The Automatic Agricultural Crop Maintenance System using Runway Scheduling Algorithm: Fuzzyc-LR for IoT Networks

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Abstract—In this framework, the crop diseases have been identified using three types of methods, fuzzy-c as a clustering algorithm, runway scheduling trains like classification algorithm, and logistic regression as prediction algorithm. These techniques are meaningful solutions for losses in yields and the quantity of agriculture production. In this work, crop disease and corresponding fertilizers are predicted based on pattern scalability by the above algorithms. It proposes a Sensor Calibration and Feed Back Method (SCFM) with RWSA for better agriculture crop maintenance with automation and Fuzzy-c, Logistic regressions are helpful in studying the datasets of the crops for classifying the disease. This research tries to identify the leaf color, leaf size, disease of plant, and fertilizer for the illness of crops. In this context, RWSA-Agriculture gives the solution for current problems and improves the F1-Score. The data collected from local sensors and remote station is estimated with the dataset, these sensor based L.R., and Fuzzy-c controls disease prediction system in SCFM and RWSA. This technique accurately regulates the dispensing of water as well as chemicals; fertilizers for crop monitor and prevent the diseases of crops. This investigation gives performance metrics values i.e PSNR=44.18dB, SSIM = 0.9943, BPP =1.46, Tp=0.945 and CR = 5.25.

Keywords—Runway Scheduling Algorithm (RWSA); Sensor Calibration and Feedback Method (SCFM); IoT; fuzzy-c; logistic regression (LR)

I. INTRODUCTION

This framework introduced an IoT based sensor calibration technique with the Runway Scheduling algorithm. Agriculture is the leading and emerging subject everywhere, and automation is compulsory. The population is increasing at a fast rate, so food gradients are necessary for people. The conventional agriculture method serves intensified results because Health monitoring of crops and disease detection is a critical task. Because of this reason, increasing the in-depth research regarding plants for the rising of the production rate is the need of the hour, which can be changed with the help of traditional methods like IoT, Machine Learning, and Artificial Intelligence. Until we cover edge computing, manual machine correlation, and static threshold methods [1][2], etc. these methods give satisfactory results, but improvement is a need for disease identification. Crop maintenance and disease detection for a plant is a crucial task in agriculture; it is complex to recognize the plant disorders manually. Therefore it requires tremendous work and maintenance, along with more processing time, export suggestions. Hence IoT based agriculture disease monitoring is used for the recognition of plant diseases for image processing and future extraction, classification. This work discusses various methods of identifying plant diseases selecting their leaves as images and applies 3-algorithms. This work also discussed some clustering and classification algorithms used in the plant disease monitoring system. AgriTech, for instance, relates to the overall use of innovation in agriculture, another side, smart agriculture is frequently used to indicate the use of IoT alternatives in agriculture. The identical refers to the definition of intelligent farming. IoT technologies also can transform several agricultural aspects. In other phrases, there are more than five methods in which IoT can improve agriculture: data, tons of details collected by smart farming sensors, e.g., weather conditions, soil quality, the advancement of crop growth, or cattle health. This information could be used to monitor your crop's specific status as well as personnel appearance, machinery effectiveness, etc. India is a cultivated country of the United States, and about 70% of the population depends on agriculture [25]. Farmers have a significant kind of variety for choosing various suitable plants and finding first-class pesticides for the plant. Disease on plant results in a sizeable reduction in the tremendous amount of agricultural merchandise. The research of plant disorder complements with the studies of visually observable styles on the flowers. Monitoring of fitness and sickness on plant plays an essential characteristic in cultivation of plant life inside the farm. In the early days, the monitoring and evaluation of plant illnesses have been performed manually utilizing the know-how person in that subject. This calls for first-rate quantity of work and calls for excessive processing time. The image processing techniques may be used inside the plant sickness detection. In most of the instances, ailment signs are visible at the leaves, stem, and fruit. The plant leaf for the detection of ailment is considered, which indicates the sickness signs. This paper offers the advent of the image processing method used for plant disorder detection.

Fig. 1 explains about generalized IoT architecture framework. In this investigation, this work is to be taken as an example. Various sensor modules collect the information and send it back to respective modules. So sensor measurements and estimations are compulsory. This estimation of the process is to perform with the SCFM mechanism.

Fig. 1. General IoT Network.

A. Automation of Crops Condition

This development and changing desires need to be utilize IoT of an agriculture industry that is going through labor shortages and increasing prices for farm work. Many farmers are finding it difficult looking to produce other, higher-outstanding crops and finding the workers to plant, hold, and harvest one's plants. This anxiety isn't new in agriculture. For all of the human records, growing agricultural cultivation has been a function of either consisting of greater laborers or finding more green tools to do the system [27]. Modern agriculture is no tremendous. In the face of labor shortages, farmers are turning to technology to make farms extra inexperienced and automate the crop manufacturing cycle. The growing interest in technology and automation is evident in venture capital investments for ag-tech startups. In 2007, in step with TechCrunch, investors contributed US$200 million to entire of 31 ag-tech startups. Ten years later, in 2017, total investment rose to over US$1. Five billion dollors are split amongst 160 startups. These startups are addressing each element of the agriculture rate chain.

Others create a software program to govern the seed, soil, fertilizer, and irrigation, and make predictions approximately on timing and yield. Some startups use drones to show conditions remotely and even comply with fertilizers, insecticides, and other treatments from above. A developing cohort of businesses is operating on agricultural robotics to construct self-sufficient tractors, combines, and even fruit and vegetable deciding on robots. Before you may automate farm operations, however, you need accurate information approximately on the state of the farm. We also need a way for self-maintaining gadgets to connect; this is the realm of the Internet of Things (IoT). IoT devices are the sensors, gauges, and machines that are connected for the duration of a farm, the use of Bluetooth, a cellular network, or a few one-of-a-kind forms of connection. More IoT devices permit growers to build up more records approximately the dominion of their farms, and IoT is showing high-quality promise for optimizing useful resource delivery and driving precision agriculture to collect maximum performance

B. Crop Monitoring System

In this section, an IoT based agriculture, cultivation, automatic cropping system has been discussed. Because of this, the accuracy of the cropping has been increased for various climatic conditions such as temperature, rain, and cold, respectively. According to this, water supply and fertilizers have to be supplied to crops. This automation continuously monitors the LCD screens. When various diseases occur, then immediately finding the diseases and suggesting particular fertilizers has been performing quickly. For crop monitoring RGB values of a leaf are required.

