PERFORMANCE MODELLING OF IOT IN SMART AGRICULTURE

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2023 International Conference on Advances in Electronics, Communication, Computing and Intelligent Information Systems (ICAECIS) | 979-8-3503-4805-7/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICAECIS58353.2023.10170558

***Abstract*— Nowadays, IoT is being used in several applications, such as smart cities, health care and innovating agriculture and other applications. Moreover, the evolution of IoT technologies such as LoRaWAN, SIGFOX, ZigBee, and others drives the industry to convert their traditional systems to IoT systems due to the need to achieve better performance. One of the most challenging applications in an IoT system is smart agriculture due to the need for high energy and water consumption to reach the desired crop yield. Several related works in different countries tried to solve this challenge for a better water consumption in irrigation process to get the maximum crop yield production. In this paper, we used artificial intelligence and deep learning to predict the crop yield and the needed parameters of the soil to achieve the best performance with minimum power consumption. Also, we used convolutional neural networks to detect the crop deficit needed for real-time monitoring. The performed simulation has shown that the proposed model outperforms other related works and will positively increase both saving resources and the performance.**

***Keywords*— artificial intelligence, crop prediction, internet of things, smart agriculture.**

I. INTRODUCTION

The internet of things (IoT) makes it possible for devices to connect to the internet, where sensors and actuators produce, send, and receive data as well as make decisions [1]. IoT simply refers to the ability to connect everything in our environment. beginning with devices, machines, mobile phones, cars, and even cities to be connected to the Internet with intelligent behaviour. Recent years have seen a significant expansion and innovation in hardware and software, which has reduced the number of human connections to the internet relative to the total number of connected devices. Numerous issues with spectrum allocation, security, energy use, and quality of service (QoS) have been raised by this expansion [2].

A. Spectrum allocation

Huge demand on various telecommunication technology created the need of managing spectrum resources. Spectrum allocation in IoT can be classified as licensed frequency bands as shown in Fig.1 used by cellular operators, and license exempt frequency bands, as shown in Fig.2, that can be used by cellular or non-cellular operators. The spectrum classification for each technology defers on each technology and application need as discussed below [3].

- Zigbee is an example of low power local area networks that are widely used, and it is designed to offer Internet connectivity to control low-cost and low power devices for short-range wireless communications [3].
- LPWAN technologies are designed to connect low bandwidth devices with low bitrates over long distances. LPWAN on the licensed spectrum can be deployed using two IoT technologies: LTE-M and NB-IoT. It can also run on unlicensed spectrum through SIGFOX and Lora [4].
- LORA targets low battery end devices where end-devices do not transmit large data, the long-range and low-power nature of Lora is usually used in monitoring applications [4].
- SIGFOX is a global network characterized by its power efficiency and low RF interference, designed to be used in applications where systems need small and infrequent bursts of data [5].
- LTE-M, a low power wide area technology, enables the reuse of the LTE installed base while supporting IoT through reduced device complexity and expanded coverage. This allows for a long battery lifetime, with the modem costs reduced to 20–25% of the current EGPRS modems [6].
- NB-IoT Narrowband-Internet of Things (NB-IoT) significantly improves the power consumption of user devices, system capacity, and spectrum efficiency, especially in deep coverage [7].

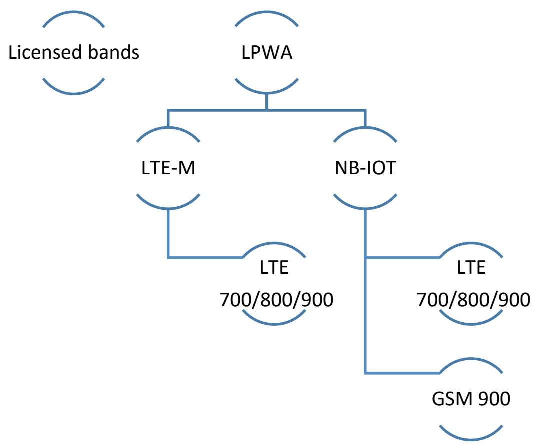


Fig. 1. licensed frequency bands [3].

