2022 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES) | 978-1-6654-7413-9/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICSES55317.2022.9914216

eAgri: Smart Agriculture Monitoring Scheme using Machine Learning Strategies

J. Venkatesh[1], K. K. Ramasamy[2], M. Aruna[3], K Praveen Kumar Rao[4], Nellutla Sasikala[5],Karthik Nasani[5]

[1]Department of CSE, Chennai Institute of Technology, Chennai - 600069, Tamil Nadu, India.
[2]Department of MECH, Paavai Engineering College, Namakkal- 637018, Tamil Nadu, India.
[3]Department of CSE, Faculty of Engineering and Technology, SRM Institute of Science and Technology, Chennai - 603203 Tamil Nadu, India.
[4]Department of CSE, Kamala Institute of Technology & Science, Karimnagar, Telangana, India.
[5]Department of ECE, Kamala Institute of Technology & Science, Karimnagar, Telangana, India.

E-mail : venkatesh.resch@gmail.com, kkrsami@gmail.com, arunaraadhi@gmail.com, praveenkumarrao.k@gmail.com, kalapraveen.sasi@gmail.com, nasanikarthik@gmail.com

Abstract-The logic of Machine Learning and its predictive strategies are applied to many different applications to attain good benefits over now-a-days. This paper associates the machine learning concept to improve the production on agricultural field as well as the novel adaptive technologies are associated into this learning concept to make a proper agricultural monitoring system in fine manner. This paper is intended to design a new Agricultural Monitoring robot called eAgriBot, in which it integrates the logic of Machine Learning and produce an intelligent predictions to prevent the crops from affections including weather conditions, rainfall and soil water level. In parallel, the eAgriBot contains a high resolution digital camera to capture the pictures of the crops and maintains that into the server unit in proper manner. In literature, there are many approaches designed to provide an automated watering system, systematic pesticide spraying and so on. But all are dependent on the human operations, in which the automatic watering system requires the manual trigger from either SMS or other internet associated operations; similarly the systematic pesticide mechanism requires the same kind of trigger to perform the action. These cases are critical in terms of monitoring the agricultural field from remote environment. The concept of Internet of Things (IoT) is associated over this approach to push and update the agricultural data collected by the eAgriBot to the Cloud Server. This entire process is controlled and manipulated by the novel machine learning strategy called Smart Learning Assisted Data Manipulation (SLADM), in which it is derived from the traditional Random Forest Classification logic with specific parameter modification called dynamic threshold fixation. In general the Random Forest logic uses the constant threshold for data processing, but in this approach dynamic principles are applied to improve the prediction accuracy. With the help of this system plants leaf disease can easily be monitored with the help of digital camera associated with the eAgriBot. It captures the crop field images and pass it to the server end for processing, in which the server end accumulates that and process that by using proposed machine learning called Smart Learning Assisted Data Manipulation. The proposed SLADM scheme is designed robustly for analyzing the both the image and data content, so that the logic identifies the severity in leaves and the data as well. In case of any severity level mismatching found by the algorithm, it immediately notifies that to the respective farmer to take an appropriate action to save the plants from the disease spread. The data available into the cloud server can easily monitored by the farmers from anywhere in the globe as well as this approach of SLADM provides an accurate agricultural field predictions, so that the farmers can easily monitor the field without any complexities and attain good production level easily

Index Terms—Agricultural Field Monitoring, Classification, eAgriBot, Random Forest, Smart Learning Assisted Data Manipulation, SLADM

I.INTRODUCTION

The agricultural production and the associated fields need technological developers to work to grow their efficacy, effectiveness and creativity in order to enhance the productivity, including environmental sensors, synthetic biology on agricultural crops and equipment. Thus, it is anticipated that there would be a decrease in operating expenses as well as adverse effects mostly on natural atmosphere, which would also eventually generate huge risks. Agriculture is critical for humanity's basic necessities, as food availability has a significant effect on society at large resilience and the agricultural production work has been flat throughout the last few decades. With respect to the survey of the World-Bank, the quantity and ratio of agriculture field based workers has been reducing from the year of 2005-to-2020. The following figure, Fig-1 illustrates that in clear manner by using the graphical representation. Workers are those who engage for a formal or informal firm, but are compensated in the terms of wages, salaries, incentive, gratuity or other forms of compensation. Women and men workers have a relatively equal proportion and the field of agriculture employs around 27% females and 30% males, accounting for more than 29% of total workers. A possible way to overcoming this manpower deficit is through the application of technological advances in the agricultural industry.For example, mostly during agricultural revolution, the development of agricultural machinery including agricultural vehicles like tractors and planters mitigated some of the potentially serious consequences associated with man-power reductions. Merely few more enterprises or agricultural processes in different countries such as Indonesia make use through machine learning and artificial intelligence initiatives, which range beyond autonomous vehicles to pruning drones and harvesting equipment [1][2].