RGB plant colour estimation by using below eq. (1).

$$f(x) = 0.2989xR + 0.5870xG + 0.114.xB \qquad (1)$$

II. PARALLEL RESEARCH

This innovation relates as a rule to a framework for computerized control and all the more explicitly to a structure for checking and overseeing crop development. Farming has been a significant part of human presence for a long time. Upgrades in thinking about yields, quickening crop development, guaranteeing the nature of harvests, and accommodating a copious and productive collect have kept on adding to the pleasure and improvement of our populace's satisfaction. Significant zones for the robotization of farming incorporate water system, security against climate, creepy crawlies, and infection, and accommodating plant nourishment. Likewise, it is critical to have the option to conjecture crop development and collect with the goal that the financial aspects of reaping and appropriation can be increasingly productive. One case of a sort of yield that has profited incredibly from slow drifts in computerized agribusiness is the grape, which proves to be fruitfully used to make wine. The present vineyards incorporate distinctive administering frameworks for giving water to yields to a water system. Instances of such structures are "trickle" or "sprinkler" frameworks where water is steered among lines of vines by a cylinder having emanating gaps dispersed at ordinary interims. The water stream can be turned on or off physically or can be mechanized with clock control, P.C., and so on. The cylinders can be raised over the ground, or at or subterranean level.

The situation of diminishing water tables, evaporating of streams, and tanks, the capricious condition introduces an earnest requirement for the legitimate use of water. To adapt up to this utilization of temperature and dampness sensors at appropriate areas for checking of yields is actualized in [8]. A scheming formed through edge estimations of temperature also soil dampness can be modified hooked on a microcontroller-based door to regulator water quantity. Photovoltaic sheets that can organize the outline also can have a duplex correspondence connection dependent on cell – Internet interface that permits data review and water system planning to be personalized over a web page [9]. The mechanical improvement in open source programming and equipment make it simple to build up the gadget which can improve observing and remote sensor system made it conceivable to use in checking and control of nursery parameter inaccuracy agriculture [7].

In papers [2][3][4] projected a rural utilization of remote sensor organize for yield field checking. These frameworks wholly furnished with two sort sensor hubs to quantify dampness, temperature, also a picture for detecting the center to think about data by taking pictures of yields. Parameters assume a significant job in settling on a decent necessary

leadership for stable return inside a period. The limitations are temperature, mugginess, and pictures. By subsequent, these techniques can accomplish great soundness of sensors through low utilization of intensity. With it, is an extensive stretch of checking the agribusiness field region. Author in [5] anticipated a nursery Monitoring System dependent on agribusiness IoT among a cloud. In a nursery, the board can screen diverse ecological parameters viably utilizing sensor gadgets, for example, light sensor, temperature sensor, relative mugginess sensor, and soil dampness sensor. Occasionally (30 seconds), the sensors gather data of agribusiness field zone and are actuality logged then put away web-based utilizing distributed also calculating the Internet of Things. [6][13][16] Documents clarify an IOT Based Crop-Field Monitoring along with Irrigation Automation framework.

In their effort to screen crop-field, a framework is created through utilizing sensors as well as indicated by choice starting a server dependent on detected information, the water scheme framework computerized by using remote broadcast, the detected information sent in the direction of a web server database. On the off chance that the water system is mechanized, at that point, that implies if the dampness of temperature fields drop beneath of the probable territory. The client container screen regulate the framework remotely through the assistance of a submission, which gives a web interface to the client. In [7] a keen dribble water organization framework is planned. In this, a versatile Android application is utilized to decrease the inclusion of humans. Also, it is used to the regulator to screen the yield region remotely. Water depletion could be reduced through the Drip Irrigation framework as it works depending on data commencing water level sensors. Selected progressively, various situated sensors are utilized to screen the earth. The field climate information gathered and sensed together with weather information from internet repositories can be used to make several efficient choices to increase crop output. If the environmental condition is warm, dry, sunny, windy, then plants require a large quantity of water, and if these variables are like a cold, wet, cloudy, low wind, then the crop needs less water. The previous research model abstracted a scheme consisting of six components that are monitoring, managing, planning, distributing information, supporting the decision, and tracking action [22].

The practical and perfect quantity of agriculture manufacturing, storing, and exporting has been significantly enhanced by the IoT cloud service system by farmers. In this research, we are presenting various architectures of IoT multi-layer platforms for the agriculture sector by using IoT technologies [25-26]. This research contributes to significant suggestions for agriculture with developing countries [23].

A sensible model for automatic farming is suggested by investigating the layer IoT model. Before that, let us identify the general construction of IoT. Establishing numerous physical gadgets by and by IoT permanently consumes a 3-layer structure. The primary layer is the incorporated request layers, which in horticulture associated requests work because it is deliberating as a U.I. Layer. It is an agriculture client, and it includes rancher's mobile applications, and individual gadgets happen to screen the farming region. As per this layer,

the farmers can take a choice to secure their harvest as more and improve sustenance creation yield. The subsequent layer is the data board layer, which contains a few obligations like arrangement and grouping of information, making, checking, essential leadership, and so forth. These jobs keep up also accomplished in this layer. The 3rd layer is a system executive's layer which speaks to the correspondence innovations like Gateway, RFID, GSM, Wifi, 3G, UMTS, as well as Bluetooth Low Energy.
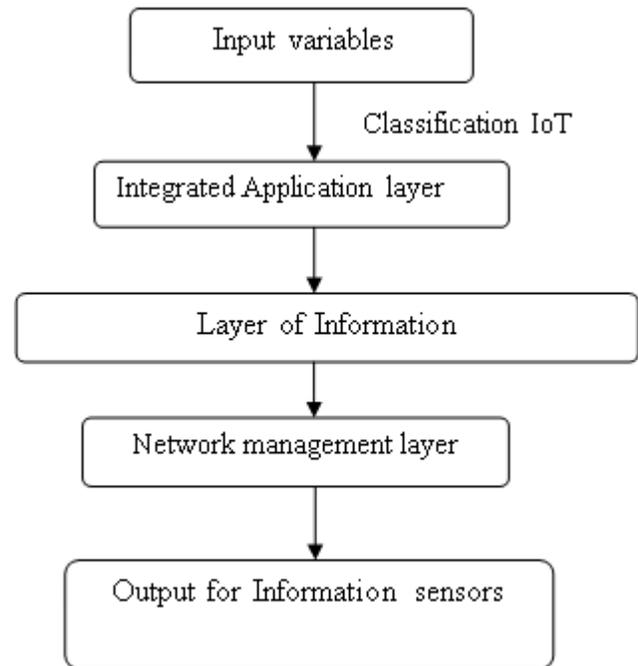
Fig. 2. Conventional Layer Model.

