A Real-Time Precision Monitoring And Detection System For Rice Plant Diseases Using Machine Learning Approach

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Abstract

Crop disease results in financial loss for farmers. Crop losses are mostly caused by diseases, pests, weeds, and animals. These elements have a significant detrimental impact on global agricultural production, which can range from 20% to 40%, according to an IRJET study. Traditionally, crop diseases have been identified by observing changes in leaf texture, colors, and shape, however this approach is ineffectual. In turn, it provides farmers with access to knowledgeable agriculturists in every continent for the detection of crop diseases on big farms. However, it appears that this strategy requires more time and is more cost- effective.

Farmers' traditional approaches for crop disease prediction fall short in a number of crucial areas when compared to modern systems for automated crop disease detection and categorization. On large farms, the amount and quality of agricultural products will decrease if a farmer does not take the disease into account. Smart agriculture is a smart digital method for farmers because it provides continuous crop disease monitoring, especially in remote agricultural fields.

When a specific causal agent consistently impacts a crop, it can be frequently affected by illness, resulting in irregularities in its physiological process. The crop's normal development, function, and other processes are also in jeopardy due to these aberrations. Modifications to its physiological and biochemical processes cause the causative agent to manifest as diseases and signs in plants.

Fig-01: Plant with Disease

INTRODUCTION

Technology has made significant progress over the past few years, particularly in the field of irrigation. IoT technology is one of the advances that constitute this progress.

The Internet of Things (IoT) refers to the networking and online communication of devices within a network. The internet of things uses sensors to collect data, which is then sent to the cloud for analysis through a controller that acts as a gateway. The data can be accessed by the user through the mobile application provided. In this trial, we are going to build a smart irrigation system which, because it is automated, eliminates the need for farmers to visit their farms for irrigation. Instead of using a smartphone app provided by the agronomist, the farmer can track the irrigation position. The captured data is stored in the cloud for subsequent analysis.

In a smart city, smart irrigation is a tool that can be utilized. IoT-based robotic agriculture is another innovative form of farming, in which a robot performs tasks such as harvesting weeds and fertilizing plants instead of a farmer. As a result, the combination of Iot and robotic farming provides a solution to many problems in the agricultural sector.

pproximately 40% of the food produced is lost to weeds, mildew, and diseases despite the use of herbicides, insecticides, and other agricultural practises. Utilising technology for pest prediction is essential to lowering food waste. Pesticide misuse also increases expenses and degrades quality, which has a detrimental effect on the environment. Therefore, it is necessary to use them less.

Robots are machines that are capable of performing specific tasks, either independently or with guidance. Engines and computer intelligence usually use in robotics. The robot's high levels of performance and reliability have a significant impact on our everyday lives. The "agrobot," the final module, completes all of the farmer's tasks. This agrobot will collect weeds and take pictures of plants that can be used to spot plant diseases and give plants the right amount of nutrients. We may even see animals in the wild on the camera and tell them to go somewhere else. The mobile app created in Android Studio allows for the control of this agrobot from anywhere in the world.

import np for Numpy
from tensorflow, import tensorflow as tf from tensorflow.keras.preprocessing, import keras Import VGG16, preprocess_input, and decode_predictions from the picture imported from tensorflow.keras.applications.vgg16 Model is VGG16 with "imagenet" weights.

