IoT Based Smart Agriculture

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ABSTRACT

Today, IOT is connected to all aspects of life from home automation, automatic, and even in health, fitness, and logistics. In the past, farmers used to check the ripeness of the soil and factors that influenced the growth of the better kind of product. But they are unable to consider the dampness climate conditions and water level, etc. The IoT plays a very vital role in the remodeling of agriculture by the facility in the wide range of new strategies to address challenges in the field. IOT modernization helps to get information on a situation such as the weather, climate, temperature, and soil fertility. There are many technological transformations in the last decades that have become technology-driven. Smart farming is a new technology in agriculture that makes agriculture more effective and more efficient. The farmer has achieved better results on the process of growing crops, making it smarter agriculture. The rapid development of IoT-based technology is redesigning every industry, including agriculture. The main focus of this study is to explore the benefits of using IoT in agricultural applications.

Key words: IOT, Deep Learning, Machine Learning, PDDS, Agriculture.

INTRODUCTION

The Internet of Things (IoT) is a communication system that extends the internet by integrating the physical and digital worlds through sensors and actuators in a balanced manner. The use of IoT technology has increased dramatically in recent decades, making it one of the most revolutionary breakthroughs in contemporary history. This technical achievement paved the way for the development of new "smart" applications that make use of the sensor-actuator interaction. One of the key advantages of IoT is the ability to better gather data to understand the assets and liabilities of the application. This could be accomplished by collecting information from the acquired data and then interpreting them for further study or enhancements [1].

Agriculture is important to the country's economy and provides a huge number of jobs. Agriculture, on the other hand, is strongly dependent on weather and climate. Changes in temperature, humidity, soil moisture, and carbon dioxide, for example, can all contribute to reduced crop production. Monitoring environmental conditions is crucial to monitoring crop growth and increasing agricultural output yield. Sensible knowledge is critical not only for decision making, but also for assessing the environmental implications of agricultural operations. Agriculture will benefit greatly from the expansion of IoT technology, particularly sensor technologies and cloud services. Recent technological advancements enable the creation of compact sensors, data storage, and transmission, resulting in cost, size, power, and flexibility benefits [2].

REVIEW OF LITERATURE

Crops such as rubber and gum are important in the economics of a nation. Recently, the food-crop-based bioenergy market has increased rapidly. As we know that a limited part of the earth's surface is suitable for agriculture due to various limitations for example, soil quality, topography and temperature, climate, and some areas are not homogeneous, and we know that each crop field has different features in terms of quantity and quality.

Nowadays, IoT plays an important role in the wide variation of industrial sectors from health to the manufacturing and agriculture industries to reduce inefficiencies and improve quality [3].

The capabilities of IoT include communication infrastructure used to connect smart things such as sensors and cars to use mobile devices, as well as data collection, cloud-based intelligent information processing, and a user interface for decision making. Farmers must return to the location several times throughout the life of the crop to have a better understanding of its state. To alleviate this burden, the idea of smart agriculture was developed, as farmers spent more than 70% of their time monitoring and understanding the crop. Observing these issues and the wide range of agricultural business applications requires technology and solutions that are suitable and have a low environmental impact [4].

RESULTS AND DISCUSSION

The following sections will provide a brief overview of the first-phase PDDS, Deep learning optimizers.

A. *Proposed first-phase PDDS*

The first phase PDDS model is shown in Figure 1. The first phase includes handpicked feature descriptors for feature extraction and tuned machine learning classifiers for disease classification. Healthy and diseased plant leaf images of tomatoes, cotton, and maize were taken directly from the agriculture field with various lighting conditions and publicly available data sets [5]. These images are captured through an android camera, and the dataset is prepared with 1000 images per class with a pixel size of 256x256. In this research, to remove noise from directly captured images and smooth the edges, a 5x5 kernel-sized median filter is utilized, as shown in Figure 2 (b). In the Opencv module, the function cv2.medianBlur (originally captured image, kernel size) is used for image filtering.