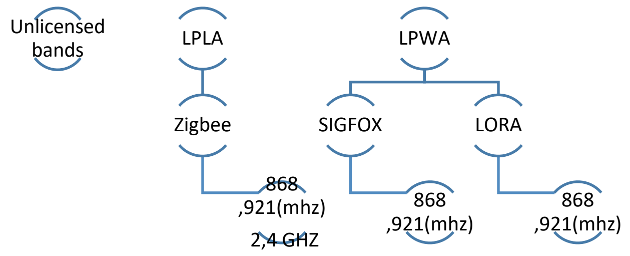


Fig. 2. License exempt frequency bands [3].

B. *Security*

Security is a critical IoT challenge. Cybersecurity attacks are a major risk in all advanced technologies, especially when using applications that depend on sensitive data. More security requires more processing power and more cost, which makes a trade-off between price and security, use cases with payments and metering require a higher level of security. Non-cellular IoT technologies are significant cybersecurity risks. While cellular LPWAN technology is ideal for sensitive use cases in which critical data is being communicated, offering some encryption features. These technologies are more vulnerable to threats related to traffic interference and encryption keys, as well as excellent quality of service [8].

C. *Key performance indicators (KPIs)*

Latency, throughput, scalability, and QoS are different KPIs that vary between the cellular and non-cellular spectrum, as shown in Table I. The selection of the technology used depends on the needs of each application.

TABLE I. CELLULAR AND NONCELLULAR OPERATORS [3]

	Non cellular unlicensed spectrum	***cellular licensed spectrum***
Latency	Slow >100 s	Fast 10 ms – 10s
Maximum throughput	Low data rate up to 50 kbps	High datarate up to 1 MBPS
Authentication and encription	Weak	strong
Jamming	Anti- jamming	Not anti-jamming
Max urban range	Up to 10 km	Up to 5 km
Max rural range	Up to 50 km	Up to 15 km
Handover	Limited handover	Handover possible
Scalability	Up to 50k devices per cell	Up to 100k devices per cell
Deployment cost	Moderate to low	Moderate
QoS	Low	High
Battery life	Very Long up to 20 years	Long up to 10 years
Real time performance	Low performance	Medium Performance

II. PROBLEM STATEMENT

We must increase efforts in water-dependent applications and improve water-saving techniques to conserve the already finite water resources under various climate change scenarios, as water scarcity is threatening national security and is one of the toughest challenges [9]. In order to use water efficiently, we must ensure that the amount of water used will produce the greatest amount of output. This will help in water conservation issue. a study conducted by Egypt's National Strategy for Adaptation to Climate Change and Disaster Risk Reduction on various agricultural areas over a 25–40-year period to forecast the growth and water requirements of Egypt's major crops These are the main crops:

- Wheat: If there is an increase in the temperature by 2 °C, wheat productivity will decrease by 9%. In comparison to the current weather conditions, this crop will use 6.2% more water. The deficit will rise to 18% with a 4 °C rise.
- Maize: Compared the current weather conditions, crop productivity will decrease by 19% by the middle of this century if temperature rises by 3.5 °C. 8% more water will be consumed as a result.
- Cotton: As a result of climate change, cotton productivity will rise. If the temperature increases by 2 °C, production will increase by 17%. In comparison to the current weather conditions, the water consumption of this crop will rise by 4.1–5.2%. Production will rise by 31% if the temperature rises by 4 °C. in comparison to the current weather conditions, water consumption will increase by 10%.
- Rice production will be 11% less productive than it would be under the current situation. There will be a 16% increase in water usage.
- If the temperature increases by 2 °C, tomato productivity will decrease by 14%. compared to the current weather conditions, the crop's water consumption will rise by 4.2–5.7%. If the temperature increases by 3.5 °C, the productivity decline will be 51% [10].