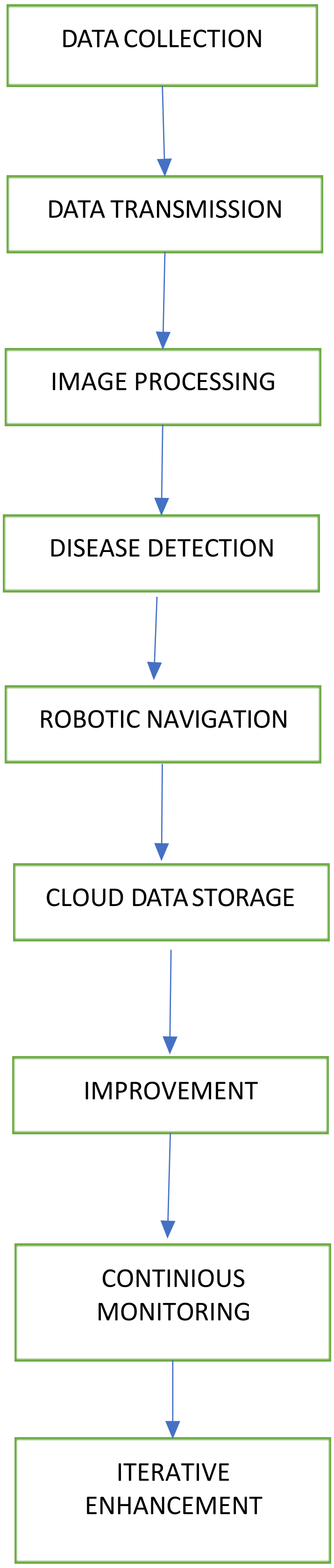
picture = image.load_img(image_path, target_size=(224, 224)); def predict_disease(image_path);
image.img_to_array(img) img_array

axis=0, img_array = np.expand_dims(img_array) preprocess_input(img_array) = img_array

predictions are determined by using the formula model.predict(img_array) and decoded_predictions (predictions, top=5).[0]

the decoded predictions back
'path_to_your_image.jpg' image_path diagnoses = diagnose_disease(image_path)

class_name, description, and score for prediction in predictions: print(f"Class: class_name, Description: description, Score: score")



Flow chart of plant leaf disease detection

METHODOLOGY

A. Data-driven Insights:

Machine learning algorithms process large volumes of data collected from IoT devices such as weather sensors, soil moisture sensors, and drones. These algorithms can uncover patterns, correlations, and trends that might not be easily apparent through manual analysis. For instance, they can predict weather patterns, identify optimal planting times, and suggest irrigation schedules based on historical data.

Yield = intercept + (slope * Weather) + (slope * SoilQuality)
+ ... + (slope * OtherFactors) NDVI = (NIR - Red) / (NIR + Red)
Distance(x, c) = sqrt(sum((x_i - c_i)^2)) f(x) = sign(w^T * x + b)
WaterDeficit = FieldCapacity – CurrentSoilMoisture

B. Crop Disease Detection:

Machine learning models can be trained to identify signs of disease or stress in crops by analyzing images captured by drones or cameras installed in the fields. These models can differentiate between healthy and diseased plants, helping farmers take timely action to prevent the spread of diseases.

C. Yield Prediction:

Using historical data on weather conditions, soil quality, and crop types, machine learning models can predict crop yields. This information assists farmers in making informed decisions about resource allocation, harvest planning, and market predictions.
$Yield = \beta_0 + \beta_1 * Weather + \beta_2 * SoilQuality + \beta_3 * OtherFactors + \varepsilon$

D. Pest Management:

Machine learning algorithms can help identify pest infestations by analyzing sensor data. They can provide early warnings when pest populations are increasing, enabling farmers to implement targeted pest control measures.
Distance(x, c) = sqrt(sum((x_i - c_i)^2))

E. Irrigation Optimization:

Sensors measuring soil moisture levels can provide real-time data about the field's water content. Machine learning models can use this data to optimize irrigation scheduling, preventing over- or under-irrigation and conserving water resources.

F. Livestock Monitoring:

In animal farming, machine learning can analyze data from IoT-enabled wearable devices attached to livestock.

G. Supply Chain Management:

Machine learning can assist in optimizing the supply chain by predicting demand, monitoring inventory levels, and predicting potential disruptions. This ensures that the right amount of agricultural produce reaches the market at the right time.

H. Cloud Computing Integration:

Cloud platforms provide the necessary infrastructure for storing and processing the massive amounts of data generated by IoT devices. Machine learning models can be deployed on the cloud, allowing farmers to access predictions and insights remotely through web or mobile applications.
DeployedModel = ML_Service(Model, Cloud_Infrastructure)
IntegratedData = IoT_Service(Data, Cloud_Infrastructure) Allocated_Resources =
Cloud_Resource_Manager(Requested_Resources)
Accessed_Insights = Cloud_App(App, Cloud_Infrastructure)

I. Scalability and Flexibility:

Cloud-based machine learning solutions offer scalability, enabling farmers to expand their operations without the need for significant hardware investments. Cloud resources can be easily adjusted to handle varying workloads and data volumes.