Zigbee and so forth. The fourth layer is a data accumulation layer that comprises a wide range of sensors, cameras, and so on. They are utilized to gather the data of harvest for enhanced in addition to simple field checking of horticulture zone. Fig. 2 demonstrates the four-layer IoT structure. But maintenance is more complex, and the energy consumption of IoT networks also increases, so move to propose a FUZZY-C RWSA-SCFM with L.R. machine-learning model is suggested.

III. METHODOLOGY

The significant objective of SCFM-RWSA is to develop and monitor various tasks of agricultural IoT systems and corresponding visualization sensors estimation system. In this system, IoT information is decelerated to SCFM. This technology has implemented and collected the multiple sensors information by using runway scheduling algorithm. SCFM gives the crop images-data to sensors visually. This representation can help for fast and accurate comparison with dataset classification and belongs to proposed agriculture systems. In this research, the Fuzzy-c model is to be used for clustering the dataset and classification perform with the Logistic regression model (Fig. 3).
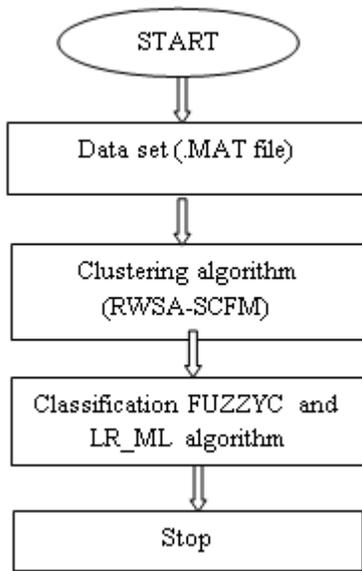
Fig. 3. Demonstrate the Complete block Diagram of the Proposed Method.

Here dataset and input images information is collected from various technical fields, and these are submitted with RWSA, FUZZY, and L.R. algorithms to achieve more throughput at the disease of crops monitoring using IoT.

A. RWSA (Runway Scheduling using SCFM)

1) Examples of iThings

Create two functions get smart (index)

Function 1 retrieving electricity plugs and sensors data frames

Index zero_fan, humidifier, and bulb

…………
………....
………….
{

Set plugs (Boolean state, index)

}

Function 2 controlling smart plugs 2

Index zero_Fan, humidifier, and blub

State explanation (1: on, 0:off)

…………
………....
………….
{

    Stop

}
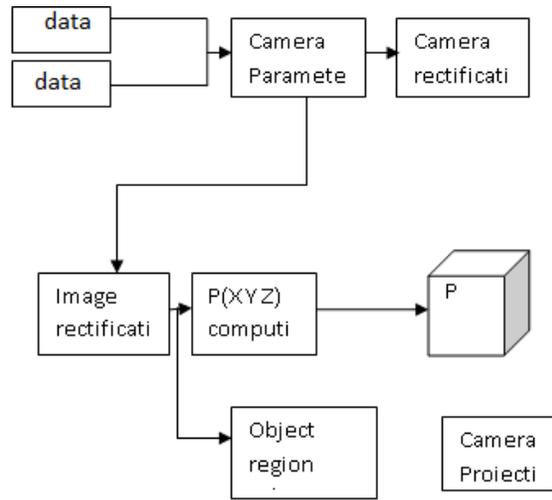
Fig. 4. RWSA-SCFM.

Fig. 4 demonstrate that the RWSA_SCFM-3D model, using this model image has been observed in three-dimensions such that 3600 monitoring is performed. In the above block diagram, the left side part demonstrates IoT things, which are connected to various electronic devices and sensors. The middle of the block diagram explains storage supporting things, which are real-time data storage devices. In front of the storage system, sensors have been divided into three stages named as offline processing stages, online processing stages, and graphical user interface unit (GUI). This GUI has been implemented by MATLAB 2015b software. Coming to the first stage, i.e. offline processing unit system, it is used for camera processing parameter estimation. In this, a relative camera position, angle, and tilting has adjusted for IoT instructions [10]. For example, if the location of the camera orientation varies concerning geometry, the following guidelines are generated in the below manner.

If camera 1 tilting > camera 2 tilt

Vary the camera 2 position

Else

Vary camera 1 position

Coming to the second stage online processing unit continually providing the data from sensors (X, Y, Z, coordinates). Using this data steps, one and three automatically updated the positions of the sensors. In the third step, the graphical Processing unit monitors the IoT information and using this information, 3D virtual instructions are automatically configured. According to this, all three phases are performed with the above function, respectively. The final right side of the block demonstrates that SCFM developed IoT information, as discussed all relates to SCFM implementation. In this case, all farmers continually and efficiently monitor the crops using sensors. This discussion is illustrated in the below section.
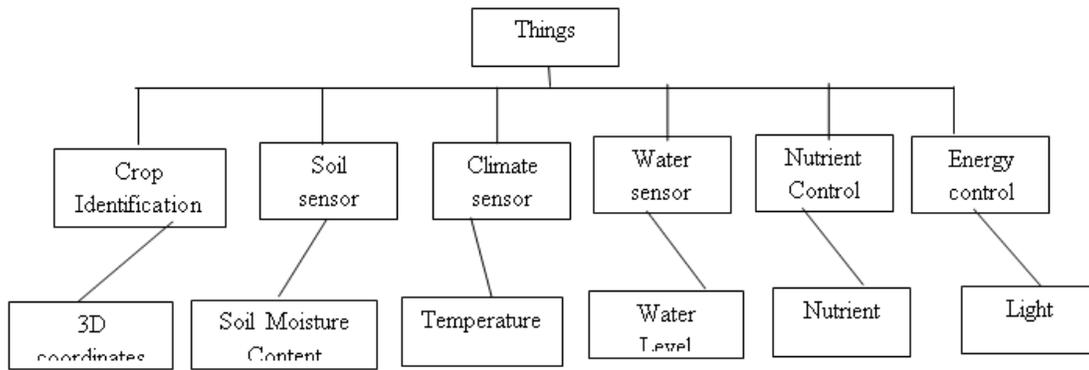
Fig. 5.   3D Parameters.