III. LITERATURE REVIEW

A. *Irrigation and water management*

The irrigation system shown in Fig.3 describes the main components of IoT, which include sensors that send data to the system based on a Markov solution in normal case and SARSA solution in case of any failure in the system, as shown in Fig.4. The output data of the system will be a decision passed to the microcontroller that will update the motor state. The model describes IoT water management for efficient rice irrigation system that is based on calculating the needed water for the system to take a decision by taking into consideration the rainfall and weather condition, to take advantage from the rainfall for a better optimization of the water resources [11].

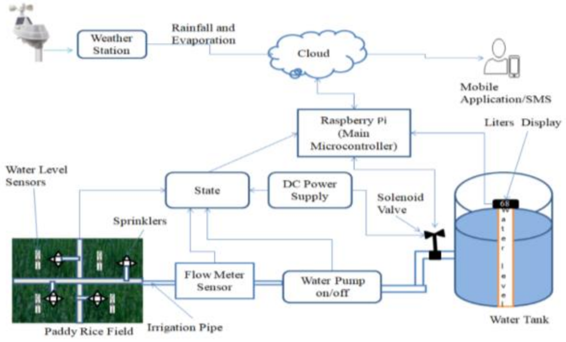


Fig.3. irrigation system solution [11]

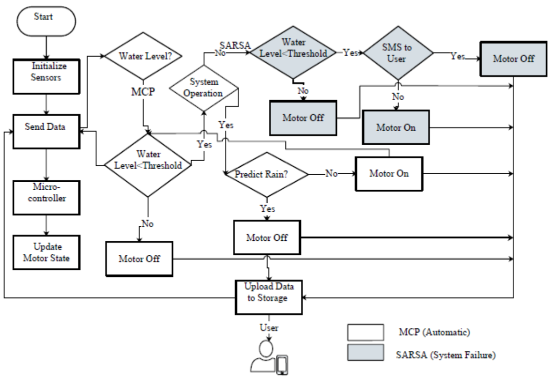


Fig.4. IoT solution [11]

The system shown in Fig.5 checks the moisture of the soil to check if it is below the threshold value to irrigate the crops or to notify the farmer in case of any issue in the system to take the necessary actions [12].

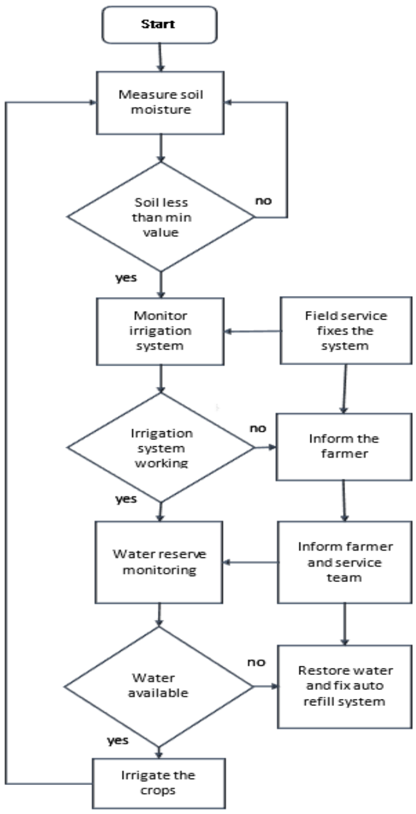


Fig.5 irrigation chart [12].

B. Livestock tracking

The geo-fencing capabilities and GPS tracking of the herd are defined by sensors fastened to the livestock collars. Several local parameters, including speed, herd body temperature, location, and livestock stress levels, are being tracked in real time. It improves the health and safety of livestock while reducing inefficiencies and operating costs. As long as the right sensors are used and physical and environmental factors are taken into account, the system's high response time yields accurate results and a high return on investment when used to manage herds [13].