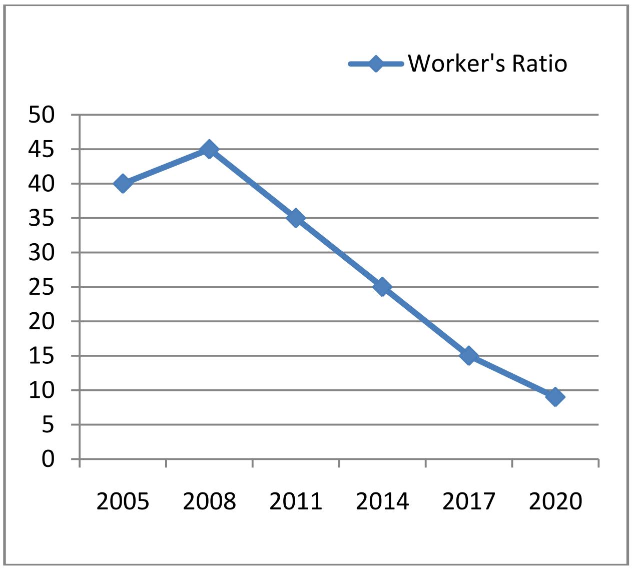


Fig.1 Agricultural Field Worker's Ratio over Past Few Decades

Numerous agricultural fields monitoring robot designs have also been developed and marketed, including facilities for watering systems with an irrigation mechanism which can be regulated via temperature and relative humidity readings through an Android Smartphone. Additionally, the Autonomous Farming Robotics method enables information through the internet, making the process globally accessible as well as adaptable. The independent machine is equipped with an irrigation system and t o ensure that crops receive adequate important nutrients, caution should be exercised in the manner of adequate water [3][4] Irrigating farmland seems to be the most critical and also time-consuming operation in agriculture field, particularly during the summer months. Human irrigation adds another level of effort as well as takes a lot of time. As a result, an efficient technology is required to address these issues and anself watering solutions will be used effectively to crop irrigation as demanded, allowing for greater control over how and when watering is required. This technique is efficient in a variety of settings, including private spaces to big crop fields, and thereby conserves water. For efficient watering, the above prototype can be executed, in which it utilizing pumps or dripping emitters and in some cases solar panels can also be used to conserve resources on a vast scale of agricultural field monitoring system [5] [6].

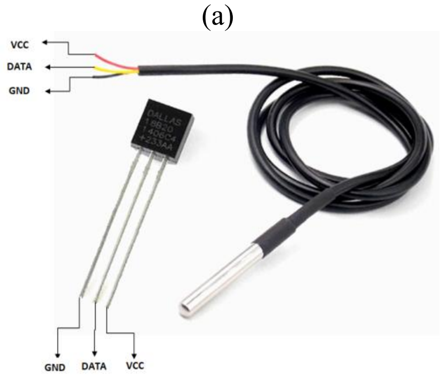
In literatures, there is several machine learning and Internet of Things (IoT) enabled schemes available to identify the crop growth and do the agriculture in systematic manner. However, all these innovations are strucked in certain level of existence due to the practical disabilities such as cost expensiveness, circuit complexity is more, not in a scalable form and performance lacking and technical requirement is expected to be high to operate such device and so on [7]. These complexities make the farmers to neglect such kind of devices and technologies to work with. Additional challenge that an agriculture robotics design is it must overcome the functioning in constrained places, which can also be extremely difficult attributable to foliage, stones and other objects that obstruct traditional automation solutions. Agricultural harvesting is a labor-intensive and huge time consumption procedure that scientists have really been studying for more than six years [8][9].

This paper is intended to design a new agricultural field monitoring robot called eAgriBot, in which it consists of multiple latest technology association such as machine learning, digital camera for crop surveillance and smart sensors such as soil moisture level monitoring sensor and temperature identification sensor. Based on these latest technology associations, the proposed eAgriBot operates in an intelligent manner and provides an excellent man free agricultural monitoring and controlling system in an efficient manner. The eAgriBot is considered to be the moving robot, in which it moves over the crop fields with auto adjusting wheels and basements. The location identification and border marking facilities inform the robot to move only the specific location with correct boundaries.

eAgriBot Design

The agricultural field monitoring robot called eAgriBot design is planned to construct with aluminum metal and the sensor units are safe enough to place inside the robot in fine manner. The sensors such as temperature and the soil moisture level identifier are associated with the eAgriBot to monitor the respective details instantly. For measuring the soil temperature, a sensor named DS18B20 is used to identify the temperature level of the farm land and the specialized soil irrigation sensor is attached with the eAgriBot to monitor the agricultural field in live manner. The following figure, Fig-2 (a) illustrates the perception of Soil Moisture Sensor and the figure, Fig-2 (b) portrays the temperature monitoring sensor in graphical manner.