J. Continuous Learning and Improvement:

Machine learning models can be continuously trained and improved with new data. As more data is collected over time, models can adapt and provide increasingly accurate predictions and insights.

DESIGN AND IMPLEMENTATION

1. System Architecture and Components:

Sensors: Use various sensors such as humidity, temperature, soil moisture, and spectral sensors to gather real-time data about the rice plants and their environment.
Robotics Platform: Employ a robotic platform equipped with mobility capabilities, including wheels or tracks, to navigate the rice field.
Camera Module: Attach a camera to the robotic platform to capture images of the rice plants. This will be crucial for disease detection using image processing techniques.
IoT Connectivity: Enable the robotics platform and sensors to communicate with a central control unit using IoT protocols like MQTT or HTTP.
Central Control Unit: Develop a central control unit that receives data from sensors and cameras, processes the data, and controls the robotic platform's movements.
Cloud Infrastructure: Set up a cloud server to store and manage the collected data, images, and disease-related

information. This also enables remote access and monitoring.
User Interface: Create a user-friendly interface, accessible via a web or mobile application, for users to monitor the system, receive alerts, and control the robot if needed.

2. Data Collection and Processing:
Sensor Data Collection: Continuously gather data from sensors placed in the rice field, including environmental parameters and plant health indicators.
Image Capture: Capture images of the rice plants using the robotic platform's camera module.
Data Fusion: Combine data from various sensors and image data to create a comprehensive understanding of the rice field's condition.

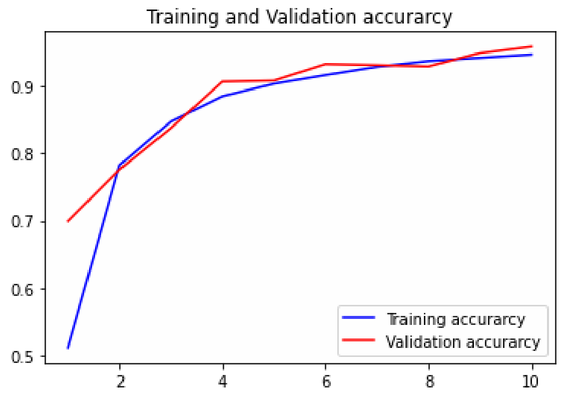


Fig-02: Accuracy graph

3. Disease Detection:
Image Processing: Apply image processing techniques to the captured images for disease detection. This involves segmenting plant parts, extracting features, and identifying anomalies.
Machine Learning: Train machine learning models, such as convolutional neural networks (CNNs), using labeled datasets of healthy and diseased rice plants. These models can then classify the disease based on the images.

4. Decision Making:
Rule-based Systems: Develop rule-based systems that consider sensor data, image analysis results, and historical information to make decisions about whether disease is present and the severity.
Thresholds and Alerts: Set thresholds for various parameters (e.g., humidity, temperature) and disease severity levels. When values exceed these thresholds, generate alerts.

5. Robotic Movement and Action:
Path Planning: Implement path planning algorithms that help the robotic platform navigate the rice field efficiently while avoiding obstacles.
Automated Sampling: Design the robot to be capable of autonomously moving to specific locations to take samples of plant tissues or soil for further analysis.

6. Remote Monitoring and Control:
IoT Connectivity: Ensure the central control unit can communicate with the robotic platform and sensors in real- time via IoT protocols.
Mobile/Web Application: Create a user interface that allows users to remotely monitor the rice field's condition, receive disease alerts, and even control the robot's movements if necessary.

7. Cloud-based Data Storage and Analysis:
Data Storage: Store collected sensor data, images, and disease detection results in a cloud-based database for historical analysis and future reference.
Data Analytics: Implement data analytics to identify patterns, trends, and correlations in the collected data that could provide insights into disease progression and environmental factors.