C. Weather monitoring

The system monitors the weather through temperature, pressure, rain, and light sensors, as shown in Fig.6 [14]. Applying this system yields the following results:

- Helped in reducing crop hazards.
- Reduces the farmers working hours.
- Optimizing resources.
- Increase the quality by getting the optimal time to harvest and sending real-time alerts [14].

D. Fertilizer management

In the system shown in Fig.7, sensors will use a GSM module to transmit feedback from the farmer to the controller, which will use it to determine how long the valves will be opened for. Following the entry of these values, the fertilizer will dissolve in the tank's water. A second valve in the field that is attached to the drip irrigation pipes receives the signal from the controller after that. Using these drip irrigation pipes, the dissolved water in the tank will be automatically irrigated. Applying this system yields the following results:

- It stops the waste of water and fertilizer resources in farming.
- It decreases the water utilization to the yield efficiency increments [15].

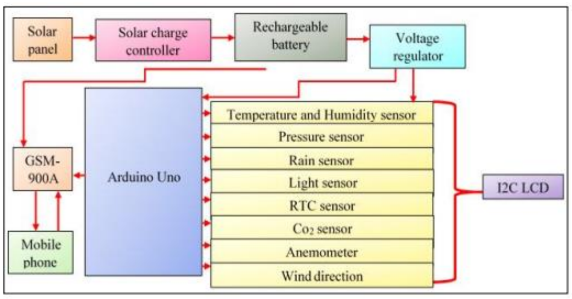


Fig.6 weather monitoring system [14].

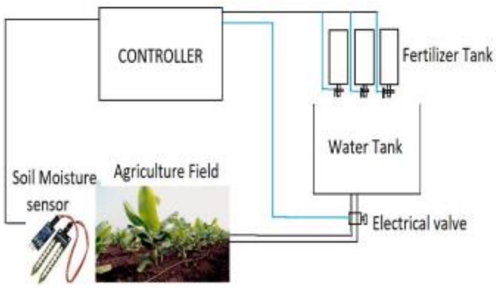


Fig.7 fertilizer management [15].

IV. Proposed Solution

In this section, we will discuss our proposed solution and algorithm. The previous work focused on using the irrigation system, livestock tracking, weather monitoring, and fertilizer management to enhance IoT model and the usage of the resources. In this paper, we will focus on the other side of the equation, which is maximizing crop production by predicting it using deep learning, and detecting crop deceases through image processing and convolutional neural network. To complement the previous work solutions to achieve the best results. In our solution, we will illustrate how deep learning algorithms can be used to optimize production, and how neural networks can be trained to predict the yield of a crop based on past data.

A. Crop prediction

The purpose of this phase is to predict the production of the given input features using neural networks through different models and to compare between the results. The input features of the neural networks consist of different crop types, humidity levels, temperature, and soil components. Major crops discussed in the problem statement were included, such as rice, cotton, wheat, and maize. We used different computing techniques and compared them with our solution. Techniques being used are:

- Prediction using random forest regressor.
- Prediction using polynomial regressor.
- Prediction using random XGB regressor.
- Prediction using adjusted sequential model.

An input layer x to an output layer y mapping is shown in Fig.8, which illustrates a neural network architecture. The hidden layers are identified as x (j), where j determines which ones should be revealed first. The output layer's structure and the inner layers' dimensions can both be freely chosen because the input layer's dimensionality, x R n, is known. The number of layers and the mapping method can both be selected by the user. A good classifier can be built with a lot of freedom thanks to this adaptable architecture [16].

Fig.9 and Fig.10 show the results of taking the mean square error and the mean absolute error between the output prediction of forest regression, polynomial regressor, and XGB regressor with their corresponding real outputs. The model’s accuracy increases as the error decreases.

