International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 05 July 2023 **Revised:** 25 August 2023 **Accepted:** 15 September 2023*

IoT-Enabled Smart Robotic System for Greenhouse Management using Deep Learning Model with STS Approach

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Abstract—A significant component of any country's Gross Domestic Product is made up of farming and agriculture. Utilizing IoT in agriculture and farming methods is essential as the global population is projected to reach around 9.6 billion by 2050. To meet such high demand, an improvisation and optimization of the current farming technologies is the need of the hour. Numerous researchers developed different application specific system for agriculture but less attention was paid towards critical aspects such as intelligence, modularity and human centric design. There is lacuna in existing developed system in the utilization of advanced technologies to their full potential. The agricultural sector wants autonomous systems that are smarter and more effective. Therefore, this research paper introduced the smart solution as an intelligent modular autonomous system with human-centric design approach for agricultural application. The developed system able to detect plant disease with more than 96% accuracy with the help of novel deep learning model designed with sharpening to Smoothening approach. The disease detection and classification results has been verified through confusion matrix method of evaluation. An intelligent robotic system has been developed to detect plant diseases using novel deep learning model and perform multiple functions like greenhouse monitoring, pesticide sprinkling etc. The robotic system has control over internet through web control system so that farmer can monitor greenhouse and control robot activity from remote place. This smart farming solution able to make farmer life simpler and perform difficult task like plant disease detection and pesticide sprinkling easily.

Keywords- Internet of Things, Deep Learning, Machine Learning, Robotic System.

I. INTRODUCTION

Agriculture and farming contribute significantly to GDP (Gross Domestic Product), not only in developing nations but also in among wealthy countries. It is crucial to use IoT in agricultural and farming practises since, by 2050, it is anticipated that there will be 9.6 billion people on the planet [1]. The agriculture sector needs to create product at a greater pace in order to keep up with the rising demand. As a result, it is urgent that existing farming methods be improved upon. Only cutting-edge environmental solutions and contemporary agricultural technologies can increase agricultural production. The need for automated technology is currently rising quickly [2]. People are looking for resources that will make their work simpler, more error-free, and quicker. Robotic automation is one such contemporary technological breakthrough that tries to help people in this endeavour. An autonomous robot has the ability to detect changes in its surroundings, make judgements depending on how it has been trained to do so, and then carry out a predetermined action [3].

The quality of green products and agricultural productivity are seriously threatened by plant diseases. Farmers and agronomists frequently face significant challenges in early identification of diseased crops and the management of their potential output damages [4]. Therefore, it is crucial for all parties involved to identify plant illnesses at the very beginning of plant growth using cutting-edge technology, take the necessary precautions, and stop additional financial losses [2]. The agriculture industry values greenhouse farming because of its controlled environmental conditions. Recent research has revealed that plant disease incidents are resulting in a decline in the mean yield creation in greenhouses. Producing these meals has become a difficult chore as a result of the numerous bacterial diseases, pathogens, and pests that assault these plants. A mechanism to identify disorders early on is therefore absolutely necessary [5]. Robotic disease detection systems in greenhouses are anticipated to enhance disease control, boost productivity, and use fewer pesticides. Farmers will have challenges feeding a growing population in the upcoming years [6]. They must guarantee food security and lessen reliance on imports. The efficient application of new technologies will enable farmers to fulfil the demands of a growing population. Automation using AI and IOT is being developed to improve how a farmer conducts a variety of tasks [7].

Numerous researchers developed different application specific system for agriculture but less attention was paid towards critical aspects such as human centric design. There is lacuna in existing developed system in the utilization of advanced technologies to their full potential. The agricultural sector wants autonomous systems that are smarter and more effective. Therefore, this research work is aim to design and developed the smart system as an intelligent modular autonomous system with human-centric design approach for agricultural application. The proposed smart system aims to enhance the features of existing system with multi-technological approach in which advanced technologies like IoT and ML will be used.

II. RELATED WORK

Numerous researchers developed different application specific system for agriculture. The various research articles has been studied. This section provides key highlights of earlier developed system, brief summary and comparative analysis of reviewed literature.

A robotic detection method for the two main pests that affect greenhouse bell peppers, powdery mildew (PM) & tomato spotted wilt virus (TSWV), is presented [1] by the author. The system's foundation was a manipulator, which makes it easier to achieve various detection stances. Principal component analysis as well as the coefficient of variation (CV) served as a base for the invention of the detection algorithms. The maximum classification accuracy for TSWV was obtained using PCA-based classification with leaf vein removal (90%) while the CV techniques also had good classification accuracy (85% and 87%). In terms of PM, PCA-based pixel-level classification success rate was high (95.2%) but poor (64.3%) for leaf condition classification.

Xenakis et al. introduce a plant Disease Diagnosis Support device that uses an IoT platform to manage a portable robotic device [2]. The system was an adaptable Internet of Things robotic framework for greenhouse cultivation scenarios with the goal of doing real-time plant disease diagnosis. A Convolution Neural Network technique of learning was used by the DDSS to diagnose and categorise early plant diseases. According to a demonstration case study, the suggested DDSS had a success classification rate of approximately 98%. Author suggested that the future work will be concentrated on expanding the training dataset with new plant photos to handle a larger set of plant diseases.

Nooraiyeen et al. research work entails the creation of an automated voice-controlled robotic car [3] that uses a microcontroller and an extensive network of image sensors to identify leaf diseases harming plants in gardens. Upon disease identification, the system uses image processing to notify the user of the most common leaf diseases in the plant and a list of preventative measures. It integrates the simple K clustering and SVM algorithm with the mobility of the robot in challenging terrain for accurate diagnosis of the leaf disease with minimal human involvement. A user-friendly voice autonomous robotic vehicle that makes plant leaf disease diagnosis easier would be the final result.