8. Alert and Reporting:
Alert Generation: When a disease is detected or environmental parameters cross critical thresholds, generate real-time alerts to notify farmers or stakeholders.
Reporting: Provide periodic reports summarizing the overall health of the rice field, disease outbreaks, and recommended actions.

9. **Maintenance and Upgrades:**
Regularly maintain and calibrate sensors, cameras, and the robotic platform to ensure accurate data collection and proper functioning.
Update the machine learning models and algorithms as new data becomes available to improve disease detection accuracy.

Fig-03: Robotic Implementation

ROBOTIC IMPLEMENTATION
The robotic implementation of the real-time precision monitoring and detection system for rice plant diseases involves integrating mobility components, sensors, cameras, and advanced algorithms to achieve accurate disease identification and proactive responses.
Robotic hardware, equipped with mobility features like wheels or tracks, enables the platform to navigate the rice field, avoiding obstacles and following predefined paths. Motor controllers ensure precise movement to specific sampling points for data collection.
Various sensors, including humidity, temperature, soil moisture, and spectral sensors, are seamlessly integrated into the robotic platform. These sensors continuously gather environmental data and plant health indicators crucial for disease detection. An integrated camera module captures images of rice plants across the field. Image processing techniques such as preprocessing, segmentation, and feature extraction enhance image quality and extract key features necessary for accurate disease identification.
Trained machine learning models, often leveraging convolutional neural networks, analyze the processed images for disease signs. Decision-making algorithms evaluate disease severity against predefined thresholds. The robot responds by navigating to specific locations, performing actions like sample collection, and generating real-time alerts to inform stakeholders of disease outbreaks.

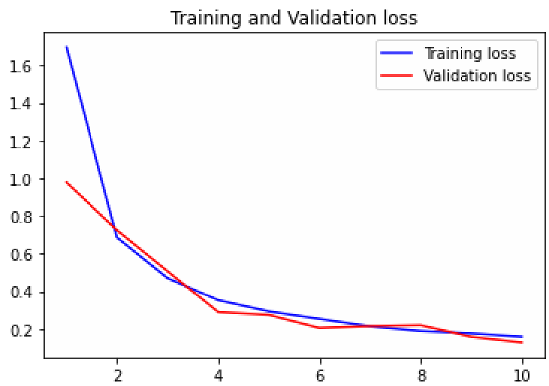


Fig-04: Accuracy Graph of validation

ALGORITHM
1. **Initialization and Data Collection:**
The algorithm starts by configuring the robotic platform with sensors and a camera, establishing IoT connectivity with the central control unit. It involves collecting real-time data from humidity, temperature, soil moisture, and spectral sensors, alongside capturing images of rice plants.

2. **Image Processing and Disease Detection:**
Processed images undergo image processing techniques for feature extraction, which are then classified by a trained machine learning model. Disease presence and severity are determined, allowing the algorithm to trigger actions based on predefined thresholds and rules.

3. **Robotic Navigation and Cloud Storage:**

The robotic platform navigates the rice field using path planning algorithms, collecting data from specified points. Collected sensor data, images, and disease information are stored in a cloud-based database, facilitating historical analysis and reporting.

4. User Interaction and Continuous Improvement:

Users access real-time data through a user interface, receiving alerts if disease severity crosses thresholds. Regular maintenance and updates are performed to enhance system accuracy and responsiveness, aligning with evolving agricultural needs.

This algorithmic approach integrates data collection, image processing, disease detection, navigation, cloud storage, user interaction, and improvement strategies, ensuring effective disease management in real-time.