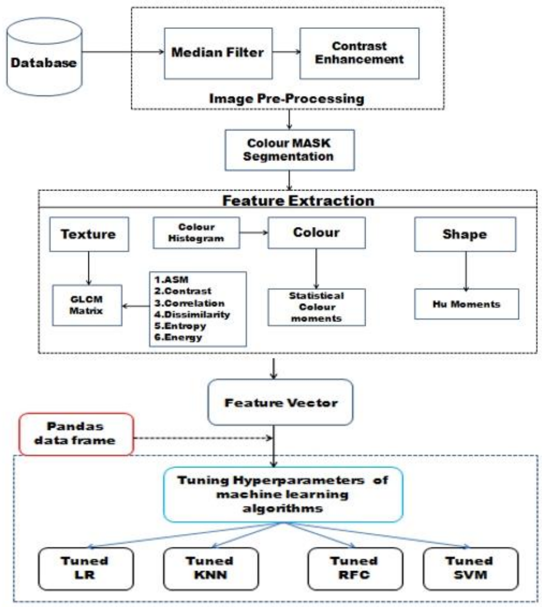

Figure 1: Proposed First Phase PDDS

Contrast Enhancement/Stretching

The captured image quality mainly depends on the captured device and the adapted technique, so the low-contrast images have to be enhanced to achieve better accuracy. First, the noise-removed image is separated into RGB channels as given in Equation (1). Then, the local minimum (Lmin) and maximum (Lmax) values of each channel are calculated by Equation (2), and the contrast range is calculated by adding these values as given by Equation (3). Finally, the individual RGB channel values were enhanced using this contrast range, as shown in Figure 2 (c).

$$R(x,y)(x,y) = \frac{n^3nn^3n}{G}$$

$$G(x,y)(x,y) = \frac{u}{n^3nn^3n} B(X,Y)x,y) = \frac{u}{n^3nn^3n} \quad (1)$$

i Є {1, 2, 3} for the respective channels R, G and B. Here the red, green, and blue channel values are represented by R(x, y), G(x, y), and B(x, y).

$L_{max} = Max(\psi_i)$, $L_{min}=Min(\psi_i)$, (2)
i{R(x, y), G(x, y), B(x, y)}

Here, the term ψ denotes the maximum and minimum functions for all values of I in which all red, green and blue channels are present.

$$L_c = Lmin_i + Lmax_i \quad (3)$$

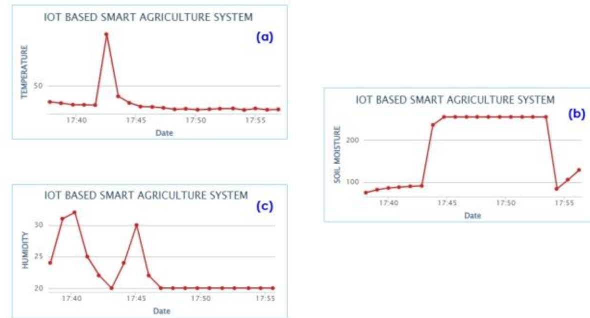

Figure 2: (a). Original version, (b). Noise-removed image, (c).Contrast-Enhanced image

HSV Color Space Segmentation

The main objective of image segmentation utilized in this research is to remove the background from captured images [6]. The contrast stretched RGB leaf image is rgb_img, which is then converted to the HSV color space hsv_img. From the Opencv module, the function cv2.cvtColor (rgb_img, cv2.COLOR_RGB2HSV) is used for this conversion. Due to the different nature of the crops used in this research, the common HSV color mask values could not be used to preserve the desired regions; three different color masks are used for the three different crops, as shown in Table 1. Finally, bitwise AND operation are performed to apply the created Mask with original leaf images. The proposed HSV segmentation results are compared with thresholding techniques like Otsu segmentation, Grab cut segmentation, as shown in Figure 3. From the results, Grab cut algorithm and Color space segmentation results are appearing the same. Still, Grab cut segmentation requires giving the desired region of interest for every image every time.