(a)



(b)

Fig.2 (a) Soil Moisture and (b) Temperature Sensor

A digital camera with 1024X720 pixel ratios is placed in front of the robot to monitor the crop fields and identify the leaf diseases based on the affection/severity levels on leaves in fine manner by using the proposed machine learning concept called Smart Learning Assisted Data Manipulation. For moving the robot from one end to the other end, a standard wheel-base is designed with four self-adjustable wheels, in which it operates according to the principles of location specified into the controller. The location specifications are clearly marked to the respective eAgriBot and place that into the corresponding agricultural fields for monitoring the crops. The controller used over eAgriBot is ESP8266 based WiFi module with pre-defined controller, in which it provides dual options such as control the eAgriBot based on the commands inserted into it as well as it provides the Wireless Communication facilities to transfer the agricultural field data and the associated crop images to the server monitoring end for manipulations. The following figure, Fig-3illustrates the perception of proposed eAgriBottransmitter section block diagram in clear manner.

The following figure, Fig-4 shows the clear view of proposed eAgriBot receiver section block diagram with respective receiver end and relay unit. The relay unit is used to systematic trigger of the water pump connected with the power source, in which it will be triggered automatically when the soil moisture sensor from the transmitter end of eAgriBot gives LOW signal and the water pump will automatically triggered off, when the eAgriBot gives HIGH signal to the receiver unit.

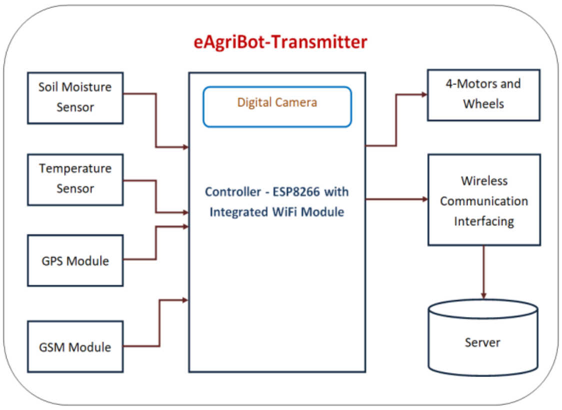


Fig-3 eAgriBot Transmitter Unit Block Diagram

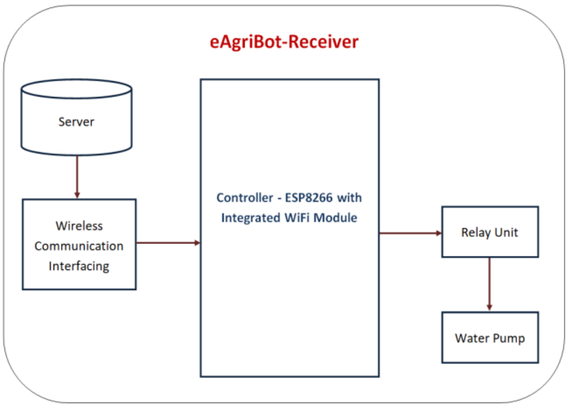


Fig-4eAgriBot Transmitter Unit Block Diagram

Location and Alert Management

The main complexity of managing the agricultural field with the help of robots is to specify the location and position where the robot needs to monitor. This complexity makes many agricultural field monitoring robots to go down and leads to poor performance. In this paper, intelligent boundary definitions are fixed to the robot to monitor exactly the places surround with defined boundaries. The following equation is used to define the boundary ratio of the agricultural fields based on the location specified with latitude and longitude determinations.

$$f(x) = B_0 + \sum_{i=1}^{n} \left(TS_n\, x \frac{L(0)}{i} + y \frac{L(1)}{i} \right) \qquad (1)$$

Where f(X) defines the function for identifying the agriculture field boundaries in four sides, B_0indicates the boundary of the field, TS indicates the total surface area of the field, X and Y are the respective marking points to move the robot accordingly and L is an array variable to manage the latitude and longitude specifications, in which the variable with indexing of L(0) indicates the Latitude and the variable with indexing of L(1) specifies the longitude of the region.