Class	Disease	Affected Plants	Train	Test
CD1	Apple scab	Apple	504	126
CD2	Bacterial spot	Peach	4337	1084
CD3	Black rot	Apple	1140	361
CD4	Cedar apple rust	Apple	220	55
CD5	Spot gray leaf	Corn	440	103
CD6	Common rust	Corn	953	239
CD7	Early blight	Potato	1600	400
CD8	Esca black measles	Grape	1107	276
CD9	Citrus greening	Orange	4405	1102
CD10	Late blight	Tomato	2327	582
CD11	Leaf spot	Strawberry	861	215
CD12	Leaf mold	Corn	761	191
CD13	Leaf scorch	Cherry	887	222
CD14	Leaf blight	Tomato	817	197
CD15	Powdery mild dew	Tomato	2310	577
CD16	Septoria leaf spot	Tomato	1417	354
CD17	Target spot	Tomato	1314	224
CD18	Tomato mosaic virus	Grape	1123	74
CD19	Tomato yellow leaf	Potato	4286	1071
CD20	healthy	-	4909	1200

Table: Different types of plant disease sand their classification

HARDWARE AND TECHNOLOGY EXPLANATION

1. Sensors:

Humidity Sensor: Measures the moisture content in the air, providing insights into humidity levels within the rice field environment.

Temperature Sensor: Monitors the temperature of the surrounding area to assess its impact on plant health.

Soil Moisture Sensor: Measures the moisture content in the soil, helping to determine irrigation requirements.

Spectral Sensors: These sensors detect specific wavelengths of light reflected by plants, enabling the analysis of plant health based on spectral characteristics.

2. Robotics Platform:

Robotic Chassis: The physical frame of the robot equipped with wheels or tracks for mobility within the rice field.

Motor Controllers: Electronics that control the movement of wheels or tracks, enabling the robot to navigate the field.

Power Supply: Batteries or other power sources that provide energy to the robot's components.

Microcontroller/Computer: Controls the robot's movements, processes sensor data, and communicates with other components.

3. Camera Module:

Camera: A high-resolution camera capturing images of the rice plants for disease detection and visual monitoring.

Camera Interface: Interface hardware and software to communicate with the camera, capture images, and transfer them to the central control unit.

4. IoT Connectivity:

Wireless Communication Modules: These could include Wi- Fi, Bluetooth, or LoRa modules that allow the robot and sensors to communicate with the central control unit.

Microcontroller/Embedded Computer: This component manages communication protocols and data exchange with the central control unit using MQTT, HTTP, or other IoT communication protocols.

5. Central Control Unit:

Microcontroller/Server: A powerful microcontroller or server that receives data from the robot and sensors, processes

information, and makes decisions.
Database: Stores historical sensor data, images, and disease detection results for analysis and reporting.
Decision-Making Logic: Software algorithms that process data, analyze disease conditions, and trigger actions such as alerts or robot movements.

6. Cloud Infrastructure:
Cloud Server: A remote server accessible via the internet that stores and manages the collected data and images.
Cloud Database: Stores data and allows for scalability, remote access, and collaboration among stakeholders.

7. User Interface:
Web/Mobile Application: A user-friendly interface accessible via web browsers or mobile devices that displays real-time data, disease alerts, and allows users to control the robot remotely.
Graphical User Interface (GUI): The visual representation of data, alerts, and robot control options.

8. Data Processing and Analysis:
Image Processing Software: Utilizes libraries and algorithms for image segmentation, feature extraction, and disease detection based on plant images.
Machine Learning Framework: Libraries and tools for developing, training, and deploying machine learning models for disease classification.

9. Alert and Reporting:
Alert System: Software that generates alerts based on data analysis results, sending notifications to users via the user interface or email.
Reporting Tools: Software that generates periodic reports summarizing disease outbreaks, plant health trends, and recommended actions.

