCNN): Convolutional Neural Networks (CNN) have been successful in machine vision applications to process crop images mainly in classification, recognition, detection and segmentation processes [24-26].

Convolution and Max Pooling Filter principles used in images can be simplified to work with one-dimensional data in the form of time series. CNN models make predictions based on current input data and do not use past observations to make future decisions. The 1-DCNN model proposed reads the data from delayed observations and extracts useful features to generate future predictions.

The architecture of a CNN is made up of a stack of connected hidden layers that are reduced in width from input

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to output. CNN thickening reduction is done to ensure condensation of information into more abstract concepts in deeper layers. Each shrinking stage generally consists of one or more convolution layers and several pooling layers connected to each other.

First a set of convolutional layers is organized using a local layer-shared filter that generates the response of the filter's convolution with its inputs in the output. The outputs of the convolutional layers usually have the same dimension as the inputs. Second, the outputs of the convolutional layers are the activations that go into the pooling layers, which use a dimension reduction operator (for example, max) to thin the layers.

As a result, a hidden neural unit has a smaller field of view than the entire input layer, that is, a neuron located in the upper layers has a field of view indicated by dashed black lines as shown in Fig. 4. This hierarchical design helps to capture the most prevalent local training characteristics and extracts the most essential parameters on a larger scale in deeper layers.

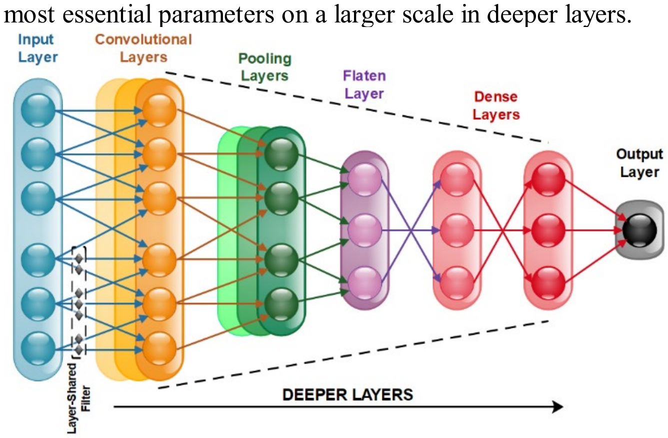


Fig. 4. Structure of the One-Dimensional Convolutional Neural Network used in this study.

The parameters learned by the convolutional layers are made thanks to the application of the layer-shared filters. All neurons in the convolutional layers share a single filter that reduces the number of parameters compared to a fully connected layers, making CNN training easier. In this work, several tests were performed using the 1-DCNN architecture. The model begins with the 1D convolutional layer composed of 16 convolutional filters, a kernel size of 3 and a Rectified Linear Unit (ReLU) as activation function. Added a max pooling layers to recover the input characteristics, into more meaningful and useful inputs. The inputs are flattened with the next flatten layer which is used to split convolutional layers and fully connected layers and get the first prediction step.

2) Architecture and parameters of the Long Short-Term Memory model (LSTM): Another deep learning architecture uses Recurrent Neural Networks (RNN) to process sequential data efficiently. RNN integrate feedback loops, allowing through them that the information persists during some training periods (epochs), by means connections from the outputs of the layers, which embedding their results on the input data.

Basically, the RNN remember previous states and use this information to predict which one will be next. The connections between nodes form a graph directed along a time sequence, so they are applied in lists to handle time series. RNNs have been introduced for sequential learning, as they are capable of storing and relating prior information.

Long Short Term Memory (LSTM) are a special type of RNN networks that have computational units with the ability to dominate or suppress input characteristics, allowing them to store only characteristic weights more important. While standard RNN can model short-term dependencies (that is, close relationships in the time series), LSTMs can learn long-term dependencies and determine the optimal time delay for time series problems. In this sense, LSTMs operate dependent on experience over time and can learn when to forget and how long to keep state information. LSTMs outperform RNNs by holding the value of the previous output for a short period.

Given this characteristic, LSTMs are used mainly for processing and estimating complex variables and combinational inputs. LSTM have been used in crops such as tomato, soybean and corn, where climate data and environmental parameters are mapped. These crop variables are periodically monitored and data are generated in the form of time series that are analyzed and processed to provide diagnosis and estimation of irrigation prescriptions in crops with very good efficiency [27-29].