The location specifications are successfully handled by using the mentioned equation and the latitude and longitude specifications are monitored by using the Global Positioning System module called GPS mentioned in the block diagram over the figure, Fig-3. Based on these specifications of location and boundaries the proposed robot eAgriBot navigates into the crop field and monitor accordingly. The eAgriBot can navigate in four directions in bidirectional manner such as forward, backward, left and right. This robot has a mobile control provisions as well, but in certain cases only it is required and most of the time automatic automations are held on for monitoring the agricultural field in an intelligent manner.

The alert mechanisms are handled by using the Global System for Mobile communications (GSM) module, in which it is also specified in the block diagram over the figure, Fig-3. By using this GSM module, the respective farmer's mobile number is accumulated from the remote server by using the controller and sends the associated alert messages regarding the emergency situations instantly without any delay.This system provides a separate web portal and Android application to register the identity of the farmers with respect to the eAgriBot index. The sensors connected with the robot identify the trigger, in which those values will be sending to the remote server by sing the interconnected controller. The trigger values are cross-validated with the proposed machine learning algorithm and the resultant value is analyzed further. The outcome of this analysis results with true, the alert notification will be immediately sent to the respective farmer based on the collected mobile number from the server and the values are normally maintained into the server end for further validation. The following equation is used to cross-validate the trigger values with the proposed trained model.

$$T_r(T, S)^{i=1-n} = \sum_{i=1}^{n} \binom{T}{S} \Omega \binom{Tx}{Sx} . i^x \qquad (2)$$

Where T_r indicates the trigger variable. T and S are the temperature and Soil moisture levels, Tx and Sx indicates the trained model temperature and soil moisture levels, in which these trained samples from 1 to n are acquired for cross-validation.

II. Related Study

Jan-Peters et al., 2020 [10] proposed a paper related to the logic of utilizing stochastic mobility algorithms, scooping movements in tea farming robot. In this paper [10], the authors illustrated such as: this system proposes a tea leaf picking robot and to extract enhanced quality tea, the robotic machine must pick the leaves from the plant's stem before harming it with cutters. To harvest the tea leaves, a complicated psychological hands movement of dragging simultaneously spinning must be replicated. Additionally, the rotations and tugging of the arm, as well as the energy consumed, varies significantly based on several factors such as leaf age, petiole breadth and borough diameter. As a result, the quantity of longitudinal and transverse action, as well as the duration of the oscillation, must be determined for each case. The intricate motion is duplicated in this study by understanding from demonstrations and the quality is determined on the basis of the limb flexibility, that is characterized like the strength absorbed per unit thickness as from arms so when clutched leaves are moderately got up. By randomly integrating the acquired movements at a proportion dictated by the limb rigidity, the proper mobility is obtained, even when no momentum is provided. The movements created by the suggested method [10] are compared to those provided by people to demonstrate the suggested approach's usefulness. Experiments have demonstrated that the proposed approach is capable of harvesting enhanced tea quality.

Pratap-Tokekar et al., 2020 [11] proposed a paper related to the concept of Understanding a Geometric Environment in the Shortest Time Frame With a Robotics Team. In this paper [11], the authors illustrated such as: an informational optimization problems is examined in this research [8] with the objective of eliminating the timeframe needed to undertake a continuously changing item. For analyzing the fundamental region, a Gaussian process regression is used. The main objective [11] is to keep the Gaussian process posterior deviation under a set point, which is just the confusion matrix in between acquired and genuine disciplines. There are three alternative solutions to the issues and t he purpose of the placement iteration is to cut down on the number of survey places while preserving a downstream deviation less than a predefined level and aim to minimize the overall amount of time needed to attend and acquire observations from measuring places that used a solitary robot system in the autonomous vehicle variant. Additionally, a multi-robot model is investigated in which the goal is to reduce the time needed for the final machine to come to a common reference place, in which it is mentioned as depot. A continuous factor concerned with methods are described that take advantage of the features of Gaussian process regression and along with the simulated result, the experimental effectiveness of the proposed strategy [11] is compared to that of other review of existing using a statistical methodology.