For the purpose of conducting research to create disease-resistant, high-yielding tomato cultivars, the author created a precise system for detecting plant diseases [4]. Control, acquisition process, Data Storage, Artificial Intelligence, and Data Visualisation are the system's five subsystems. An SSD MobileNet V2 FPNLite 640x640 with a mean inference time of 3.71 seconds and a mAP value of 77.25% was used to implement machine learning. The goal of another research work was to develop a technique to identify diseases [5] that induce yellowing in greenhouse plants. Plant yellowing is a condition that affects plants that are grown in greenhouses on a regular basis. The pathogens responsible for the tomato plant's yellowing had been discovered. The Neural Network ssd inception v2 coco model was trained to recognise leaves. The API used ResNet-50 and ResNet-101 feature extractors to do object detection. In this method, the diseased plant leaf was identified and its condition was determined using image processing & some machine learning algorithms like SVM and RF. Here, the HOG feature vector & colour features are employed to extract features.

The research project carried out by Anwar et al. intends to create a robotic arm [6] for the experimental setup-based detection and categorization of several tomato leaf diseases. A sequential model utilising CNN had been developed as a result of this research activity. The technology was able to detect tomato plant diseases with classification training accuracy of around 98.27%, and the accuracy of the validation was 90.80%. Suhag et al. [7] proposed an architecture for IoT-enabled soil nutrition & plant disease detection. It employs a range of sensors to collect photometric data on plants at different intervals. The farmer will get all the data with the help of the Internet of Things. To classify the photos, a local binary thresholding algorithm was used. When harvest time comes around, robots identify and categorise photographs.

Pak et al. proposes an algorithm appropriate for smart farms [8] when coupled with SLAM technology. A suitable algorithm for smart farms was examined through field experiments, and the features of the grid-based Dijkstra procedure. The author performed experiments in surroundings with static and moving barriers while speculating about path planning for agricultural robots that would pick, spray, and transport crops. The majority of autonomous agricultural systems will be built on an autonomous mapping and navigation system. In order to build a

3D farm map on both the edge side and cloud, Zhao et al. proposes [9] a ground-level mapping and navigating solution that uses the technology of computer vision with the Internet of Things (IoT). By forcing the robot vehicles to send continuous frames directly to the appropriate edge node, high effectiveness and rapidity of the mapping step are made possible. Additionally, extensive arranging and intensive deep computing are made possible by cloud computing. By utilising the dynamically distributing compute resources to edges, the system was adaptable to larger-scale fields as well as more complicated environments. The results of the evaluation show that Mesh-SLAM beats other algorithms in terms of mapping & localization precision, accuracy, and yield prediction error. Autonomous robots will be used in precision agriculture (PA) in the future to carry out numerous agricultural tasks. Robotic vehicles must be relative localised to the furrow centerline in order to operate autonomously within one. The coordinates of the vehicle in addition to all the stalks from the crop rows on either side of the furrow are needed for this relative location acquisition. Due to the sheer volume of crop stalks to be measured, a thorough geographic survey of the entire field is required beforehand. In order to determine the relative placement of the vehicle in the furrow throughout the early and late growth seasons, LeVoir et al.suggests [10] using a number of algorithms based on computer vision in conjunction with a low-cost camera and a LiDAR sensor.

The comparative analysis of different methodology for plant disease detection on the basis of multiple parameters indicated in Table 1.

TABLE I. COMPARATIVE ANALYSIS OF DIFFERENT METHODOLOGY FOR PLANT DISEASE DETECTION

Ref. No.	Method	Crop	Dataset Sample	Classification States	Performance Measures
1	PCA & CV	Pepper, Tomato	--	Tomato spotted wilt virus (TSWV) & Powdery mildew (PM)	For TSWV, PCA Accuracy = 90% CV Method Accuracy = 87% For PM, PCA Accuracy= 95.2% CV Method Accuracy= 64.3%
2	Three layered CNN module	Tomato	1000	Healthy, Bacterial, Viral, Late Blight	Classification Success Rate = 98%
3	K clustering and SVM algorithm	Basil leaf	--	Healthy leaf and Bacterial Blight	--
4	SSD MobileNet V2	Tomato	--		mAP value = 77.25% Average inference time =3.71 seconds
5	SSD inception v2 coco mode,	Tomato	1500	leaf mold, healthy and yellow leaf curl leaves	Testing accuracy= 98.61%, validation accuracy= 99%
6	CNN Model	Tomato	25000	10 classes of diseases	Training Accuracy =98.27% Validation Accuracy = 90.80%

The use of autonomous robots in public spaces under unpredictability and challenging environmental circumstances is a serious threat to their dependability and safety. The navigation method for directing a robot across grape rows for field surveillance is suggested by Rovira-Más et al. in this article [11]. The method relies on local perception and is created by combining three complementing methods: 3D vision, lidar, and ultrasonics. Shadrin et al. describes an embedded system that has been enhanced with AI to ensure continuous analysis and on-site forecasting of plant leaf growth dynamics [12]. The embedded solution can execute the neural network-based AI on board and is based on a low-power embedded sensing device with a GPU. The long short-term memory network and a recurrent neural network, is used as the system's brain. The suggested method ensures the system's autonomous functioning for 180 days with Li-ion battery. Modern mobile graphics chips are used for "smart" analysis and autonomous device control. This pilot study throws up numerous opportunities for applications of intelligent monitoring, particularly in the field of agriculture.