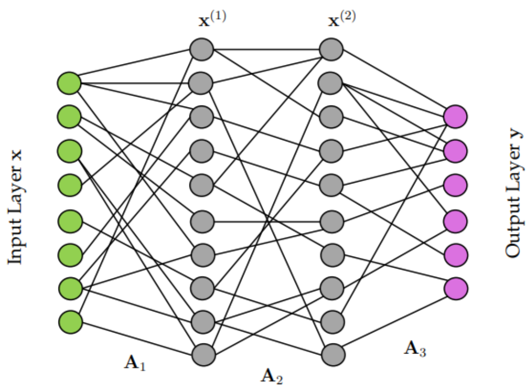
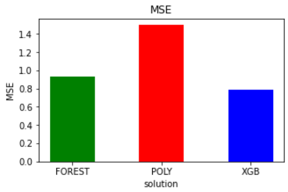


Fig.8. neural networks architecture [16].



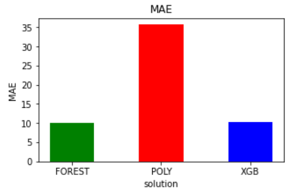


Fig.9 Mean square error Fig.10 Mean absolute error

While implementing the sequential model, hyperparameters shown in Table II must be adjusted, which are:

- Learning rate.
- Optimizer type
- Activation functions
- Number of hidden layers
- Number of epochs
- Batch size
- Validation split

Results shown in Fig.11 and Fig.12 describe the effect of training the model through 20 epochs on the mean square error and the mean absolute error between the crop prediction and the real output, which makes this model far better than the previously discussed models. As shown in Fig.11, after 20 epochs, the neural networks reached a mean square error equal to 3.5. Fig.12 shows the mean absolute error after 20 epochs. The neural networks reached a mean absolute error equal to 0.544. Fig.13 shows that the training set and test set follow each other, which means that the model is not overfitting or under fitting.

TABLE II. Hyperparameters

Parameter	***Value***
Learning rate	0.01
Optimizer type	Adam
Activation functions	RELU
Number of hidden layers	3
Number of epochs	20
Batch size	500
Validation split	0.2

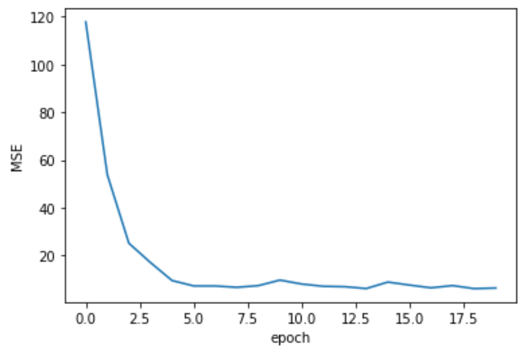


Fig.11. Mean square error.

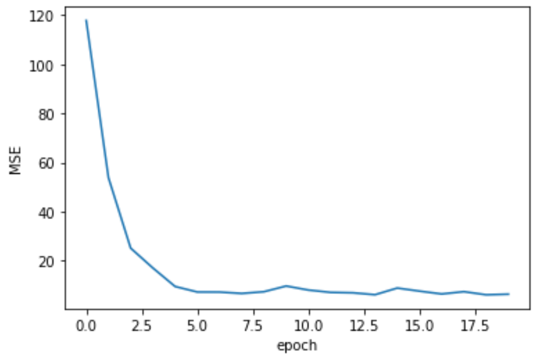


Fig.12. Mean absolute error.

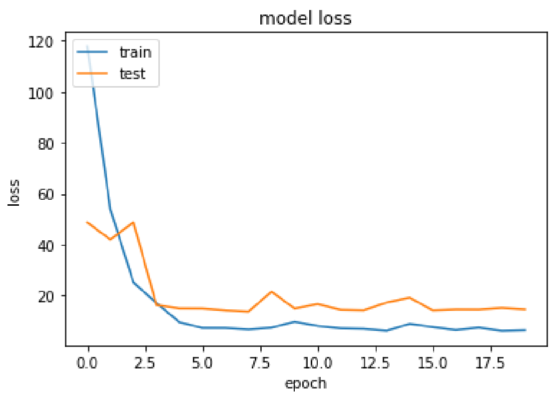


Fig.13. Model loss.