Jinhui-Li ers et al., 2020 [12] proposed a paper related to the recognition and positioning of fruit cultivating plants for vision based reaping robots. In this paper [12], the authors illustrated such as litchi bunches appear spontaneously as well as unevenly in fruit orchards, it is hard to comprehend and find many litchi bunches' fruit bearing limbs at the same period. This is really a tough challenge for visual based gathering robots because it requires uninterrupted supply throughout the environment and the purpose of this work was to build a good estimate for precisely as well as dynamically detecting and locating fruit bearing limbs of several litchi groups in wide areas using RGB depth cameras throughout the environment. The pictures were segmented into three groups using a semi - supervised approach called Deeplabv-3. A pre processing system is presented to align divided RGB pictures and to eliminate fruitless stems. Following that, the twig binary map picture was handled using framework separation and trimming processes, leaving just the mainline denominations of branches remained. Filtering the images in the 3D region of the limb structure map using a non-parametric concentration geospatial classification method including uncertainty is being used to find the fruit bearing limbs corresponding to almost the same litchi groups. Furthermore, using singular value decomposition, a 3D straight line was matched to every other group, with the continuous signal corresponding to the position of fruit-bearing branches. To evaluate the suggested technique, 452-pairs of RGB Depth photos got gathered across various light conditions and the findings indicate that the correctness of detecting a litchi berries limb is around 83%, the spatial resolution is 17.29° || 24.57° and the computation time for determining an unique litchi berries limb is 0.464 seconds. Investigations in the environment demonstrate that this strategy is successful for guiding the robot through constant plucking activities.

Kondaka et al., 2020 [13, 14] proposed a paper related to a dynamic replication and analysis of rectangular robot design based on narrow territories. In this paper [13], the authors illustrated such as: in general, rectangular robots consist of a porous layer as well as an underlying actuator mechanism. These machines are used for a range of tasks, spanning rescue operations to farming. Because one of the significant benefits of rectangular robots is the capacity to function on uneven terrain, similar machines' performance evaluation and route planning have already been investigated exclusively on flat terrains. This paper develops a unique method for evaluating the equilibrium models, emissions and isolation assessment of this robot moving across difficult territories. The route optimization techniques are constructed to discover the optimizing the parameters using the proposed innovation diffusion theory, dissociation evaluation and conceptual design. One of the benefits of such a study is that those same methods may be utilized either with quantitative or observational environment knowledge.

III. SYSTEM METHODOLOGIES

In this paper, a new machine learning strategy is introduced called Smart Learning Assisted Data Manipulation (SLADM), in which it is derived from the conventional machine learning approach, called Random Forest (RF) Classifier. The conventional RF classification technique is a well-known, scalable, robust and user-friendly learning procedure, in which it utilizes the property of hyper parameter tuning option but in certain cases the algorithm can operate efficiently even without adopting this hyper parameters tuning logic. This algorithm is mostly used in the real-time evaluations for classification strategies due to its robustness, simplicity and it attains best possible optimum solutions in outcome.

This paper is intended to design a new robotic machine called eAgriBot with the adaptation of multiple latest technologies such as machine learning, digital image processing and prediction logic. So, that a new machine learning logic is designed with respect to the conventional principles. In this proposed system, a novel learning approach is designed called as SLADM based on the hyper tuning of conventional RF classification methodology with modified input parameters such as Temperature level of the agricultural field, Soil Moisture Level and the crop images acquired from the digital camera connected over the eAgriBot. Based on these input parameters the entire robotic operations are handled with proper manner and the collected real-time details from the agricultural land is transmitted to the processing server end through the logic of ESP8266 WiFi controller placed into the robot. The proposed Smart Learning Assisted Data Manipulation logic is designed with respect to the operations of both data and image processing, in which it received the data from the eAgriBot and segregate it based on the textual and image oriented features. The extracted data is assembled into the respective storage unit, in which the storage environment is allocated as two separate portions. One is assigning for accommodating the textual data and the other portion is allocated for the image oriented data processing, in this highly volatile memory is assigned for textual feature processing and scalable memory is assigned for image oriented processing. Because usually the processing of images requires more memory as compared to the textual data oriented processing.

So, that the volatile memory is assigned to textual data processing, in which it assigns the unwanted memory storage to the scalable memory unit for processing the image oriented features if necessary. The movement of eAgriBot is controlled by using border definitions, in which it specify the exact location details of the robot to move around accordingly. The robot follow the commands specified into the controller and operate the motors connected into it accordingly with respect to GPS based location extraction norms. The moving robot captures the image from the agricultural field and store it into the server end sing WiFi connections, in which the proposed classification logic called SLADM accumulates the image features based on the pre-processing logic as well the feature extraction principles. The pre-processing logic modulates the size and structure of the input crop image in fine manner using the following formulation.

$$\boldsymbol{I(x) \leftarrow \sum_{i=1}^{n} S.\,i(\sqrt{O^{P}-256})} \qquad \textbf{\textit{(3)}}$$