Abdelhafid et al. [13] carry out a number of duties with the robot, including data collection and operation management utilising a prescription map. The promotion of the use of an autonomous robot depends heavily on its localization. This inexpensive approach uses an Arduino equipped with a GPS module to collect localization information that will be used for robot navigation. The findings of the trial indicate that the technology offers sufficient localisation quality for agricultural robots. Megalingam et al. [14] goal in creating this work was to create an agricultural robot that could plough automatically. Robots surely play a crucial part in the automated farming procedure in the field of agriculture. Robotics are being used increasingly frequently in the field and enhancing production in agriculture. The system attempts to create an agricultural farming machine [32] that can organically and unintentionally

International Journal on Recent and Innovation Trends in Computing and Communication
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plough a restricted region. A LiDAR sensor is used. The sensor recognises field borders and impediments in the field. The system's brain and heart, the Raspberry Pi, enables swift, accurate, and autonomous movement.

Hussain et al. offer an autonomous robotic system [15] that attempts to enhance the conditions in the agricultural sector. The system consists of a mechanically mobile robot structure that can move through a field of farms. Convolutional neural networks are used in a machine learning module to identify weed plants in the field. The construction of a spraying model allows for precise application of herbicides to the recognised weeds as well as drip irrigation, which conserves water. A network of mobile robots acting as data collectors and actuators to manage the environment was deployed together with a fully autonomous system for maintaining greenhouses [16]. Based on the sensor readings, a fuzzy controller will regulate the greenhouse's watering system, humidifiers, and heating and cooling systems. The mobile robot moves around the greenhouse according to a predetermined map, collecting soil samples for testing while onboard sensors record information about the surrounding climate. The plant will be photographed by a camera installed on the moving robot, which will identify sick crops based on the colour and texture of the leaves. It started with K-mean clustering to differentiate the disease & then machine learning classification method was employed to identify the disease. The plant disease detection technique was developed utilising image processing to determine the precise disease of the plant. Existing plant recognition methods and technologies did not adequately account for numerous significant environmental and non-environmental constraints and considerations, which resulted in inaccurate plant identification in outdoor settings [17]. Therefore, there was a need to create real-time, mobile systems for identifying plants in natural settings. These issues were discussed in this work, which also discusses the use of autonomous mobile robots and semi-robots for the identification of wild plant species in outdoor settings. The suggested method combines cutting-edge deep learning techniques [34] [35] with an autonomous field robot to perform accurate plant detection in difficult conditions.

III. PROPOSED METHODOLOGY

The multi-featured autonomous robotic system for smart farming has been proposed in this paper for which the system overview is shown in Figure.

1. The robotic system uses novel deep learning model [18] [19][33] for detection of plant diseases and provides statistics on web system in IoT environment. The different actions like robot powering, pesticide sprinkling system has been controlled by web platform.

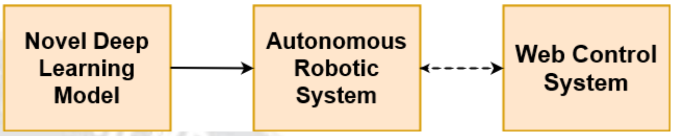

Figure. 1 System Overview

A. *Deep Learning Model for Plant Disease Detection*

The novel deep learning model with STS approach has been designed which uses three layers of convolution [20]. The model uses mixed pooling techniques with "Average-Max-GlobalMax" hierarchy while framing effective STS approach. The mixed package of pooling techniques has been sandwich between convolutional layers as per STS approach. The model has been trained by large dataset (10000 images of tomato plant leafs) which passes through multiple layers of convolution to extract low level to high level features. The average pooling techniques has been used which smoothens the output image of first convolution layer (16*3). The sharpning of images has been done with max pooling technique [21] after second convolution layers (32*3). The global max pooling method uses for hard sampling after last convolutional layers (64*3). Hence, the STS approach has been incorporated with mixed pooling techniques which results in complex novel deep learning model [22] for plant disease detection [23] as shown in Figure 2. The resultant vector generated by fattening procedure has been fed to fully connected layers (128) which recognized the features and classify images into 10 different classes (Diseases).

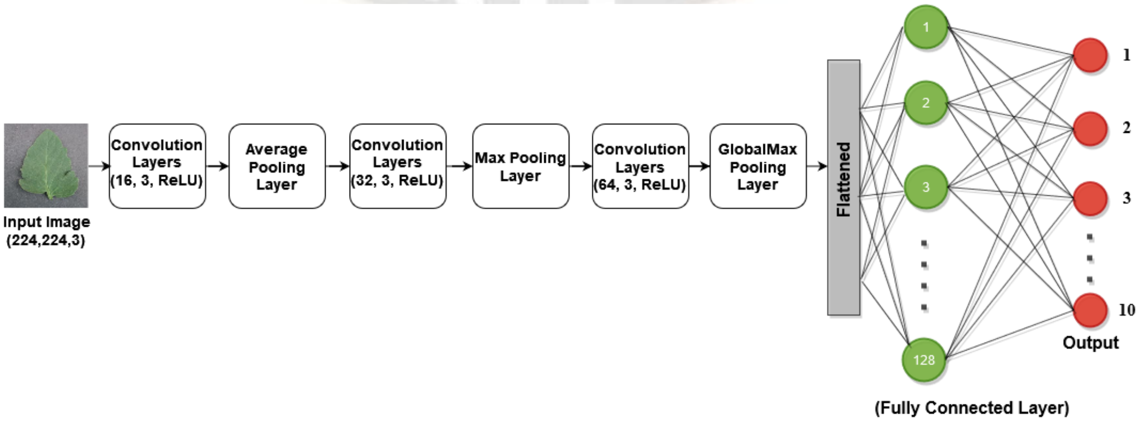

Figure. 2 Novel Deep Learning Model with STS Approach

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The system uses Tensorflow Lite Model which streamlines the various processes with multiple libraries while using deep learning model on device. The dataset images has been resized to 224x224 and splits into training and validation dataset with 80:20 ratio with batch size of 32. The models has been trained at learning rate of 0.01 with 1000 images of each disease. The sample dataset is shown in Figure 3. The normalization of dataset has been done in range of 0 to 1 with Map normalization function. The model used ReLU activation function and Softmax prediction function in respective block. The dropout rate of 0.2 has been used to avoid overfitting issue.