The solution to the vanishing gradient problem is the LSTM model that contain specially designed units called gates and memory cells. The gates are simply neurons with weights or gains that have the ability to learn: The gates surround the memory cell C^t to control the information flow. After training, the input gate it controls which entries are significant enough to remember. The forget gate f^t decides how long and what past state memory should be retained. The output gate o^t determines the amount of memory that is used to produce the output. The integrated operation of the gates allows the network to remember information from the past and discard non-essential information.

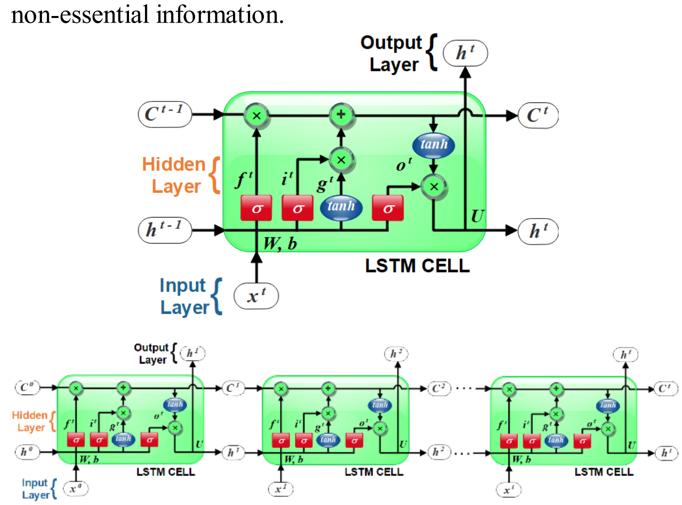


Fig. 5. Structure of the LSTM Neural Network used in this study.

The LSTM architecture proposed and implemented in this work uses a model known as “many to one”, which means that multiple data inputs can be predicted in the form of time series to predict a single value [30]. Fig. 5 shows the LSTM architecture developed where a single input layer was arranged that receives the input data x^t, a single hidden recurring layer that stores the information in a hidden state h^t in the memory cell of the LSTM and a single layer output o^t. The hidden layer contains the memory units of the LSTM that manage and control the input, output and storage of data. *Tanh* or *sigmoid* transformation operators are provided in each LSTM memory cell that scale the data to facilitate the information flow.

Each memory cell contains one or more memory cells and four multiplicative gates: input i^t, forget f^t, cell g^t and output o^t [31], to overcome the short-term memory limitation of the RNN. The memory cells memorize the value of the temporary state in arbitrary time intervals and the four gates control the opening or closing of the flow from the new input x^t to the next cell since it enters through the input gate i^t.

The learning process discriminates what information is important and what is not, as time passes while the assigned weights are updated. The relationships that define the operation and structure of the model of each LSTM memory cell are defined in (4) to (9) with initial values of the state of cell $C^0 = 0$ and of the recurring output $h^0 = 0$:

$$i^t = \sigma(W_i x^t + b_i + U_i h^{t-1}) \tag{4}$$

$$f^t = \sigma(W_f x^t + b_f + U_f h^{t-1}) \tag{5}$$

$$g^t = \tanh(W_g x^t + b_g + U_g h^{t-1}) \tag{6}$$

$$C^t = f^t \oplus C^{t-1} + i^t \oplus g^t \tag{7}$$

$$o^t = \sigma(W_o x^t + b_o + U_o h^{t-1}) \tag{8}$$

$$h^t = o^t \oplus \tanh(C^t) \tag{9}$$

Where x^t is the input at time t, C^t is the current cell state and h^t the output layer hidden at time t. Furthermore, σ is the sigmoid function, *tanh* is the hyperbolic tangent function. Vectors U define the weights of each gate in the hidden output layer, vectors W are the weights of each gate in the input layer, and b are the additive training bias vectors for each gate. The operator $\oplus$ is the Hadamard multiplier that performs the vector product to generate outputs of the same dimensions as the input.

In the LSTM model, an epoch corresponds to one pass of all the training examples. For each epoch a loss function is used to evaluate how well the specific algorithm models the dataset. If the predictions deviate too much from the actual results, the loss function will produce a large value. The number of LSTM cell units proposed in the model was 32. Dropout is a technique used during training to avoid overfitting.

F. *Hyperparameter tuning and reproducibility*

Hyperparameters determine the structure of the network model and how it is trained. The results of multiple simulations of the same algorithm with different hyperparameters varied in this work. For the training of the irrigation prediction models in the potato crop, several hyperparameters were selected and iteratively tested to determine the best performances of the deep learning models such as the number of neurons or nodes per layer, batch size, number of layers, dropout values, number of epochs, activation functions and optimizers. Table II describes the hyperparameters selected to train the deep learning models that presented the best results.