Where I(x) indicates the image pre-processing function variable, S indicate the overall size of the input crop image, O^P indicates the original pixel values of the input and that will be reduced with respect to the maximum pixel range of 256. The image is further processing for extracting the features of the resized pixels, in which the following equation is used to extract the features of the image in clear manner.

$$\mathbf{F^{P}(x) \leftarrow Max^{P} + (\textstyle\sum_{i=1}^{n} \boldsymbol{P(x)} + I(x)\{R(i).G(i).B(i)\})} \quad \mathbf{(4)}$$

Where F^P indicates the feature extraction function variable, Max^P indicates the maximum pixel range of the selected input image for feature extraction, P(x) indicates the minimum pixel level of the input image and it will be incremented upto the last pixel of the image with respect to the color coordinates R, G and B.

IV. RESULTS AND DISCUSSIONS

This section describes the experimental analysis of the proposed machine learning approach called SLADM with respect to the data and image processing logics. The resulting emulations are done by using the OpenSource code development tool called Python with embedded logics are completed by using C language. The resulting nature of the proposed approach is properly attained with expected outcome ratio and the following figure, Fig-5 illustrates the step-by-step process of manipulating the images and identifies the affections in crops using leaf images.

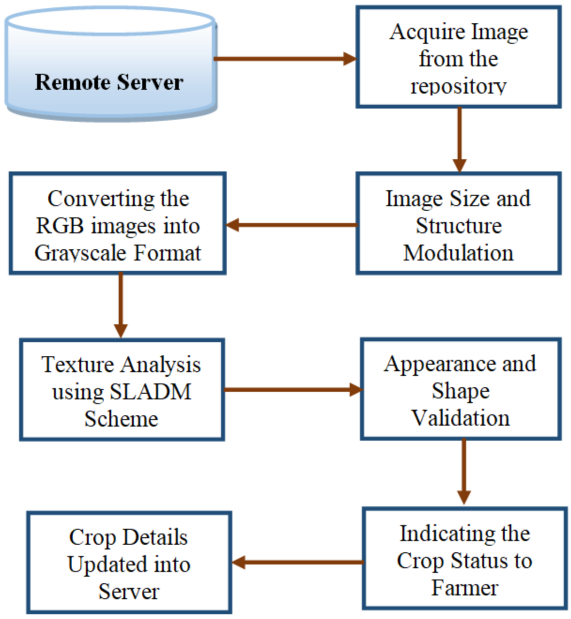


Fig.5 Process Flow Diagram for Crop Image Estimation to Detect the Presence of Diseases in Leaves

The following figure, Fig-6 illustrates the view of number of times the soil moisture level identification sensor detect the trigger level and the respective triggers sent to water pump area by using the WiFi controller unit. In this diagramitic representation, the perception of nmber of triggers detected by using the soil moisture sensor and number of triggers detected by using the soil moisture sensor is clearly shown in graphical manner. This estimation is defined based on the placement of such soil moisture sensor into the agricultural land for 10 continous days and attin the results accordingly.

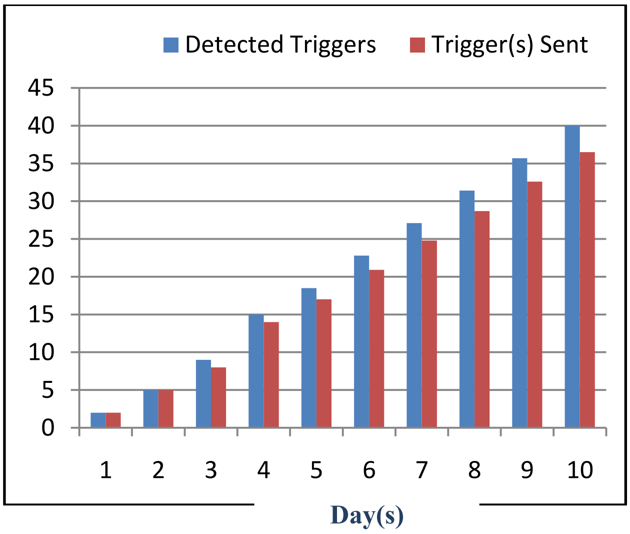


Fig.6 Soil Moisture Sensor Trigger Estimation

The following figure, Fig-7 illustrates the view of proposed approach data maniplation accuracy with respect to the temperature prediction levels, in which the proposed temperature estimation sensor DS18B20 accumulates the temperature ratio of the respective agricultural land and send that to the processing server unit. In server end it verifies the temperature level and return the proper predictions based on the model trained with respect to the proposed machine learning procedure SLADM. The resultant figure, Fig-7 portrays the prediction accuracy of the temperature sensor and the proposed SLADM logic in clear manner with graphical representation.