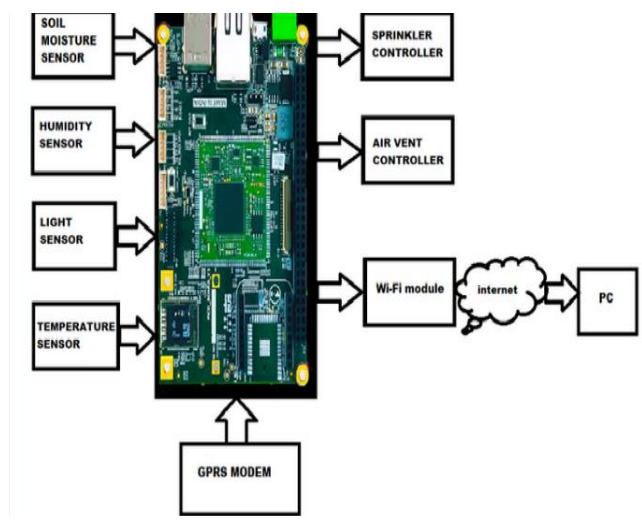

Figure 3: Smart greenhouse automation

Table 1: Color Masks for Tomato, Cotton, and Maize Leaves

Crop	Upper Green	Lower Green	Upper Brown	Lower Brown	Upper Yellow	Lower Yellow
Tomato	[86,255 ,255]	[36,0,0]	[30,25 5,200]	[8,60,20]	[40,255, 255]	[21,39,64]
Cotton	[86,255 ,255]	[36,0,0]	[30,25 5,200]	[8,60,20]	[255,255 ,255]	[3,3,3]
Maize	[86,255 ,255]	[36,0,0]	[30,25 5,200]	[8,60,20]	[255,255 ,255]	[21,30,5]

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EXPERIMENTAL RESULTS

A. *Deep Learning Optimizers*

At first, the SGD optimizer is used to train the above-mentioned well-known architectures based on validation accuracy, and the best CNN model is selected. Then, the six DL Optimizers with the specifications presented in Table 2 are utilized to improve classification accuracy.

Table 2: Hyper Parameters of DL Optimizers, LR=Learning Rate

S.NO	DL Optimizers	Particular
1	SGD	LR =0.001, weight decay=0.0005, momentum=0.9.
2	Adagrad	LR =0.001, epsilon=1x10-7.
3	RMSProp	LR =0.001, rho=0.9, epsilon=1x10-7.
4	Adam	LR =0.001, betal =0.9, epsilon=1x10-8.
5	Adadelta	LR =1.0, rho=0.95, epsilon=1x10-6.
6	Adamax	LR =0.002, betal=0.9, epsilon=1x10-8.

In this research, 10,000 images with 14 different classes are collected directly from the agriculture field and publically available datasets (Plant Village, TNAU Agriculture University). In addition, there are eight other classes for the classification of tomato plant diseases: Tomato leaf mold, early blight, septoria leaf spot, target spot, bacterial blight, late blight, spider millets and healthy tomato. In addition, for Cotton crops, two classes like Cotton healthy, Cotton viral diseases, and maize crops, four categories namely Maize nutritional, common rust, Cercospora_leaf_spot, and Northern_Leaf_Blight are selected.

B. *Tuning ML Classifiers*

The 532 features extracted, the machine learning models tuned with their hyperparameters for their best classification values, and the tuned models utilized for the proposed First phase PDDS.

The most critical parameters that are taken from the default Python specification to tune the performance of LR are the C value [100, 10, 1.0, and 0.1], the solver ['newton-cg', lbfgs', and 'liblinear'] and the penalty [l2']. These parameters are tuned with the above values for the tomato, maize, and cotton characteristics. From Table 2, the newton-cg solver with C value 100 gives 85.50% accuracy for tomatoes, 96.25 % accuracy for maize features, and C value 10 gives 88.80% accuracy for cotton leaf features.

Table 3: LR-Tuning Results

C Value	Penalty	Solver	Accuracy %		
			Tomato	Cotton	Mazie
100	L2	newton-cg	85.50	88.00	96.25
		lbfgs	81.87	88.00	94.68
		liblinear	83.37	87.50	93.25
10		newton-cg	81.12	88.50	95.00
		lbfgs	79.87	88.50	95.00
		liblinear	79.75	88.00	94.37
1.0		newton-cg	74.25	86.50	92.70
		lbfgs	74.50	86.50	92.70
		liblinear	72.62	87.50	91.62

C. *SVM Tuning*

From the default Python SVM classifier specification, the parameters selected are kernels- ['linear', 'poly', 'rbf'], C value - [10, 1.0, 0.1] and gamma scale [6]. Table 4 shows that SVM with C value 10 and kernel as poly gives 85.62% accuracy for tomato, 97.12% accuracy for maize features, and the same C value and kernel as rbf give 92.50% accuracy for cotton leaf features [7].

