Smart irrigation integrate to IOT technology based on deep learning's algorithm LSTM

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Abstract— agriculture is very important to live humans, indeed it is the axis of energy for them, but any imbalance can threaten the food system, the progress of agriculture is essentially dependent on the irrigation which can be in two forms either by rain or by human irrigation, but the problem is that the rain does not have an organized schedule, its presence is random, we cannot count on it to a continuous way because its frequency is random, but we can predict when it rains by approximation with an uncertainty of time and duration and quantity. for this we have invented an intelligent system capable of predicting when it rains, after a communication of the sensors with cloud in order to optimize the use of irrigation, and to have coherence in the event of absence of rain, we go to irrigation in an automatic way, this irrigation is controlled according to parameters depending on the humidity of the soil and the phase of the planting, and annual season. thanks to IOT technologies integrated with sensors and drone.

Keywords: IOT, irrigation, fertilization, cloud

I. INTRODUCTION

Technology has recently played a major role in the development of the agricultural industry, and today it is possible to grow crops in the desert using technology Humans have always been at the mercy of nature and climatic changes in the past, as agricultural production relied entirely on annual rainfall, temperature and humidity changes. However, with the tremendous technical developments and the entry into the world of the digital revolution and artificial intelligence, it is now possible to control this, as agricultural technology is constantly evolving Digital agriculture is also inevitable with the increase in human numbers, the constant need for more food, and urban sprawl that has reduced the size and area of arable land in the world. Traditional agriculture is financially costly, from preparing the soil and receiving seeds to using fertilizers to fertilize the soil, using pesticides to control pests and diseases, up to the harvest stage, all operations require a lot of money, and fertilizers and pesticides, for example, consume a large part of agricultural investment. As it can give a complete picture of the farmer,[5] from the quality of the soil to the level of moisture and the intensity of the winds, these methods can help in identifying a large number of factors that farmers can base their decisions on. IoT sensors will be able to monitor nutrient levels in the field and provide farmers with accurate insights as to when and where to plant crops to maximize gain and avoid crop waste.

This paper has as structure after the abstract introduction then, related work, proposed method, data used , tools exploited, and finishing with conclusion and future work , references.

II. RELATED WORK

for [7,4,11]about management of irrigation by IOT and controlling system irrigation automatically using mobile connected to raspberry which integrated to moisture sensors and measure the level of moisture to test it if it is below to proper level a signal,the raspberry send signal to start water pump, and send motor, temperature, moisture's statistics to mobile a d keep it synchronized with the farmers. for [3,6] smart irrigation and monitoring system based on iot technology [2]integrated with android phone using zigbee protocol wireless communication connected to specific network to make connection between station and nodes and treat data in server by dint of using java application and propose using cloud in order to save all this data.

[9,10,1,8]propose an overview about the recent generations of sensors integrated to iot and wsn technologies for smart system irrigation. and water management can limit waste of water. four layers: first layer for collecting data from sensors and second layer for controlling connection between system's units, the third layer for allowing decision and planning path for robots which can be supplying by solar energy for more

performance and the last layer for application which make checking visualising data and getting alerts for users.

III. PROPOSED METHOD

our method consists in connecting a component raspberry pi 4 contains a program which processes the data sent by the humidity sensors located at the extremities of the agricultural zone, and drone which takes captures for the plants on a periodic basis every three days (modifiable as needed) at midday so that the sun will be perpendicular to the ground and will have no effect or influence from the sun's rays for the image processing that will be used to make the right decision for fertilization, the raspberry pi 4 is connected to the irrigation administration system which gives access to raspberry to control the irrigation start and the irrigation stop time in an autonomous

SMART IRIGATION
Test Humidity
Rainfall predicition

TRACKING PROGRESS
verifying Size/Color plant's period

Fig.1: Tux, global system for smart irrigation and fertilization

IV. DATA

The dataset contains 10 years of weather from different places on Australia.

Our dataset contains about 23 variables in order to predict if it well rain or not.

Date	145460 non-null	object
Location	145460 non-null	object
MinTemp	143975 non-null	float64
MaxTemp	144199 non-null	float64
Rainfall	142199 non-null	float64
Evaporation	82670 non-null	float64

Sunshine 75625 non-null float64 WindGustDir 135134 non-null object WindGustSpeed 135197 non-null float64 WindDir9am 134894 non-null object WindDir3pm 141232 non-null object WindSpeed9am 143693 non-null float64 WindSpeed3pm 142398 non-null float64 Humidity9am 142806 non-null float64 Humidity3pm 140953 non-null float64 Pressure9am 130395 non-null float64 Pressure3pm 130432 non-null float64 Cloud9am 89572 non-null float64
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-
Cloud9am 89572 non-null float64
Cloud3pm 86102 non-null float64
Temp9am 143693 non-null float64
Temp3pm 141851 non-null float64
RainToday 142199 non-null object
RainTomorrow 142193 non-null object

Table 1: variables of dataset

the table presents our database based on Australie statistics for the rains that fell during the ten years least of 2013 to beginning of 2024, we have tried to present the average for each month for the years. we have tried to group the country according to three atmospheric zones, a zone at the top of the country has a cold climate, a zone in the middle represents an average climate and the other zone represents a desert climate

V. TOOLS



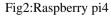




Fig3: humidity sensor

for the tools, we need a raspberry pi 4 with performance at least GHZ in RAM, and speed 1.6 GHZ and power supply of 5.1 V 4A 20.4 W. and 50 V power supply drone, contains a camera with a minimum 40 Mega Pixel camera in order to have a clear and exact vision. quantity humidity sensors depending on our use case distributed at the ends of the farm. system of drip irrigation pipes, allows to pass irrigation water and fertilization mixed with



Fig.4: Drone with camera

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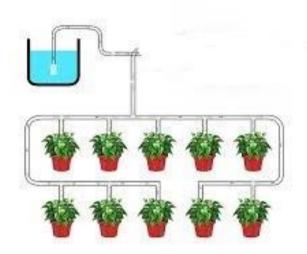


Fig.5: irrigation's system

This figure represents a simple setup for automated irrigation.