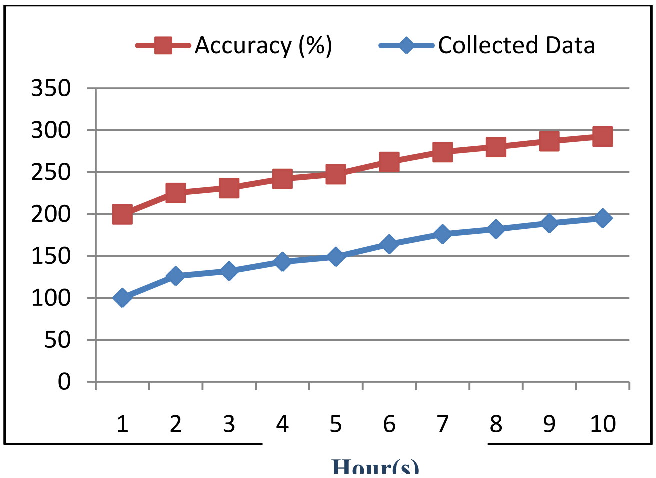


Fig.7 Temperature Sensor Accuracy Level Estimation

The following figure, Fig-8 illustrates the view of input leaf image acquired from the eAgriBot, in which the digital camera placed infront of the robot captures the image from the agricultural field and sent to the server end for processing. This figure, Fig-8 acquires that image for further process such as pre-processing, feature extraction and classification.

Fig.8 Input Image Captured by using eAgriBot

The following figure, Fig-9 illustrates the view of Pre-processed image nature and the extracted features are smmarized into the array unit for classification, in which it is important to identify the disease presented into the leaf image.

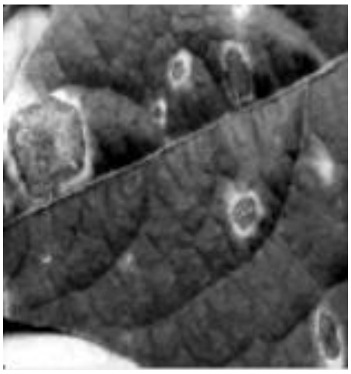
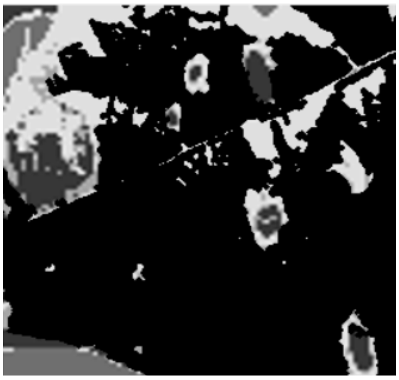
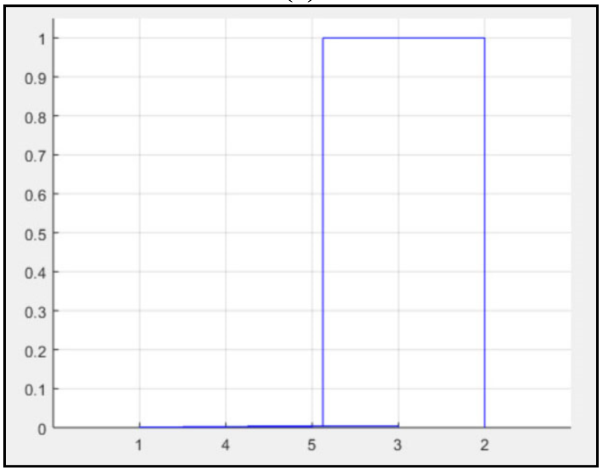


Fig.9 Cluster View with Glaucoma Image Objects

The following figure, Fig-10 (a) illustrates the view of classification portion of the image processing logic, in which it is useful to predict the leaf image acquired from eAgriBot contains the disease or not. This classification strategy is acquired from the machine learning principles, so that the accuracy levels of classification is fine enough to identify the healthiness of the leaf. And the figure, Fig-10 (b) illustrates the graphical representation of the accuracy parameters, in which the proposed machine learning approach produces the accuracy ratio of 99.2%. This accuracy measurement is illustrated via the graphical representation over the mentioned figure in clear manner.