B. Robotic System for Smart Farming

All the sub topics should be numbered as shown above. Numbering should be made correctly [4, 5]. The proposed smart farming system as shown in Figure 4 consist of Raspberry Pi 4 controller, power source, high definition camera, robotic assembly components, pesticide model and web based platform. The Raspberry Pi 4 controller is a heart of system which perform advanced controlling actions.

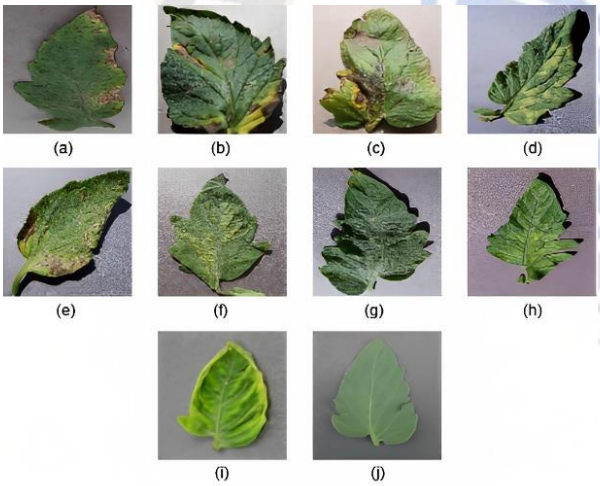

Figure. 3. Sample dataset Tomato Plant Leaf Diseases (a) Bacterial Spot (b) Early Blight (c) Late Blight (d) Leaf Mold (e) Septoria Leaf Spot (f) Spider Mite (g) Target Spot (h) Mosaic Virus (i) Yellow Leaf Curl Virus (j) Healthy Leaf

The Raspberry Pi 4 controller has been trained with novel deep learning model designed to detect tomato plant diseases [24]. The high definition camera has been interfaced with controller which is used to capture image/video during detection of plant diseases. The system uses battery operated power supply.

The pesticide model has been developed with solenoid valve and sprinkler whereas ultrasonic sensor has been mounted of pesticide tank to provide empty/filled status of tank. The complete setup ride on robotic assembly designed with motors, drivers and relays. The proposed robotic system can be control from remote place in IoT environment [25] with the help of web based platform. The web based platform is useful in controlling robot action as well as maintaining the statistical status of disease detection system.

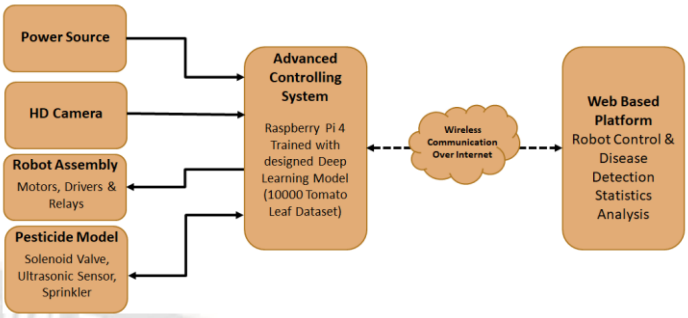

Figure. 4 Proposed Smart Farming System

C. Path Management for Robotic System

The autonomous robotic system manages the path as predefined rules as per the structure of green house and crop locations. The proposed robot moves on the line follower structure as shown in Figure 5. Assume that the distance between two plants is X/2. The robotic system monitor the greenhouse through both side of plantation line.

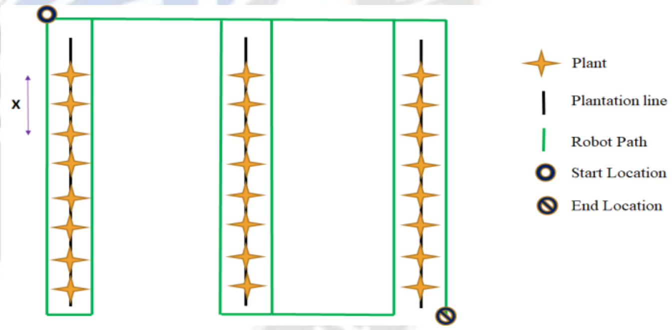

Figure. 5 Path for Robot Movement

D. Work Flow of Robotic System

The algorithmic steps to operate robotic system in IoT environment is given below and shown in Figure 6.

- Power ON Robotic System through web control platform in IoT Environment
- Robot moves forward on predefined path for distance X.
- High definition camera capture leaf samples for detection of diseases and process with deep learning model.
- If disease has been detected with captured leaf samples then respective pesticide sprinkling system gets activated as per disease detected.
- Robot moves reverse for distance X/2 and then move for distance X while sprinkling the pesticide.

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- The pesticide model and disease detection status has been updated on web platform over the internet.
- If disease not found with captured leaf samples then it will check whether robot reaches destination or not. The process continues until robot reaches destination.
- Once robotic system reaches destination, it will come back to its original location and respective status updated on web control panel.