B. Crop deceases prediction

In this section, we will focus on getting image detection of crop deceases using neural networks. Our model is trained to detect the following:

- Bacterial leaf blight
- Brown spots
- Leaf smut

We applied the adjusted sequential model, using the hyperparameters stated in Table III to detect crop deceases. The results in Fig.15 and Fig.16 show that the loss is decreasing while training the neural networks and that the prediction accuracy is increasing. The graph in Fig.15 shows that the training set and the test set follow each other, which means that the model is not overfitting or under fitting.

TABLE III. HYEPERPARAMETERS

Parameter	***Value***
Learning rate	0.001
Optimizer type	Adam
Activation functions	RELU
Number of hidden layers	3
Number of epochs	100

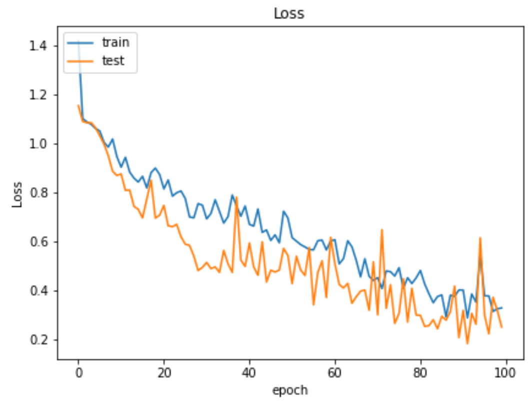


Fig.15. Loss versus epoch number.

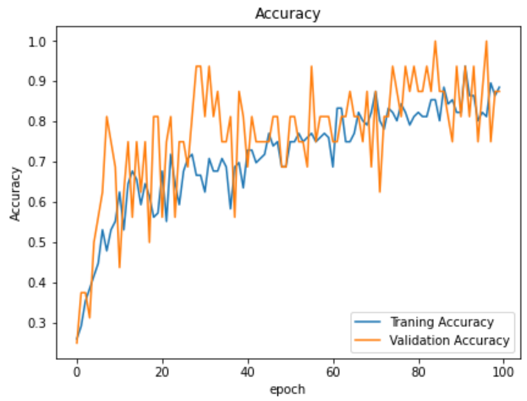


Fig.16. Accuracy versus epoch number.

V. CONCLUSION

Previous work focused on the irrigation system and water management. In this paper, we focused on crop prediction and crop decease detection. In the crop prediction solution, we used a data set that includes different input features that directly affect crop production. We compared between several neural networks algorithms by implementing them using Python code to minimize the prediction loss. By optimizing the sequential model, we achieved a mean absolute error equal to 0. 544. In the second part of our work, we focused on real time monitoring to detect crop deceases. We implemented an algorithm using convolutional neural networks and achieved a mean absolute error equals to 0.75. The integration of the IoT system is illustrated in Fig.17.

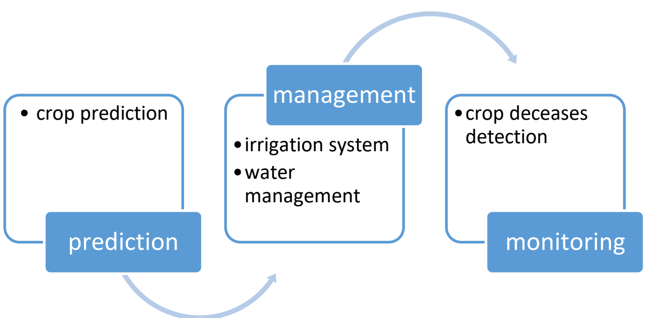


Fig.17. IoT system.

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