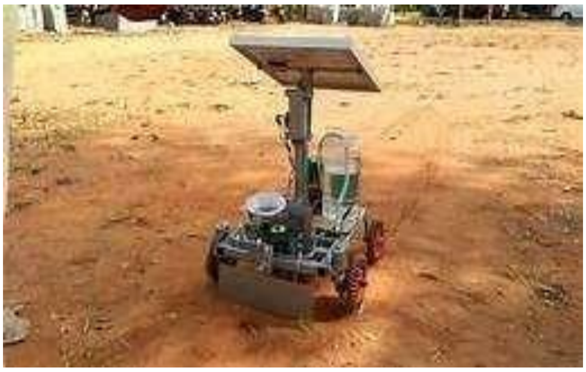


Fig-05: Sensor Implementation

EXPERIMENTAL RESULTS

In the context of a real-time precision monitoring and detection system for rice plant diseases employing an Internet of Things (IoT) based robotics approach, a series of comprehensive experiments can yield valuable insights into the system's performance and capabilities. One of the primary metrics to evaluate is the accuracy of disease detection. By comparing the system's classifications against ground truth data, metrics such as precision, recall, F1-score, and overall accuracy can be computed. These metrics provide a clear understanding of the system's ability to distinguish between healthy and diseased plants, forming a critical aspect of its functionality.
Another crucial aspect of the system's effectiveness is its response time. The time taken for the system to detect the presence of a disease and subsequently generate an alert is of paramount importance in facilitating timely interventions. Conducting experiments to measure this response time under various disease scenarios can highlight the system's ability to quickly identify outbreaks, enabling swift and effective countermeasures.
An essential consideration in disease detection is the minimization of false positives and false negatives. False positives (healthy plants misclassified as diseased) and false negatives (diseased plants not detected) can lead to unnecessary interventions or missed disease outbreaks, respectively. By assessing and fine-tuning the system's algorithms and parameters, these rates can be balanced to optimize accurate disease identification.
In tandem with disease detection, the robotic platform's navigation and control capabilities are equally vital. Experimentally evaluating its efficiency in traversing the rice field, avoiding obstacles, adhering to designated paths, and reaching specific sampling points provides insights into the system's overall functionality and adaptability to the agricultural environment.
The correlation between sensor data and disease occurrences is a noteworthy experiment to undertake. Analyzing changes in environmental parameters such as humidity, temperature, and soil moisture in relation to disease outbreaks can offer valuable insights into potential early indicators of plant health deterioration.

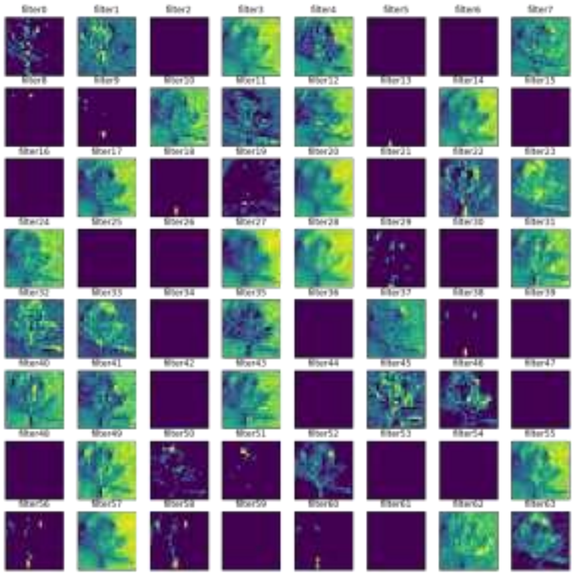


Fig-06: Enhancement of plant leaf

System reliability and maintenance play a pivotal role in real-world deployment. Experimental observations over an extended period, including various weather conditions and potential hardware or software failures, will help ascertain the system's robustness and ability to provide continuous and accurate monitoring.

Furthermore, the efficacy of cloud data management and retrieval can be assessed through experiments. Measuring the system's response times for retrieving historical data and generating reports from the cloud infrastructure offers insights into its scalability and real-time data accessibility.

Lastly, user interaction and interface evaluations are essential. Gathering user feedback on the user interface's intuitiveness, clarity of information, and effectiveness in providing real-time updates and alerts can guide improvements to ensure user satisfaction and efficient system operation.

FUTURE STUDY

In order to predict paddy leaf disease accurately, there are methods for detecting plant diseases that sometimes require lengthy training periods. Notably, accuracy suffers as data are spread over more categories, prompting the development of more accurate techniques for classifying paddy leaf diseases. The deep similarities present in photographs of paddy leaves present a significant challenge to accurate image classification. These issues could be solved, leading to a faster and more accurate identification of rice leaf disease formation.