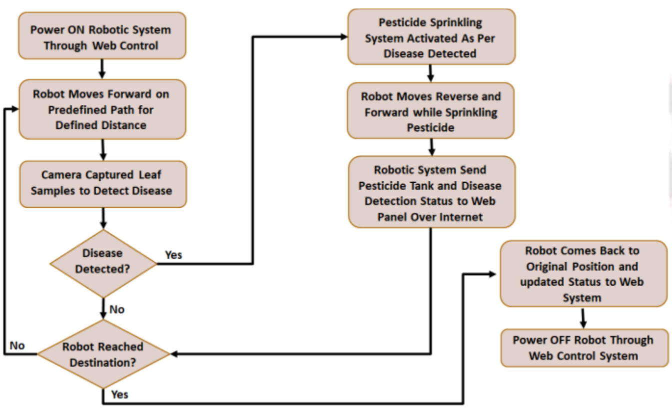

Figure. 6 Work Flow Diagram of Robotic System

E. Web Platform Development

The Figure 7 shows the component diagram of web control system. The live video streaming module plays an important role in monitoring the activity of robotic system. The graphical view module is useful for showing statistical analysis of disease detection whereas other module show the detected disease [26] name in real time environment. The ON/OFF button is used for controlling the power of robotic system. The LED panel helps to indicate the position of robotic system. The status bar system is helpful to indicate the empty/filled status of pesticide tanks.

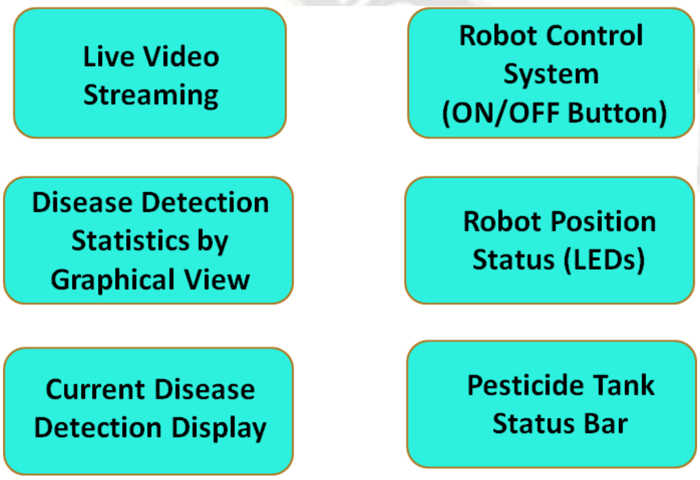

Figure. 7 Component Diagram of Web Control System

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The complex experimentation has been carried out for testing proposed novel deep learning model and results validated with hardware implementation of robotic system for disease detection and pesticide sprinkling management. The detail experimental work is discussed below.

A. Deep Learning Model Evaluation

The novel deep learning model has been framed with STS approach and trained with 10000 dataset images obtained from Kaggle platform [31]. The dataset consist of 1000 images each of nine different diseases frequently occurs in tomato plant and 1000 images of healthy plant leafs. The system has been setup with Intel(R) Core(TM) i5-8250U CPU @ 1.60GHz [27] and programmed with python 3.7. The NVIDIA GeForce RTX2080 Ti 12GB GPU has been used over 64-bit operating system and uses Tensorflow Keras Utility. The model has been trained for 20 epochs with learning rate of 0.01. The designed model has been evaluated and tested with complex analysis. The STS approach provides validation loss of 12.6%, training loss of 28.8%, validation accuracy of 95.4% and training accuracy of 96.5%. The results of designed model compared with different state of art model and Figure 8 show that the model with STS approach provides better performance as compare to other.

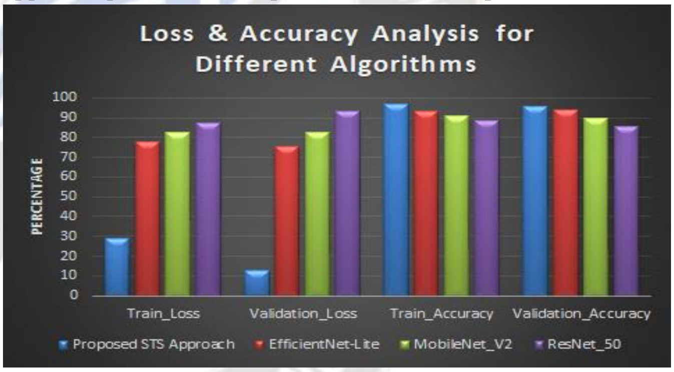

Figure. 8 Comparison of Proposed System with Different State of Art Models

The performance of disease detection model also verified by confusion matrix [28] as shown in Figure 9. It indicates that more than 96% average sample true value matches with predicted values while classifying and predicting particular disease of tomato plant. It shows that designed model is very effective in predicting diseases in plant.

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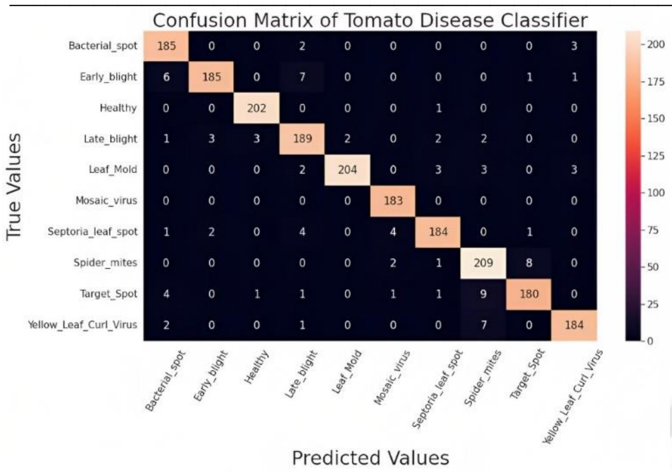

Fig. 9 Confusion Matrix

B. *Deep Leaning Model Validation With Hardware*

The TFLite model has been generated for trained deep learning model and used in Raspberry Pi 4 for detection of plant diseases. The screen has been interface with Raspberry Pi 4 to visualize the output while validating designed deep learning model. The Figure 10 indicates that the deep learning model recognized the Spider Mite disease with confidence score of 95%.