B. Parameters Related to 3D Communication

In this section, the usage of various IoT devices, and functionality has been explained. Various electronic devices like sensors, motors, and humidity sensors are arranged hierarchically. Further, agriculture systems like soil, crop, water, nutrients, and climatic conditions are associated with the following IoT crop monitoring system [6]. Various sensors provide some data such as crop identification, soil sensor, climate sensor, water sensor, nutrient control, and energy control system.

Fig. 5 explains that SCFM – IoT system of 3D parameters mechanism in this step by step crop monitoring System composed of a farm – crop mechanism. This model is illustrated below.

- region farm :farmer management

- region sensor : sensor monitoring action

- region plant : crops disease monitoring

- Region IoT: electronic sensor devises composition.

Above all steps are related to SCFM region-based modal. Hear all multiple cameras are adjusted with a particular position by using visualize the 3D coordinate system. Therefore all coordinates of crops are recognized by utilizing the horizontal visualization. In this investigation, IoT based crop monitoring with a multihull camera has been deployed to measure accuracy and efficiency. According to the wireless sensor system, this implementation has been developed and verified in [11] shown in Fig. 4.

C. Algorithm-Runway Scheduling Algorithm (RWSA)

Fig. 6 demonstrates the runway scheduling algorithm for crop disease prediction and classification. In this figure total, nine steps are utilized to classify the disease and suggest the proper fertilizer.

IoT's effective operation, and especially execution, is critical to the technology system as a whole throughput. Scheduling run-off arrivals and departures is a complicated issue that needs to tackle various and often competing factors of effectiveness, safety, and equity between any scenarios. One strategy to runway scheduling that emerges from operational and fairness considerations is the restricted position shift (CPS), which demands that an operating position

of the device in the optimized sequence does not deviate considerably from its place in the first-come-first-served series.

RWSA rules, as shown in Fig. 6 are the rules for former, plant and sensing development to receive the storage data from the transmitter. The main advantage of RWSA is the data available in the storage devices if it does not appear than it retransmits the information from one node to another node. A simple example of RWSA is illustrated here, i.e., plant one is located at x-node, and plant two is located at y-node if the exchange of information has performed by using [12] shown in runway scheduling algorithm.
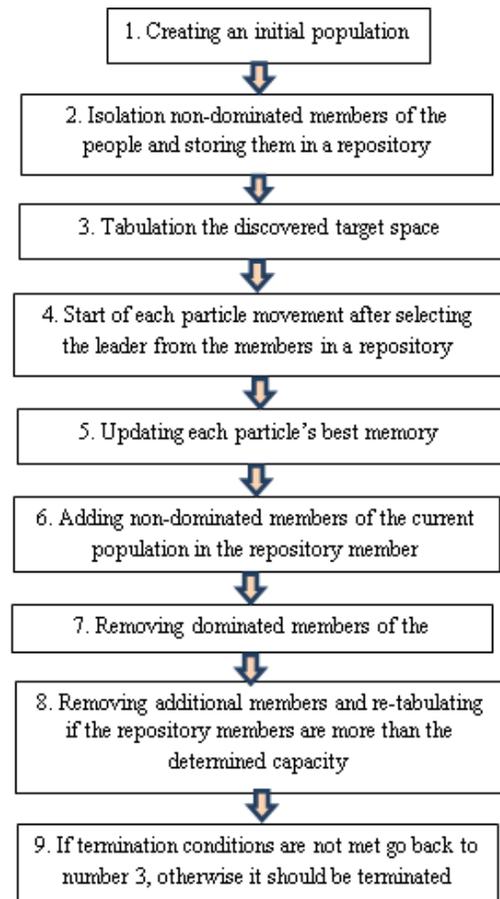
Fig. 6.   Rwsa Algorithm.

D. IoT Agriculture Monitoring with Multi-Cameras

The IoT model, which is explained above, works based on below Fig. 10 principle. In this, x,y,z assessors are randomly adjusted by longitudinal directions of the screen. In this, parallel screens are utilized to continuously monitor the crops and leaves. Here, principle access changed the focal length, and optical access adjusted the lens diameter and image plane is customized by the quantum segment. Sensor camera calibration is correctly regulated by the RWSA algorithm. Hence, accurate coordinates are confined for capturing. So, evaluation and improvement of cameras automatically adjusted.

$$C = \begin{bmatrix} R \\ t \end{bmatrix} k \tag{2}$$

$$C = \begin{bmatrix} f_x & 0 & 0 \\ s & f_y & 0 \\ c_x & c_y & 1 \end{bmatrix} \tag{3}$$

F_x= x-axis focus, F_y= y –axis focus, C_x= center of x-axis point, C_y= center of y-axis point, C= rank of Eigen matrix.

Where stiff changes since 3D world organize to 3D camera coordinates are a rotation R and a conversion t, termed extrinsic parameters, and c represents the rank of the system. K is the intrinsic parameter representing a two-dimensional (2D) image coordinate projective transformation from 3D camera coordinates. The inherent matrix of the camera is described as equation 1 and 2 also in Fig. 7.

Fig. 8 explains sensor calibration flow chart, in 1st step preparation of data from camera is collected in pattern manner in addition to next step, calibration is processed with weight balancing method in the third step to evaluate the data set and improve the functionality of cameras & processing of IoT network[15].

E. Screening Analysis

Above all, the review contains four parts here. Identification of screening eligibility include the blocks depending upon the n no of samples find the records. Frame size is decided by sample availability and records exclusion.