DISCUSSION

The paddy disease prediction approach was applied using HC+IW-SSO and 2665 pieces of data were classified using a Python script. The algorithms employed were multi-class SVM, DT, SVM, NN, RNN, CNN, HC, and versions with different optimisation techniques (SMA, GOA, DA, SSO), with a ratio of 30% testing and 70% training. With a sensitivity of 0.92053, HC+IW-SSO demonstrated its best performance at the 80th LP.

The convergence cost of IW-SSO was compared to that of traditional methods for different iterations (0 to 25), and the latter's higher efficacy was highlighted. The DNN+LMBWO model for paddy leaf disease detection was evaluated using Python and compared against other approaches(DNN+SSO, DNN+PRO, DNN+BES, and DNN+CMBO) using varying learning percentages (50%, 70%, 60%, and 80%) using a Kaggle dataset with four categories of paddy disease images (brown spot, hispa, leaf blast, healthy).

CONCLUSION

The report proposes an agricultural IoT system that uses WSNs, pointing to improved performance from previous simulation assessments. Zigbee outperforms Bluetooth and Wi-Fi in terms of energy use and battery life. Edge computing in the Internet of Things (IoT), offers lower latency than cloud computing by expanding the number of edge servers.To reduce latency and load on the cloud, the system utilizes Wi-Fi for internet access, sensor nodes with Zigbee connectivity for data collection, and edge computing. A web-based tool provides real-time data surveillance and alarms for smart farming.

This study presents three new illness prediction implementations: Preprocessing, improved segmentation, hybrid classification with MLP and optimised LSTM, a four- stage approach using preprocessing, segmentation, feature extraction, NFC, and optimised DNN classification, and DCNN-CS using preprocessing, segmentation, feature extraction, and DCNN classification.The use of multi- spectral photography and GSM messaging is used by this system to regularly gather data, analyze it, and make decisions based on image positions, resulting in increased field management and productivity.