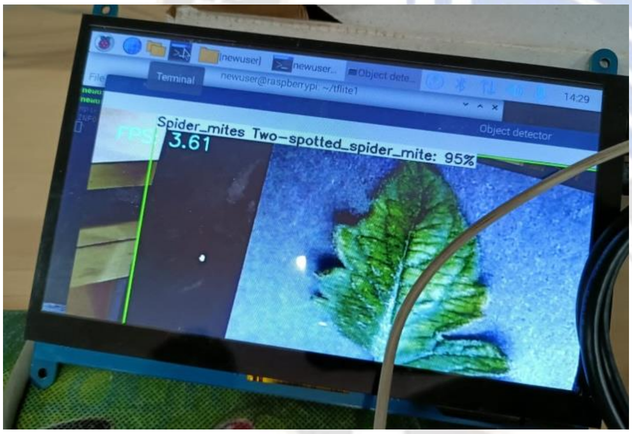

Figure. 10 Deep Learning Model Validation with Hardware

C. *Hardware Assembly of Robotic System*

The hardware assembly of robotic system is shown in Figure 11. The TFLite model is installed in Raspberry Pi 4 controller with the help of external memory card. The HD camera has been interfaced with Raspberry Pi 4 controller to capture images/videos while detecting tomato plant diseases. The pesticide tank contain solenoid valve to operate the sprinkler as per requirement and can have control over internet. The robotic assembly has been designed with four DC motors, Wheels, Motor Drivers and relays.

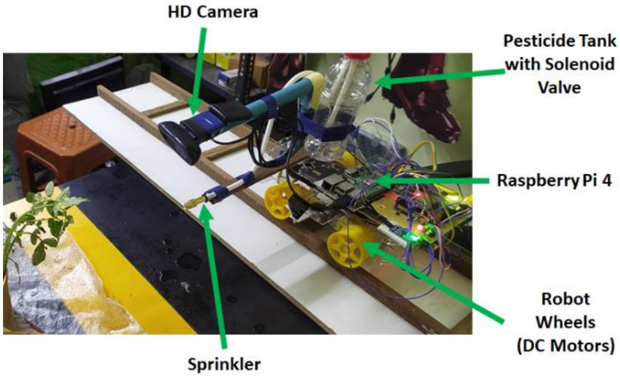

Figure. 11 Hardware Assembly of Robotic System

D. *Web Control System*

The web control system shown in Figure 12 has been designed for multiple module components. During compilation, the system generates HTTP address for local server. This address can be used to view the web panel in web browser. The web panel has live streaming component for real time monitoring. It also contains switch to ON/OFF the robotic system in IoT environment [29]. The Figure 13 shows live streaming mode and also Figure 14 shows live disease detection mode on web system which indicates that Leaf_Mold disease [30] has been detected with confidence score of 97%.