F. Offline Preparation Stage

This offline processing stage consists of the superimposition of IoT data associated with physical objects. The examples of these objects are plants, leafs, and space; the view of cameras grabbing this digital data in an effective manner. In this constrain, the offline processing stage estimates the parameters of a camera with respect to the intrinsic and extrinsic composite behavior. The overall calculations of orientation image classifications rectify the disease by the RWSA algorithm among this orientation. Distorted images are adjusted by automatic lengths rectification system. However, to estimate the condition by the calibration method, which is shown below. The essential information which is acquired from Fig. 8 gives the apparent functionality of screening analysis of data. In this total, 4 stages are screening the duplicate and original records based on included, eligibility, screening, and identification parameters.
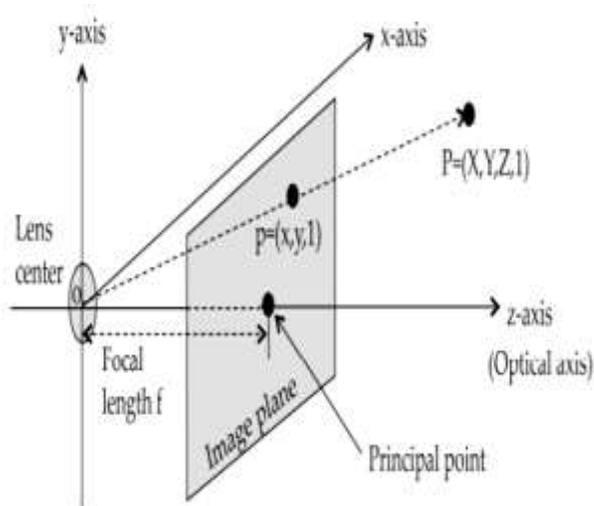
Fig. 7. Sensors of Camera Calibration.
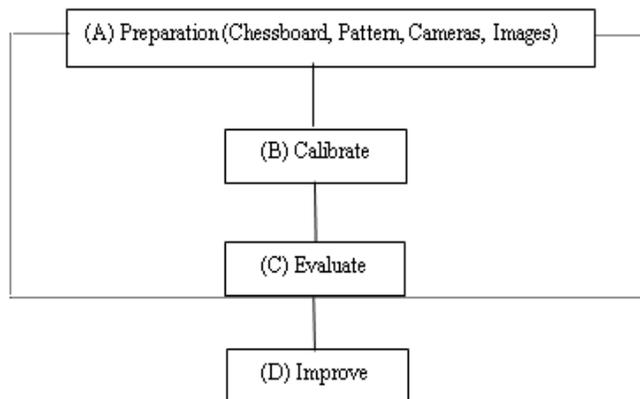
Fig. 8. Evaluation of Data.

The overall functionality is designed by a software called MATLAB 2015b, and cameras are calibrated with respect to their images clearly shown in Fig. 9.

Here sensing unit is an essential module; it can be searching signals continually from conditional blocks using eq.3 gives the ADC to application algorithm nothing but SCFM.
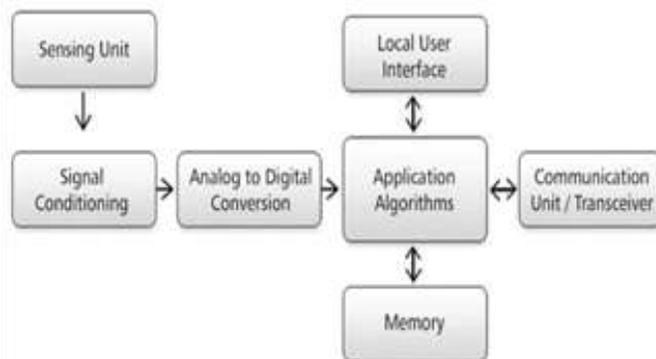
Fig. 9. IoT Data Evolution Process.
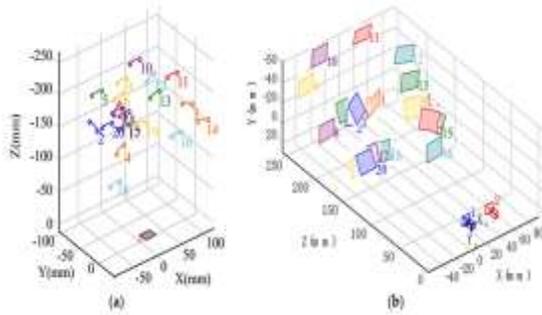
Fig. 10. Graphical Representation of Data.

Memory is a local storage. It can be a cloud or a storage unit and the final transceiver cloud be sending and receiving data continuously and calibrating the feedback if correct controlling is achieved. If SCFM is not reached to calibration, then it processes for feedback modeling, which is mentioned in equation 3 and shown in Fig. 10.

G. Fuzzy-C Algorithm (Clustering of IoT –Agricultural Datasets)

In this section, we are using the grouping of datasets that have been analyzed using a fuzzy-c algorithm. This algorithm gives a better accuracy point with the help of weight balanced load equalization system.

Fig. 11 demonstrates the fuzzy-c clustering model using the fuzzification technique. In this fuzzy logic involves phase adjustment, rule evaluation, and aggregation. Camera direction ROI (region of interest) is analyzed with calibration by proposed SCFM and clustering with the FUZZY-C method. At every step, this adjustment is observed clearly. In this phase, the input variables are represented as fuzzy sets with three values high, Medium, and low. Table I shows the Fuzzy load function for the input and output variables. The triangular fuzzy (trimf) set is used in our model.
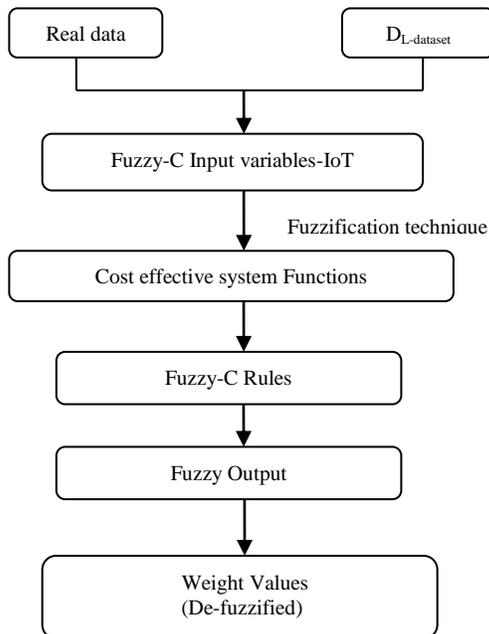
Fig. 11. Flow of FUZZY_C Model.