(a)



(b)

Fig.10(a) Classification Perception and (b) Accuracy Ratio

V.CONCLUSION AND FUTURE SCOPE

This proposed Machine Learning based Robot called eAgriBot is suitable for small and large scale agricultural fields to monitor the land in an efficient manner. The experimental proofs show the efficiency in terms of accuracy measurements and graphical representations. The proposed machine learning approach Smart Learning Assisted Data Manipulation provides a dual support for processing textual data as well as the image data in fine manner with best accuracy ratio of 99.2%. This kind of robotic model eliminates the stuggles of farmers and provides a huge support to them to improve their productivity as well as improve their levels in society. The latest technologies are so helpful in this application to operate the robot in intellectual manner. The resulting section shows the proper proof for all the mentioned things in proper manner such as the resulting figure, Fig-6 portrays the view of soil irrigation sensor working efficiency with respect to the surveillance of continuous ten days over the agricultural land. The resulting section figure, Fig-7 shows the efficiency of temperature sensor and the following figures on that sections are clearly demonstrating the intelligence of the proposed logic SLADM. For all the proposed approach is fair enough to monitor the agricultural field in an efficient manner.

In future, the work can further be enhanced by means of adding some more sensors such as humidity measurement sensor; light intensity identification sensor and so on to provide more efficiency to the robot as well as it improves the intelligence of the robot.

REFERENCES

[1] Thomas C. Thayer, Stavros Vougioukas, Ken Goldberg and Stefano Carpin, "Multirobot Routing Algorithms for Robots Operating in Vineyards", IEEE Transactions on Automation Science and Engineering, July 2020.

[2] The Trading-Economics Web Source. Available Online:

[3] https://tradingeconomics.com/indonesia/employment-in-agriculture-percent-of-total-employment-wb-data.html

[4] C.J.Choaue-Moscoso et al., "Efficient Tmnlementation of a Cartesian Farmhot Robot for Agricultural Armlicationsin the Region La TAhertad-Peru" IEEE ANDESCON, 2018.

[5] M.F.Mustafa et al., "Structural Design of Cartesian Vacuum System for Loose Fruit Collector (FFC) Machine" TEEE International Circuits and SvstemsSvmnosium, 2019.

[6] T. Manimegalai, T. N. Ravishankar, L. Kannagi, K. Kannan and G. Anitha, "A Novel approach for Data mining Classification using J48DT Classifier for Intrusion Detection System," 2022 IEEE 11th International Conference on Communication Systems and Network Technologies (CSNT), 2022, pp. 601-607, doi: 10.1109/CSNT54456.2022.9787632.

[7] M.Ramadiansyah, W.Wahab and Nasril, "Modelling, simulation and control of a high precision loading-unloading robot for CNC milling machine," International Conference on Quality in Research: International Symposium on Electrical and Computer Engineering, 2017.

[8] Maheswaran, U., Kallam, R. B., Arathi, B., Prawan, K., &Anitha, G. (2021). Efficient plant leaf disease identification Material Fabrication using lightweight device. Materials Today: Proceedings, 47, 381-386.2015 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC), 2015, pp. 1-3, doi: 10.1109/ICCIC.2015.7435728.

[9] Govindaraj, Dr. (2021). Skin Lesion Detection Based on Fuzzy Logic. International Journal of Innovative Technology and Exploring Engineering. 8. 516. 10.35940/ijitee.J8826.0881019

[10] Govindaraj, Dr&Logashanmugam, E.. (2019). Multimodal verge for scale and pose variant real time face tracking and recognition. Indonesian Journal of Electrical Engineering and Computer Science. 13. 665. 10.11591/ijeecs.v13.i2.pp665-670

[11] KurenaMotokura, Masaki Takahashi, Marco Ewerton and Jan Peters, "Plucking Motions for Tea Harvesting Robots Using Probabilistic Movement Primitives", IEEE Robotics and Automation Letters, 2020.

[12] Varun Suryan and PratapTokekar, "Learning a Spatial Field in Minimum Time With a Team of Robots", IEEE Transactions on Robotics, 2020.

[13] Anita Sofia Liz DR, P SrideviPonmalar, G Saritha, J Surendiran “An Efficient Bifurcating Brokers Service Scheme for Protecting Investor Secrecy in e-Trading ”European Journal of Molecular & Clinical Medicine, ISSN 2515-8260, Volume 7, Issue 11, 2020.

[14] Kondaka, L.S., Thenmozhi, M., Vijayakumar, K. et al. An intensive healthcare monitoring paradigm by using IoT based machine learning strategies. Multimed Tools Appl (2021). https://doi.org/10.1007/s11042-021-11111-8.