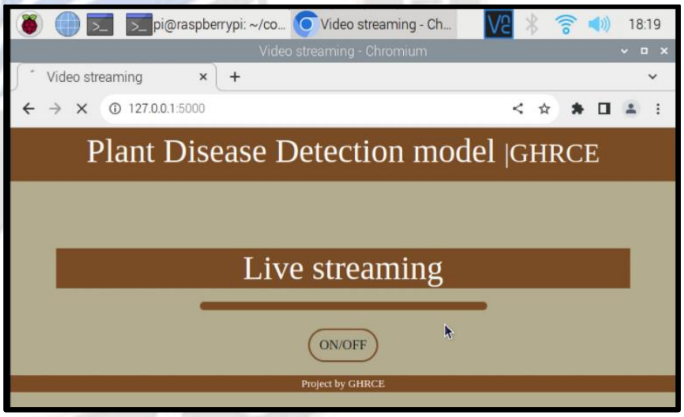

Figure. 12 Web Control System

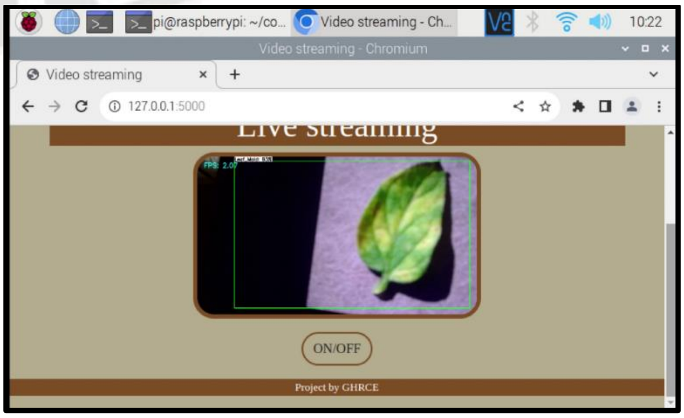

Figure. 13 Live Streaming Mode

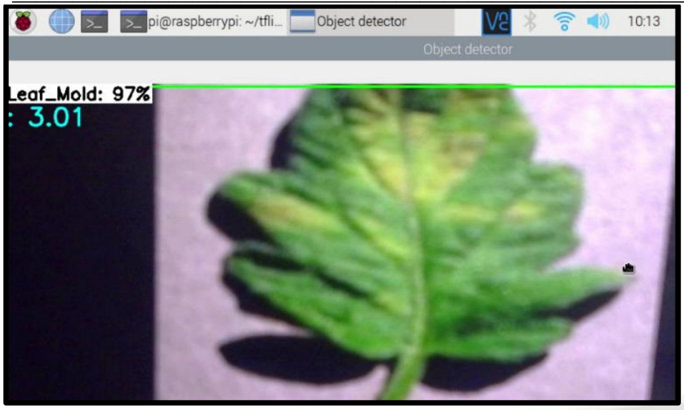

Figure. 14 Live Disease Detection Model

V. CONCLUSION AND FUTURE SCOPE

The smart solution as an intelligent modular autonomous system with human-centric design approach for agricultural application has been designed. The developed smart farming system aims to enhance the features of existing system with multi-technological approach in which advanced technologies like Internet of Things and deep learning will be used. The novel deep learning model has been framed with STS approach for detection of plant diseases. This model obtained training accuracy of 96.5% and validation accuracy of 95.4%. The plant disease detection and classification results has been verified with confusion matrix which shows more than 96% accuracy. An autonomous robotic system has been developed by installing novel deep learning model in it. It shows about 96% accuracy on Raspberry Pi 4 device in detecting plant diseases. An intelligent robotic system has been developed to detect plant diseases using novel deep learning model and perform multiple functions like greenhouse monitoring, pesticide sprinkling etc. The robotic system has control over internet through web control system so that farmer can monitor greenhouse and control robot activity from remote place. This developed model able to make farmer life simpler and perform difficult task like plant disease detection and pesticide sprinkling easily. In future, this model can be furnished by adding pesticide recommendation system and developing reconfigurable model that could be applied in any scenario.

REFERENCES

[1] N. Schor, A. Bechar, T. Ignat, A. Dombrovsky, Y. Elad and S. Berman, "Robotic Disease Detection in Greenhouses: Combined Detection of Powdery Mildew and Tomato Spotted Wilt Virus," in IEEE Robotics and Automation Letters, vol. 1, no. 1, pp. 354-360, Jan. 2016.

[2] A. Xenakis, G. Papastergiou, V. C. Gerogiannis and G. Stamoulis, "Applying a Convolutional Neural Network in an IoT Robotic System for Plant Disease Diagnosis," 2020 11th International Conference on Information, Intelligence, Systems and Applications (IISA, Piraeus, Greece), 2020, pp. 1-8.

[3] A. Nooraiyeen, "Robotic Vehicle for Automated Detection of Leaf Diseases," 2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT), Bangalore, India, 2020, pp. 1-6.

[4] R. R. Darmawan, F. Rozin, C. Evani, I. Idris and D. Sumardi, "IoT and Machine Learning System for Early/Late Blight Disease Severity Level Identification on Tomato Plants," 2021 13th International Conference on Information & Communication Technology and System (ICTS), Surabaya, Indonesia, 2021, pp. 288-293, doi: 10.1109/ICTS52701.2021.9608788.

[5] S. Fernando, R. Nethmi, A. Silva, A. Perera, R. De Silva and P. K. W. Abeygunawardhana, "Intelligent Disease Detection System for Greenhouse with a Robotic Monitoring System," 2020 2nd International Conference on Advancements in Computing (ICAC), Malabe, Sri Lanka, 2020, pp. 204-209.

[6] M. M. Anwar, Z. Tasneem and M. A. Masum, "An Approach to Develop a Robotic Arm for Identifying Tomato Leaf Diseases using Convolutional Neural Network," 2021 International Conference on Automation, Control and Mechatronics for Industry 4.0 (ACMI), Rajshahi, Bangladesh, 2021, pp. 1-6.

[7] S. Suhag, N. Singh, S. Jadaun, P. Johri, A. Shukla and N. Parashar, "IoT based Soil Nutrition and Plant Disease Detection System for Smart Agriculture," 2021 10th IEEE International Conference on Communication Systems and Network Technologies (CSNT), Bhopal, India, 2021, pp. 478-483.

[8] J. Pak, J. Kim, Y. Park and H. I. Son, "Field Evaluation of Path-Planning Algorithms for Autonomous Mobile Robot in Smart Farms," in IEEE Access, vol. 10, pp. 60253-60266, 2022.

[9] W. Zhao, X. Wang, B. Qi and T. Runge, "Ground-Level Mapping and Navigating for Agriculture Based on IoT and Computer Vision," in IEEE Access, vol. 8, pp. 221975-221985, 2020.

[10] S. J. LeVoir, P. A. Farley, T. Sun and C. Xu, "High-Accuracy Adaptive Low-Cost Location Sensing Subsystems for Autonomous Rover in Precision Agriculture," in IEEE Open Journal of Industry Applications, vol. 1, pp. 74-94, 2020.

[11] F. Rovira-Más, V. Saiz-Rubio and A. Cuenca-Cuenca, "Augmented Perception for Agricultural Robots Navigation," in IEEE Sensors Journal, vol. 21, no. 10, pp. 11712-11727, 15 May15, 2021.

[12] D. Shadrin, A. Menshchikov, A. Somov, G. Bornemann, J. Hauslage and M. Fedorov, "Enabling Precision Agriculture Through Embedded Sensing With Artificial Intelligence," in IEEE Transactions on Instrumentation and Measurement, vol. 69, no. 7, pp. 4103-4113, July 2020.

[13] E. F. Abdelhafid, Y. M. Abdelkader, M. Ahmed, E. H. Doha, E. K. Oumayma and E. A. Abdellah, "Localization based on DGPS for Autonomous Robots in Precision Agriculture," 2022 2nd International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET), Meknes, Morocco, 2022, pp. 1-4.

[14] A. P. A and R. K. Megalingam, "Autonomous Agricultural Farming Robot for Automatic Ploughing in a Closed Field,"

2022 IEEE 19th India Council International Conference (INDICON), Kochi, India, 2022, pp. 1-6.

[15] M. Hussain, S. H. A. Naqvi, S. H. Khan and M. Farhan, "An Intelligent Autonomous Robotic System for Precision Farming," 2020 3rd International Conference on Intelligent Autonomous Systems (ICoIAS), Singapore, 2020, pp. 133-139.