For Rp, Low = 0 to 3 weights, Medium = 2 to 5 weights, High=4 to 9 weights

For DZL, Low = 0 to 3 cluster, Medium = 2 to 5 cluster, High =4 to 7 cluster For w, Low = 0 to 3, Medium = 1 to 3, High = 2 to 5.

Ep= interphase fuzzy, DL= de-fuzzification

$$fuzzy\_C = [\sum Z_{allrules} \ f_i \ * \ \alpha \ (f_i) / \sum_{all \ rules} \alpha(f_i) \ ] \tag{4}$$

Zall= all rules of fuzzy logic, fi= current stage of function, $\alpha(f_i)$= coefficient of fuzzy-C

Table I demonstrates that When E .P. of a node is low, then it could not move ahead of the packets to Z.L. Therefore, it needs to be in a sleeping kingdom for a longer time. However, if the node is closer to Z.L., it has to be lively a piece bit earlier. Hence in rule no 2, 3, w is assigned as High, and in rule 1, it's far assigned Medium. If the E .P. is medium, then the w is assigned a Medium cost, regardless of the gap to Z.L. Hence rule no, 4, 5, and six, Medium price is assigned to w. Finally, if the E_P is excessive, then the node may be in the energetic node for a greater time. Hence in rule eight and 9, w is about as Low fee. However, if the space to Z.L. is less, then w rate is about to Medium, in rule 7.

TABLE I.   DECISION USING FUZZY LOADS

Rule no.	E_P	D_L	weights value
01	High-1	Low-0	Medium-M
02	High-1	Medium-M	Low-0
03	High-1	High-1	Low-0
04	Low-0	Low-0	Medium-M
05	Low-0	Medium--M	High-1
06	Low-0	High-1	High-1
07	Medium-M	Low-0	Medium-M
08	Medium-M	Medium-M	Medium-M
09	Medium-M	High-1	Medium-M

Algorithm
_____

1.   source $S_i = 1,2, ... N$

2.   intermediate node $N_j, j = 1,2 .... K$

3. N_j estimates E_P and D_L

4. RE_P and D_L are passed as input variables to a Fuzzy –C model

5.   Fuzzification is performed over the input and output variables

6.   Fuzzy Rules are applied as per Table I, and fuzzy output is returned.

7.   Estimation is performed, and the value w is returned.

8.   Estimate the duty cycle of N_j based on the output w

9. N_j is put in sleep mode for the period of $Time_{sleep}$

10.   End For

11.   End For

This above FUZZY-C algorithm is applied on datasets. From this, we get information like similar elements and variables. Using of this method gives accurate clustering among real data and reference data.

H. Logistic Regression

LR (logistic regression) is a basic supervised machine learning model. This model is mainly using a classification of designs in every field. This L.R. is used for the classification of disease finding and fertilizer estimation purposes. In category trouble, the target variable (or output), y, can take the handiest discrete values for a given set of functions (or inputs), X. Contrary to well-known perception, logistic regression is a regression model.

Mathematical computations of LR

The hypothesis for linear regression is $h(X) = \theta 0 + \theta 1 * X$

$$h(X) = \frac{1}{1+e^{-(\theta 0 + \theta 1 * x)}} \tag{5}$$

The hypothesis of linear function which is used for regression analysis

$$J(\theta_0, \theta_1) = \frac{1}{2m} \sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})^2 \tag{6}$$

$J(\theta_0, \theta_1)$ is the regression coefficent for LR

$$h(X) = \frac{1}{1+e^{-(\theta 0 + \theta 1 * x)}} \tag{7}$$

$$h(X) = \theta 0 + \theta 1^* \times \tag{8}$$

$$J(\theta) = \frac{1}{m} \sum_{i=1}^{m} Cost(h_\theta(x(i)), (y(i)) \tag{9}$$

$$= -\frac{1}{m}[\sum_{i=1}^{m} y^{(i)} \log h_\theta(x^{(i)}) + (1-y^{(i)}\log(1 - h_\theta(x^{(i)}))] \tag{10}$$

Eq 6 to 7 explains about linear functionality of tree classification for weight balancing.

$$P(y=1/x;\theta)=h_\theta(x) = \frac{1}{1+e^{-\theta^T x}} \tag{11}$$

Eq 10 explains about the inverse of hypothesis function

$$J(\theta) = \frac{1}{m} \sum_{i=1}^{m} Cost(h_\theta(x(i)), (y(i)) \tag{12}$$

$$-\frac{1}{m}[\sum_{i=1}^{m} y^{(i)} \log h_\theta(x^{(i)}) + (1-y^{(i)}\log(1 - h_\theta(x^{(i)}))] \tag{13}$$

$$J(\theta) = \frac{1}{m} \sum_{i=1}^{m} Cost(h_\theta(x(i)), (y(i)) \tag{14}$$

$$Cost(h_\theta(x), y) = \begin{cases} -\log(h_\theta(x)) & \text{if } y = 1 \\ -\log(1 - h_\theta(x)) & \text{if } y = 0 \end{cases}$$

Note: y=0 or 1 always. Equation 12 to 15 demonstrate that cost-effective function classification and estimating the accurate pathology for disease prediction. Entire LR mathematical computations give classification of plant diseases. Based on this calculation the tp and efficiency. h(x)= LR classification factor.

Fig. 12 shows that 3D camera image training of land selected for testing, here wheat plants are taken into account for the experiment a) is the main camera image and b) is the rectified image for IoT devices, c) is for proposed selection by SCFM.
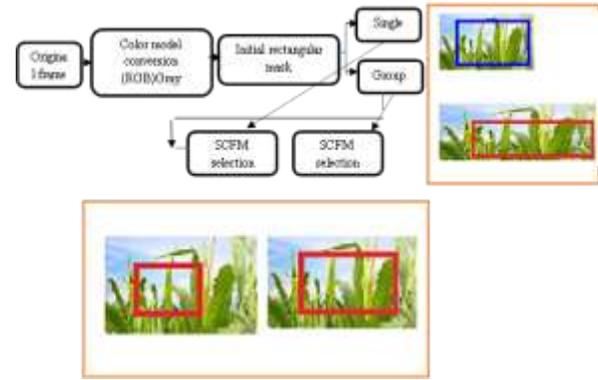
Fig. 12. Crop Diseases Estimation Model.