TABLE II
HYPERPARAMETERS SETTED TO TRAIN DEEP LEARNING MODELS.

Neural Network Model	Hyperparameters	
1-DCNN LSTM	Nodes per Layer	64, 128, 256
	Epochs	64, 128
	Batch Size	16, 32, 64
	Activation Function	ReLU
	Neurons	64, 128, 256
	Optimizer	Adam
	Dropout Size	0, 0.1, 0.2

Models with 16 and 32 nodes performed very poorly and were excluded from the experimental results. Finally, the network architectures were tested with 64, 128, and 256 nodes per layer. The activation function ReLU was used to capture the non-linear relationship between input and output, as it looks for positivity in the input arguments. If the input value is positive, it is returned the value; otherwise, if the value is less than zero, value zero (0) is returned as the final output.

The optimization algorithm selected to minimize the loss function was Adam optimizer. The Adaptive Moment Estimation Algorithm (Adam) allows to calculate an adaptive learning rate for each of the parameters. Adam also maintains an exponentially decreasing sum of the past gradients. This optimizer works very well in practice as it converges faster, and the overall learning speed of the model is also quite fast and efficient, compared to other optimizers.

G. *Implementation Details*

TensorFlow library for numerical applications was used together with *Keras Deep* Learning library. Keras allows the configuration and training of deep neural networks developed on the Python® programming platform. For matrix calculations, model evaluation and graph display, *Numpy*, *Scikitlearn* and *Matplotlib* libraries were used in Python®. The deep neural network models were trained using a computer equipment with the next specifications: CPU: 2.5 GHz, Intel Core I7, and 12 GB of RAM.

H. *Model Evaluation Metrics*

To evaluate the prediction performance of the implemented deep learning models, two evaluation metrics were used. To measure the losses of the deep learning models, the Mean Square Error (MSE) function was applied, which calculates the variance presented by the model, defined in (10):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i - \hat{y}_i}{y_i}\right)^2 \tag{10}$$

To evaluate the precision of the irrigation prescription forecast, the Coefficient of Determination R^2 was used. R^2 is a statistical measure that calculates the variance explained by the model on the total variance showed in (11):

$$R^2 = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \bar{y})^2 - \sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2}} \tag{11}$$

Where N defines the number of total observations, y_i is the true value at the i_{-th} time, $\hat{y}_i$ is the estimated value by the model at the i_{-th} time, and $\bar{y}$ is the average of the true values and i varies from 1 to N. The higher the R^2 score, the smaller the differences between the observed data and the adjusted values.

III. Analysis and Discussion

A. IoT System

A network of four cyber-physical systems was implemented for the prescription and application of irrigation in an experimental potato crop (Fig. 6). It was proposed that the networks of intelligent systems for the application of irrigation have reactive powers for the prescription and application of irrigation, since they depend on the perception they have of their environment and the irrigation conditions programmed by the user.

Fig. 6. Experimetal Potato Crop used in this study.

Fig. 7. Mobile Application for Irrigation Management and Monitoring.

The availability of WiFi connectivity in the study area was necessary for the display, visualization and interpretation of the information in the crop. A mobile application was developed to control and visualize the status of growing agents, connected to devices in the field, through a cloud computing platform (Cloud-FireBase), hence the importance of having a connection to Internet Fig. 7.

B. Training and Testing Performance

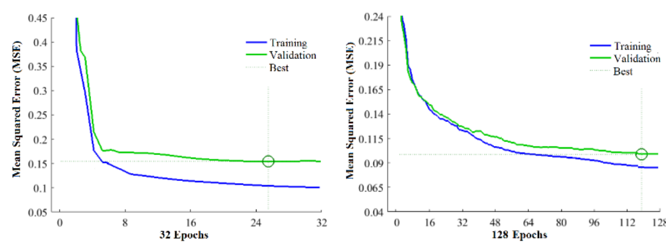
The efficiency of deep learning algorithms can be determined by evaluating the models with the application at runtime or by calculating evaluation metrics. The overfitting and underfitting effects of machine learning models can be evaluated by comparing losses in the training and testing stages of the prediction algorithms. In the training of the 1-DCNN model for the weather station, the results showed that the experiments were able to predict the irrigation prescription with an MSE lower than 0,105 and validation values around 0,157. The losses in the prediction of the irrigation prescription for the implemented LSTM model were lower compared to the 1-DCNN model, where the MSE obtained was 0,082 and 0,096 for training and validation data respectively.

The lower training and validation losses for the LSTM model are evident due to increased functionality in the computational units of the LSTM cells. This trend of training and validation losses data is listed in Table III.