[16] T. Dharmasena, R. d. Silva, N. Abhayasingha and P. Abeygunawardhana, "Autonomous Cloud Robotic System for Smart Agriculture," 2019 Moratuwa Engineering Research Conference (MERCon), Moratuwa, Sri Lanka, 2019, pp. 388-393.

[17] M. F. Kazerouni, N. T. M. Saeed and K. -D. Kuhnert, "Exploration of Autonomous Mobile Robots through Challenging Outdoor Environments for Natural Plant Recognition Using Deep Neural Network," 2019 IEEE 15th International Conference on Intelligent Computer Communication and Processing (ICCP), Cluj-Napoca, Romania, 2019, pp. 279-285.

[18] M. J. Gaikwad, P. S. Asole, and L. S. Bitla, “Effective study of machine learning algorithms for heart disease prediction,” 2022 2nd International Conference on Power Electronics & IoT Applications in Renewable Energy and its Control (PARC), pp. 1–6, 2022.

[19] V. Bahel, P. Bhongade, J. Sharma, S. Shukla, and M. Gaikwad, “Supervised classification for analysis and detection of potentially azardous asteroid,” 2021 International Conference on Computational Intelligence and Computing Applications (ICCICA), pp. 1–4, 2021.

[20] K. P. Rangar and A. Khan, “A machine learning model for spam reviews and spammer community detection,” 2022 IEEE World Conference on Applied Intelligence and Computing (AIC), pp. 632– 638, 2022.

[21] V. Kushwaha and P. R. Maidamwar, “An empirical analysis of machine learning techniques for brain tumor detection,” 2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS), pp. 405–410, 2022.

[22] A. Gahane and C. Kotadi, "An Analytical Review of Heart Failure Detection based on IoT and Machine Learning," *2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS)*, Coimbatore, India, 2022, pp. 1308-1314.

[23] N. Kosarkar, P. Basuri, P. Karamore, P. Gawali, P. Badole and P. Jumle, "Disease Prediction using Machine Learning," 2022 10th International Conference on Emerging Trends in Engineering and Technology - Signal and Information Processing (ICETET-SIP-22), Nagpur, India, 2022, pp. 1-4.

[24] P. Kolhe, K. Kalbande and A. Deshmukh, "Internet of Thing and Machine Learning Approach for Agricultural Application: A Review," 2022 10th International Conference on Emerging Trends in Engineering and Technology - Signal and Information Processing (ICETET-SIP-22), Nagpur, India, 2022, pp. 1-6,.

[25] S. Shahakar, P. Chopde, N. Purohit, A. Vishwakarma, A. Nite and A. K. Sharma, "A Novel Machine Learning and Deep Learning Driven Prediction for Pre-diabetic Patients," 2023 6th International Conference on Information Systems and Computer Networks (ISCON), Mathura, India, 2023, pp. 1-6.

[26] M. Agarwal, A. Kotecha, A. Deolalikar, R. Kalia, R. K. Yadav and A. Thomas, "Deep Learning Approaches for Plant Disease Detection: A Comparative Review," 2023 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), Bhopal, India, 2023, pp. 1-6.

[27] M. Bende, M. Khandelwal, D. Borgaonkar and P. Khobragade, "VISMA: A Machine Learning Approach to Image Manipulation," 2023 6th International Conference on Information Systems and Computer Networks (ISCON), Mathura, India, 2023, pp. 1-5.

[28] R. Kumar Yadav, P. Ujjainkar and R. Moriwal, "Oral Cancer Detection Using Deep Learning Approach," 2023 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), Bhopal, India, 2023, pp. 1-7.

[29] P. Nirale and M. Madankar, "Design of an IoT Based Ensemble Machine Learning Model for Fruit Classification and Quality Detection," 2022 10th International Conference on Emerging Trends in Engineering and Technology - Signal and Information Processing (ICETET-SIP-22), Nagpur, India, 2022, pp. 1-6.

[30] J. Mahilraj, P. Sivaram, B. Sharma, N. Lokesh, B. Bobinath and R. Moriwal, "Detection of Tomato leaf diseases using Attention Embedded Hyper-parameter Learning Optimization in CNN," 2023 6th International Conference on Information Systems and Computer Networks (ISCON), Mathura, India, 2023, pp. 1-6.

[31] https://www.kaggle.com/datasets/kaustubhb999/tomatoleaf?select=tomato.

[32] Kallam, S. , Chakrabarti, P. , Hung, B.T. and S, S.S. 2023. Remote Health Monitoring IoT Framework using Machine Learning Prediction and Advanced Artificial Intelligence (AI) Model . *International Journal on Recent and Innovation Trends in Computing and Communication*. 11, 5 (May 2023), 42–47. DOI:https://doi.org/10.17762/ijritcc.v11i5.6523

[33] Kumar, K.A. and R, A. 2023. Intelligent Early Diagnosis System against Strep Throat Infection Using Deep Neural Networks. *International Journal on Recent and Innovation Trends in Computing and Communication*. 11, 5 (May 2023), 01–11. DOI:https://doi.org/10.17762/ijritcc.v11i5.6519.

[34] Tamilselvi, T. ., Lakshmi, D. ., Lavanya, R. ., & Revathi, K. . (2023). Digital Companion for Elders in Tracking Health and Intelligent Recommendation Support using Deep Learning. *International Journal on Recent and Innovation Trends in Computing and Communication*, *11*(3), 145–152. https://doi.org/10.17762/ijritcc.v11i3.6331

[35] Patil, A. ., & Govindaraj, S. K. . (2023). Enhanced Deep Learning Models for Efficient Stroke Detection Using MRI Brain Imagery. *International Journal on Recent and Innovation Trends in Computing and Communication*, *11*(3), 191–198. https://doi.org/10.17762/ijritcc.v11i3.6335.