Fig. 12 is the original frame selected for data samples followed by color model RGB applying the rectangular mask for the region of selection SCFM is applied on trained IoT Network image [17]. The ROI (region of interest) is described by utilizing the rectangular masks (blue line).

$$ROI = [x \, y \, w \, h] \tag{14}$$

The rectangular region of interest is adjusted with x,y coordinates, and these are extended to height h and width w. the geometrical center of region explained by (red line).

$$ROI = [x^1 \, y \, w \, h] \tag{15}$$

Commencing Sustainability these two points, as illustrated in Fig. 13.

Fig. 14 demonstrates the region of interest camera adjustment system by using 2 centers that are c1 and c2 the point x at camera 1 and x at camera 2 are projected method [14]. To determine the p, p' objectives are inserted by backpropagation rays. The centers c1 and c2 are randomly modified by the coordinate system mechanism. In this mechanism, SCFM-RWSA optimization techniques help for tilting adjustment at classification step leaf disease, and corresponding fertilizer has identified. This explanation experimentally proved in MATLAB software.
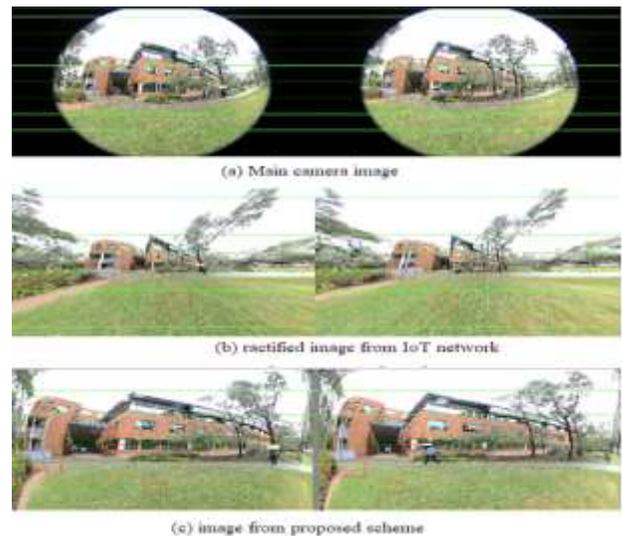
Fig. 13. 3D Camera Image Training.
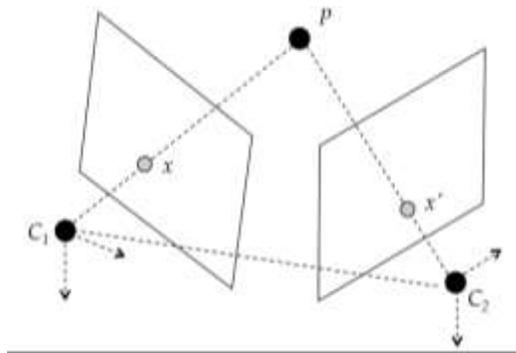
Fig. 14. Coordinate Management.

To validate the SCFM IoT preprocessing algorithm is used to calculate the disease diameter and type of disease. In this system, the RWSA classifier gives the advantage over IoT data by a real-time former crop protection system. This investigation explains that various trees like a palm tree, wheat, rice crops are taken as input and perform the two tasks of disease identification and classification. Final crop disease and our own fertilizer is the output of our research.

Graphical 3D rotation and final crop image outputs are observed by using Display and iteration methods with the help of camera projection. The graphical 3D view is balanced with the coordinate adjustment system [19,20].

IV. RESULT AND DISCUSSION

Using the existing method the proposed findings are compared, and also plant monitoring is done with day wise manner 1st day sowing the seeds 1-45 days watering process, 7 greenhouse and organic fertilizers adding 25 days for leaf color and leaf size analyzed. 45 day observe the results. Shown in Table II.

Fig. 15 demonstrates that every stage performance is analyzed with three algorithms. This is the best IoT based agriculture monitoring system for disease prediction. Here fertilizer type is estimated according to the corresponding disease.

Table III and Fig. 16 explains that manual, SCFM, manual SCFM comparison, n is the no of point to be analyzed mean function for average the probability, S.D. is the standard deviation t is time delay p is the distance using these parameters calculating the result which plant leaf is healthy, and color of leaf and all using this gives the fertilizers to plants [21] has a single main stem plus 2-3 tillers per plant. With better increasing circumstances and reduced plant density, the amount of farmers tends to rise. Filleting begins at the 3-4 point of the leaf, about when it is possible to see the first nodal roots. Final output is shown in Fig. 17 (also see Table IV).

Fig. 18(a) to (c) and 19(a) to (c) demonstrate that diseases finding outcome combination of RWSA-fuzzy-c and L.R. machine learning algorithms. Therefore crop diseases are easily identified, and corresponding fertilizers are suggested.

Dataset: This investigation Indiana pine data set is used for classification and preprocessing. This implementation is performed on Matlab code in this folder Accuracy_Data.mat, and below datasets are taken as reference

Dataset 1: https://www.quantitative-plant.org/dataset/plant-database

Dataset 2: http://helminen.co/plant-disease

Dataset 3:https://plantvillage.psu.edu/

Fertilizer: In this project Nitrogen Fertilizers are used as agents for anthracnose disease. Balanced amounts of plant vitamins, mainly nitrogen are also used. Desirable drainage of fields (in conventionally flooded vegetation) and nurseries is ensured. Fields are smooth. Weed hosts and plow below rice stubble, straw, rice ratoons, and volunteer seedlings which could serve as hosts of bacteria are removed.

TABLE II. PERFORMANCE ESTIMATION

NO OF DAYS	PROCESS
01	Seeds estimation
01-60	Watering process
15	Applying fertilizers
13,19,22,55	Organic fertilizers
35	Leaf color and size
55	Final results.

Fig. 15. Performance Analysis.