. A water reservoir is positioned in the upper left corner, connected to a network of pipes or tubes that extends horizontally across a row of potted plants. Each plant is equipped with a drip irrigation system, indicated by the small tubes extending from the main pipe to the base of each pot. This setup allows for efficient watering of multiple plants simultaneously.

Overall, it illustrates a basic concept of automated irrigation, where water is delivered directly to the root zones of plants, ensuring optimal humidity levels for healthy growth. These systems can be further enhanced with IoT technology and deep learning algorithms, as

discussed earlier, to create smart irrigation solutions that optimize water usage based on real-time data and predictive analytics.

VI. RESULT AND DISCUSSION

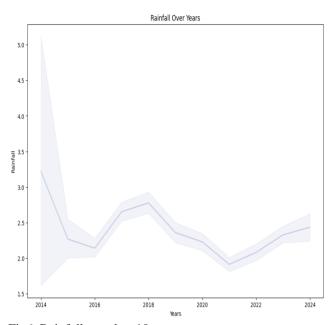


Fig6: Rainfull over last 10 years

This figure showing rainfull measures in the last ten years ago from least of 2013 to beginning 2024.

The training based on LSTM algorithm give the result

showing in table 2 and curves on figure

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	precision	Recall	f1-score	support		
0	0.86	0.96	0.96	20110		
1	0.75	0.81	0.81	5398		
			0.85	25508		
macro	0.81	0.71	0.81	25508		
avg						
weighted	0.84	0.85	0.85	25508		
avg						

Table2: table show progress of training LSTM algorithm. The accuracy arrive to 85%

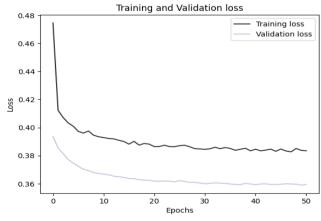


Fig 7:training's LSTM algorithm Loss for 50 epochs This figure displays the training and validation loss of LSTM model across multiple epochs.

The training loss, depicted by the black line, decreases steadily as the number of epochs increases. This indicates that the model is effectively minimizing its error on the training dataset during the training process, which is expected behavior.

The validation loss, shown by the purple line, also decreases initially but tends to stabilize or even slightly increase after a certain number of epochs. This divergence between the training and validation loss suggests that while the model continues to improve its performance on the training data, it may not generalize as well to new, unseen data represented by the validation dataset.

Overall, monitoring the training and validation loss is crucial for assessing the performance and generalization capability of the LSTM model. A decreasing training loss coupled with a stable or decreasing validation loss indicates that the model is learning effectively without overfitting, while a significant gap between the two may indicate overfitting and the need for adjustments in the model architecture or training process.

according to curves on fig7 we can see training is stable from epoch 20

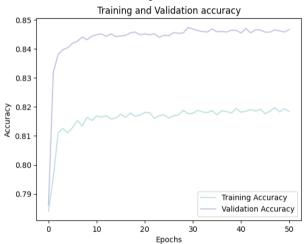


Fig 8: training's LSTM algorithm Validation for 50 epochs

This figure illustrates the training and validation accuracy of a LSTM model over multiple epochs. the linear axis represesnt epochs, about 50, which are iterations over the entire dataset during the training process. The other axis represents the accuracy of the model on both the training and validation datasets.

As the training progresses through epochs, both the training accuracy (depicted by the light blue line) and the validation accuracy (depicted by the dark blue line) initially increase. This indicates that the model is learning and improving its performance on both the training and validation datasets.

However, after epoch 10, the training accuracy continues to increase, while the validation accuracy starts to plateau or even decrease slightly. This suggests that the model

may be overfitting to the training data, meaning it is becoming too specialized to the training dataset and may not generalize well to new, unseen data.

Overall, this figure provides insight into the training dynamics of the machine learning model, showing how its performance evolves over successive epochs and highlighting the importance of monitoring both training and validation accuracy to assess model generalization.

a) Irrigation our smart irrigation system basically allows you to optimization ofirrigation water consumption and The prediction of rain is done according to a chained process. The decision is made according to raspberry pi 4.

b) fertilization

The use of drones in the treatment and fertilization of crops saves time, water and energy, and increases yields, especially for crops that are difficult to reach. It could be the ideal solution. They can be exploited completely independently and programmed to operate according to specific schedules and routes according to the appropriate situation. so we can program the drones in order to get pictures and send it to Raspberry pi 4 which can make treatment and get decision about quantity which need plant to grow up right. this quantity must be perfect, because if it's not enough, the plants will not grow up quickly and can not get a perfect size. on the other side if quantity is too much, probably we can have anomalies also will waste fertilizer and that make an other problem for farmers for consumption.

VII. CONCLUSION

to conclude the iot is the most innovative technology allowing to have functionalities to improve and facilitate the life of the human being. our system based on two essential aspects irrigation and fertilization based on the iot by integrating with some complementary components of our device raspberry pi 4 programmed to execute a process so that it can make a treatment and give the right decision and compatible with the situation by collecting the data provided by the sensors such as the humidity sensor and the drone... as a perspective we want to continue to continue our march in order to have a more precise complete automatic system for fertilization that must be compatible with the type of existing product, without having reference to a human, it must do the treatment in an autonomous way .

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