REFERENCES

1) Kour V.P. and Arora S. (2020) „Recent developments of the Internet of Things in Agriculture: A Survey‟, IEEE Access, pp 129924-129957, doi: 10.1109/ACCESS.2020.3009298
2) Y. S. Pei and Y. Y. Zhao, "Procedia Environmental Risk evaluation of groundwater pollution by pesticides in China: a short review," vol. 13, no. 2011-2012.
3) D. F. Nettleton, D. Katsantonis, A. Kalaitzidis, N. Sarafijanovic-Djukic, P. Puigdollers, and R. Confalonieri, "Predicting rice blast disease: machine learning versus process-based models," BMC Bioinformatics, vol. 20, no. 1, Oct. 2019, doi: 10.1186/s12859-019-3065-1
4) Anitha S. and Padma T. (2020) „A web service-based internet of things framework for mobile resource augmentation‟, International Journal of Communication Systems, Vol 33, doi:org/10.1002/dac.4475
5) Chen XianYi1, 2, Jin ZhiGang2, Yang Xiong3" Design of Tropical crops pests monitoring system based on wireless sensor network" 978-1-4577-14153/12/$26.00 ©2012 IEEE
6) S. S. Zarbafi, B. Rabiei, A. A. Ebadi, and J. H. Ham, "Association mapping of traits related to leaf blast disease in rice (Oryza sativa L.)," Australasian Plant Pathology, vol. 49, no. 1, pp. 31–43, Dec. 2019, doi: 10.1007/s13313-019-00674-8.
7) Alexandros Z., Athanasios T., et al., (2020) „Wireless Sensor Network Synchronization for Precision Agriculture Applications‟, EconPapers, Vol 10, pp 1-20
8) Ravi Kishore Kodali and Borade Samar Sarjerao, (19th October, 2017) "A Low Cost Smart Irrigation System Using MQTT Protocol", IEEE Region 10 Symposium (TENSYMP), pp. 19th October, 2017.
9) O. Ronneberger, "Invited Talk: U-Net Convolutional Networks for Biomedical Image Segmentation," Bildverarbeitung für die Medizin 2017, pp. 3–3, 2017, doi: 10.1007/978-3-662-54345-0_3.
10) Nhu-Ngoc D., Thi-Thao N., Minh-Quan L., Thuy Nguyen T., Woongsoo N. and Sungrae C. (2020) ‟Self- Calibrated Edge Computation for Unmodeled Time- Sensitive IoT Offloading Traffic‟, IEEE Access, Vol 8, pp 110316 – 110323, doi:10.1109/ACCESS.2020.3001572
11) GulamAmer, S.M.M. Mudassir, M.A Malik3, (May 2015) "Design and Operation of Wi-Fi Agribot Integrated System", IEEE International Conference on Industrial Instrumentation and Control, May 2015.
12) J. Zhang, G. Lin, X. Yin, J. Zeng, S. Wen, and Y. Lan, "Application of artificial neural network (ANN) and response surface methodology (RSM) for modeling and optimization of the contact angle of rice leaf surfaces," Acta Physiologiae Plantarum, vol. 42, no. 4, Mar. 2020, doi: 10.1007/s11738-020-03040-0.
13) Vishal Kumar A., Vishal S. and Monika S. (2022) ‟On QoS evaluation for ZigBee incorporated Wireless Sensor Network (IEEE 802.15.4) using mobile sensor nodes‟, Journal of King Saud University – Computer and Information Sciences, Vol 34, pp 27-35, doi:org/10.1016/j.jksuci.2018.10.013
14) W. Zhou et al., "Prediction of cadmium concentration in brown rice before harvest by hyperspectral remote sensing," Environmental Science and Pollution Research, vol. 26, no. 2, pp. 1848–1856, Nov. 2018, doi: 10.1007/s11356-018-3745-9.
15) Cheikh Saliou M.B., Bernard O.S., Ibrahima D. and Ibrahima N. (2019) ‟Home Edge Computing Architecture for Smart and Sustainable Agriculture and Breeding‟, Proceedings of the 2nd International Conference on Networking, Information Systems & Security, March, Article No.: 45, pp 1–7, doi:org/10.1145/3320326.3320377
16) Jiuxiang Gu, Zhenhua Wang, Jason Kuen, Lianyang Ma, Amir Shahroudy, Bing Shuai, Ting Liu, Xingxing Wang, Gang Wang, Jianfei Cai, and Tsuhan Chen, "Recent advances in convolutional neural networks", Pattern Recognition, vol. 77, pp354-377, 2018.
17) Achilles D.B., Maria S.P., Panagiotis D., Aglaia Liopa T., Pantelis B., George S., George K., Wan S. ans Sotirios K.G. (2020) ‟Internet of Things (IoT) and Agricultural Unmanned Aerial Vehicles (UAVs) in smart farming: A comprehensive review‟, Internet of Things, Vol 18, https://doi.org/10.1016/j.iot.2020.100187
18)] R. Thangaraj, S. Anandamurugan, and V. K. Kaliappan, "Automated tomato leaf disease classification using transfer learning-based deep convolution neural network," Journal of Plant Diseases and Protection, vol. 128, pp. 73–86, Nov. 2020, doi: 10.1007/s41348-020-00403-0.
19) Fan J., Zhang Y., Wen W., Shenghao G, Xianju L. and Xinyu G. (2020) ‟The future of Internet of Things in agriculture: Plant high-throughput phenotypic platform‟, Journal of Cleaner Production, Vol 280, pp 1-15, https://doi.org/10.1016/j.jclepro.2020.123651
20) N. V. R. R. Goluguri, K. S. Devi, and P. Srinivasan, "Rice-net: an efficient artificial fish swarm optimization applied deep convolutional neural network model for identifying the Oryza sativa diseases," Neural Computing and Applications, vol. 33, no. 11, pp. 5869–5884, Sep. 2020, doi: 10.1007/s00521-020-05364-x.
21) Miguel A. Zamora-Izquierdo, Jose Santa, Juan A. Martinez, Vicente Martinez, Antonio Skarmeta. (2018)‟A Smart farming IoT platform based on edge and cloud computing‟, bio systems Engineering, doi:10.1016/j.biosystemseng.2018.10.014.