TABLE III
PERFORMANCE PRECISION METRICS FOR THE BEST ITERATION OF THE DEEP LEARNING MODELS

Model	Training Dataset		Validation Dataset	
	MSE	R^2	MSE	R^2
1-DCNN	0,105	0,812	0,157	0,867
LSTM	0,082	0,881	0,096	0,919

Fig. 8. shows the comparison of the loss of precision of the deep learning models during the training and validation of the dataset for the irrigation prescription of the potato crop in terms of the number of epochs.



a) b)

Fig. 8. Training and Validation loss curves for the best training performance in predicting irrigation prescription. *a)* Loss for 1-DCNN. *b)*. Loss for LSTM.

The number and size of the hidden layers were important for the design and evaluation of the deep learning models. The highest R^2 value and the minimum MSE = 0,157 for the 1-DCNN model were obtained when 32 epochs were configured, a dropout of 0, batch size of 32 and 32 epochs with score of R^2 = 0,867. For the LSTM model with 64 cells, dropout of 0.2, batch size of 64 and 128 epochs, the best performance was obtained with an MSE = 0,096 and R^2 = 0,919.

These two models had a favorable statistical performance and therefore the selection of one of these models over the other depends on the available data.

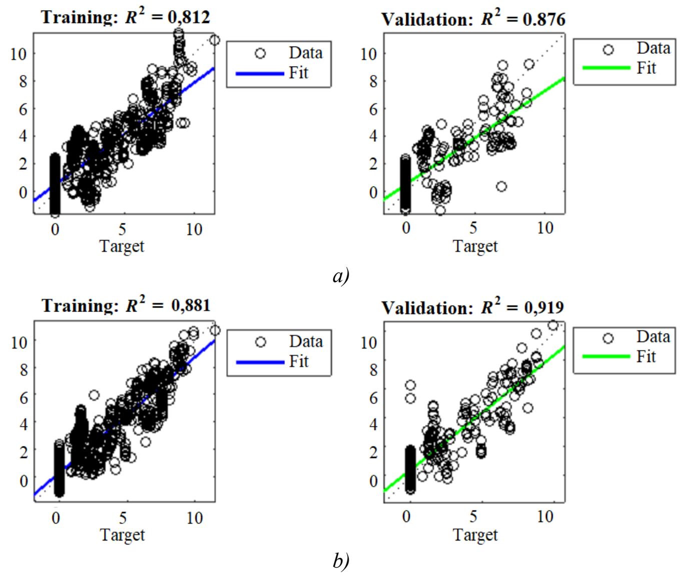


Fig. 9. Irrigation prescription forecast evaluation for trained and validated deep learning models and their correlation score. *a)* 1-DCNN Model, *b).* LSTM Model.

IV. Conclusions

Potato crop in the Department of Boyacá plays an important role in the economy and food security of the region and the country, since a large part of the population depends on it for their livelihood.

In this work, a precision irrigation prescription prediction system was developed in an experimental potato crop that integrates remote sensing, IoT and machine learning technologies.

Today, IoT has expanded its capabilities to support smart and sustainable agriculture. This type of technological applications for agriculture allow the farmer to efficiently manage the crop, increasing productivity and product quality, improving crop yield and optimizing the use of water resources.

An irrigation prescription prediction system was designed and implemented using IoT technologies that automatically communicate the central processing station with the measurement station and the weather station to make decisions about the application of precise irrigation in the crop. The central system receives weather data from the environment that was entered by two verified deep learning algorithms, stored on RaspBerry Pi platforms.

The estimation of the irrigation prescription in a potato crop was developed using two deep learning models: 1-DCNN and LSTM. The models were trained using as inputs climatic variables such as the maximum temperature, the average temperature, the minimum temperature, the amount of water in the soil at two depths, the wind speed and the calculation of the Evapotranspiration of the crop.

When performing the training and validation processes with the deep learning algorithms, the LSTM model outperformed the estimation of irrigation prediction when compared with the results obtained by the 1-DCNN model. The lowest training and test losses for the hybrid LSTM model were 0,082 and 0,096. The LSTM performance algorithm had the highest determination coefficient, obtaining a coefficient of determination R^2 = 0,919, compared to the 1-DCNN model score, which obtained a score of R^2 = 0,86.

Although the LSTM model presented better prediction results in the irrigation prescription in the potato crop with respect to the results of the 1-DCNN model, the differences in the irrigation prescription estimates of the deep learning models were successful. Validation of these deep learning models allowed farmers to properly schedule potato crop irrigation according to water supply predictions.

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