TABLE III. COMPARISON OF METHODS

Method	N	Mean	Standard deviation	TS	PS
Manual[10]	15	2.488	0.2672	-	-
Manual-SCFM[11]	15	2.1428	0.2343	28.181	<0.001
SCFM-Fuzzy[12]	15	2.2414	0.2313	29.121	<0.001
RWSA-FUZZY-LR	15	0.3470	0.04270	29.912	<0.001
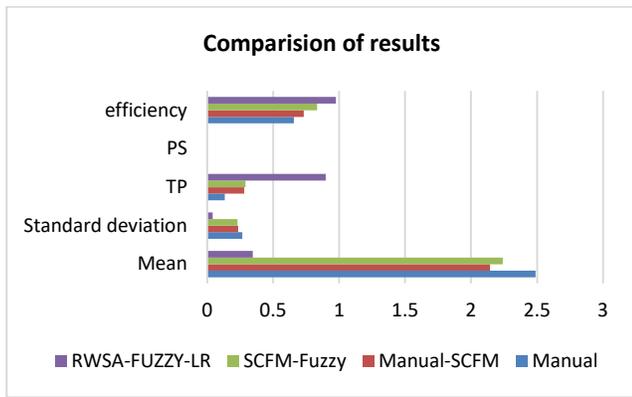
Fig. 16. Comparison of Work.

(c)

Fig. 18. (a) Cluster Finding Output of RWSA. (b) Input of our Proposed RWSA. (c) Diseases Finding.

Table VI and Fig. 20 explains that the comparison table between DWT and RWSA method here, all parameters are improved compared to the existed method [24].

Table V explains that results from the RWSA algorithm using this IoT technique finding an image of plant and diseases.

TABLE IV. T_P AND EFFICIENCY

Method	Mean	Standard deviation	T_P	PS	efficiency
Manual	2.488	0.2672	0.1342	<0.001	0.6567
Manual-SCFM	2.1428	0.2343	0.28181	<0.001	0.7312
SCFM-Fuzzy	2.2414	0.2313	0.29121	<0.001	0.8345
RWSA-FUZZY-LR	0.347	0.0427	0.92912	<0.001	0.9754

Fig. 17. Final Output.
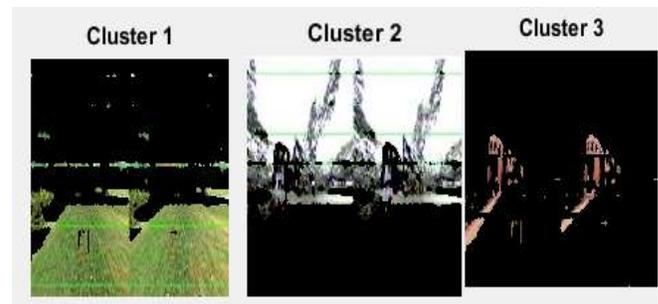
(a) Cluster Finding Output of RWSA.

(b)

Fig. 19. (a) Cluster Finding Output of RWSA. (b) Input of our Proposed RWSA (c) Diseases Finding.

(a)

(b)
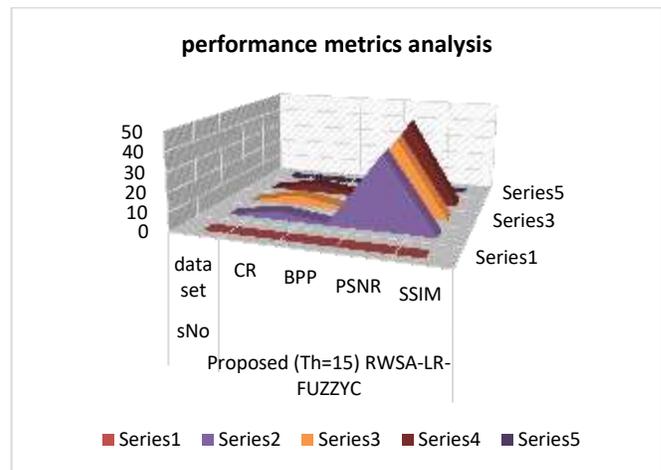
Fig. 20. Performance Matric Analysis.

TABLE V.   RESULTS FROM ANALYSIS

Dataset	Threshold Value	CR	BPP	PSNR (db)	SSIM	Efficiency %
Dataset 1 https://www.quantitative-plant.org/dataset/plant-database	5	3.94	2.22	49.78	0.9997	58.34
	10	4.65	1.81	43.05	0.9970	73.33
	15	4.96	1.23	39.14	0.9961	79.85
	20	5.87	1.14	37.51	0.9859	85.96
	25	5.74	1.12	35.52	0.9851	88.26
Dataset 2 http://helminen.co/plant-disease	5	4.88	1.73	49.74	0.9975	72.72
	10	5.48	1.44	43.93	0.9968	86.13
	15	5.59	1.41	40.69	0.9957	89.48
	20	5.64	1.37	38.24	0.9906	90.57
	25	5.79	1.28	38.22	0.9887	92.23
Dataset 3 https://plantvillage.psu.edu/	5	4.79	1.85	49.91	0.9993	78.94
	10	4.89	1.71	45.12	0.9966	86.14
	15	5.25	1.46	44.18	0.9943	87.46
	20	5.78	1.42	40.27	0.9915	90.61
	25	5.89	1.37	39.99	0.9883	92.61

TABLE VI.   COMPARISON WITH EXISTING VS. PROPOSED METHOD

Dataset	GA Genetic algorithm				3-DWT (Th=15)				Proposed (Th=15) RWSA-LR-FUZZYC			
	CR	BPP	PSNR	SSIM	CR	BPP	PSNR	SSIM	CR	BPP	PSNR	SSIM
Dataset 1	4.11	1.81	36.18	0.9940	4.64	1.72	37.18	0.9902	4.65	1.23	39.14	0.9961
Dataset 2	5.12	1.49	39.54	0.9941	5.59	1.46	40.68	0.9937	5.59	1.41	40.69	0.9957
Dataset 3	5.11	1.48	39.94	0.9942	5.25	1.50	40.73	0.9946	5.25	1.46	44.18	0.9943

V. CONCLUSION

In this investigation, a crop monitoring system with IoT platform has been designed, various methods have been implemented, but accuracy, disease finding with respect to fertilizers has not been designed. Therefore, a real and accurate IoT based agriculture monitoring system is necessary. In this work IoT crop monitoring system has been implemented for disease finding and classification model. Moreover, RWSA-FUZZYC and L.R. - IoT crop monitoring system achieved high accuracy and throughput, and this agriculture monitoring system gives better results for farmers. The threshold value 15 RWSA-SCFM method obtained PSNR=44.18dB, SSIM = 0.9943, BPP =1.46 and CR = 5.25. These results are more accurate compared to existed methods. So, the implemented method is better than conventional techniques.

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