Table 4: SVM Tuning Results

Gamma	C	Kernel	Accuracy %		
			Tomato	Cotton	Maize
Scale	0.2	poly	85.62	92.00	97.12
		rbf	84.75	92.50	95.46
		linear	84.62	89.00	95.25
	1.0	poly	75.50	91.00	92.87
		rbf	74.12	90.00	92.00
		linear	77.37	89.00	93.25
	0.1	poly	59.25	84.00	87.50
		rbf	56.50	83.00	87.12
		linear	66.25	79.50	88.87

D. *KNN Tuning*

The parameters selected from KNN default Python specification are n_neighbors [3, 4], metric ['euclidean', 'manhattan'] and weights ['uniform', 'distance']. From Tab.3, n_neighbors as 4 with metric= manhattan, weights = Distance gives 82.75% accuracy for tomato, 90.12 % for cotton and n_neighbors =3 with euclidean metric and distance as weight gives 99.21% accuracy for Maize leaf features.

Table 5: KNN- Tuning Results

Xdf	Metric	Weights	Accuracy %		
			Tomato	Cotton	Mazie
3	euclidean	uniform	79.75	90.00	98.62
		distance	81.00	89.00	99.21
	manhattan	uniform	80.62	90.50	97.50
		distance	82.00	89.37	99.00
4	euclidean	uniform	77.62	88.00	97.75
		distance	80.87	89.50	99.20
	manhattan	uniform	80.25	89.00	97.00
		distance	82.75	90.12	99.00

E. *RF Tuning*

For tuning, the parameters selected from RF default Python specification include max_features ['sqrt', 'log2'] and n_estimators [10, 100, and 1000]. From Tab.4, max_features= sqrt, n_estimators =1000 gives 95% accuracy for Cotton, 99.50% accuracy for Maize and with same max_features no estimators as 100 gives 90.12% accuracy.

Table 6: RF Tuning Results

Max_feature	n_estimation	Accuracy %		
		Tomato	Cotton	Mazie
sqrt	10	82.50	91.00	99.12
	100	90.12	93.00	99.21
	1000	89.50	95.00	99.50
log2	10	82.00	91.00	98.96
	100	88.00	92.23	99.34
	1000	88.62	93.50	99.37

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CONCLUSION

In this study, non-contact AFM, four-point sheet resistivity meter and U-3900 spectroscopy were used to explore the cause of the sheet resistance drop of H2SO4-doped PEDOT:PSS films, which was observed in previous research. Surface roughness, sheet resistance, and transmittance of the doped PEDOT:PSS solution, which is obtained by adding different molar concentrations of H2SO4, are significantly affected. Surface roughness decreases from 1.268 nm to 0.822 nm once H2SO4 doping is complete. The surface of the PE-DOT doped with H2SO4 has been shown to be: The PSS film was smoother when compared to the surface of the doped PE-DOT: PSS film. The addition of weak sulfuric acid increases the resistance of the sheet from 604 to 216 ohms per square inch. The reduction in sheet resistance may be attributed to the replacement of nonconductive anions of certain PSS- with conductive anions of HSO4-, i.e., the substitution reactions will be advantageous for the increase in conductivity owing to the substitution reactions. Increased weight ratio of H2SO4 to PEDOT has been shown to be beneficial PSS results in a reduction in the transmittance of the doped PEDOT: PSS film. Transmission of the PEDOT:PSS film doped with H2SO4 with a 0.5M H2SO4 concentration is greater than 91% in the visible wavelength region between 400 and 700 nm. The great transparency and low sheet resistance of the H2SO4-doped PE-DOT:PSS films, on the other hand, indicate that they may be employed as transparent conductive electrodes in optoelectronic devices, as shown in this study.

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