Grenze International Journal of Engineering and Technology, June Issue

Edge-AI based Plant Leaf Disease Identification and Prevention for Smart Agriculture

Santhosh B J[1] and Dr. Balarengadurai C[2]
[1]Research Scholar, Dept. of CSE, Vidyavardhaka College of Engineering, Mysuru-570002, Visvesvaraya Technological University, Belagavi-590018
[2]Professor, Dept. of CSE, Vidyavardhaka College of Engineering, Mysuru-570002, Visvesvaraya Technological University, Belagavi-590018

***Abstract*—Smart agriculture has surfaced as a revolutionary method to enhance crop productivity and sustainability. One critical aspect of this paradigm is the integration of Edge-Artificial Intelligence (Edge-AI) for efficient plant disease identification and prevention. This study investigates the latest developments in employing Edge-AI techniques for the control of plant leaf diseases in smart agriculture.**

The article commences by providing a synopsis of the challenges posed by plant diseases in agriculture and their potential implications for global food security. It underscores the necessity for proactive identification of diseases and prevention strategies to mitigate these challenges. The survey then delves into the integration of Edge-AI technologies at the edge of the agricultural ecosystem, enabling real-time processing and decision-making. The analysis encompasses a thorough examination of diverse Edge-AI models and algorithms utilized for identifying plant leaf diseases, highlighting both their strengths and limitations. Principal techniques, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and ensemble learning methods are emphasized in the context of their effectiveness in identifying diverse types of plant diseases. The survey highlights the importance of edge computing in enabling localized processing and decision-making, reducing latency and dependency on centralized systems. It explores the integration of sensor networks, Internet of Things (IoT) devices, and Edge-AI in creating a robust and responsive smart agriculture ecosystem.

The paper also addresses challenges and open research issues in the field, including data privacy concerns, model robustness, and the need for standardized datasets. Additionally, it discusses emerging trends such as federated learning and blockchain for secure and collaborative disease management.

This study offers an extensive overview of the cutting-edge Edge-AI technologies for identifying and preventing plant leaf diseases in smart agriculture. By comprehending the present landscape and anticipating future directions, researchers and practitioners can make informed decisions to create scalable and efficient solutions for sustainable and resilient agricultural systems.

***Index Terms*— Convolutional Neural Networks (CNN), Edge-AI, IoT, Recurrent Neural Networks (RNN), Smart Agriculture.**

I. INTRODUCTION

Modern agriculture is undergoing a transformative shift towards increased efficiency and sustainability through

Grenze ID: 01.GIJET.10.2.997

the integration of advanced technologies. One of the pivotal challenges facing global agriculture is to widespread occurrence of plant diseases, capable of exerting a significant impact crop yield, food security, and economic stability. In response to this challenge, smart agriculture has emerged as a promising approach, leveraging cutting-edge technologies to monitor, analyze, and manage crop health in real-time.
Central to the success of smart agriculture is the integration of Edge-Artificial Intelligence (Edge-AI), a paradigm that involves deploying AI algorithms directly on edge devices, such as sensors and cameras, situated within the agricultural environment. This approach enables real-time data processing and decision-making at the source, reducing the reliance on centralized systems and minimizing latency. In the context of plant disease management, Edge-AI assumes a pivotal role in rapid identification and prevention of diseases affecting plant leaves.
This survey seeks to offer a thorough overview of the current state-of-the-art in Edge-AI-based identification and prevention of plant leaf diseases in the context of smart agriculture. The introduction sets the stage by highlighting the significance of tackling plant diseases within the realm of global agriculture, emphasizing the need for proactive and technologically advanced solutions. As we delve into the survey, we will explore the diverse range of Edge-AI models and methods that have been utilized for detection and mitigate plant leaf diseases efficiently.
The introduction also lays the groundwork for understanding the broader implications of integrating Edge-AI into the agricultural landscape. By exploring the advantages of localized processing, reduced latency, and increased autonomy afforded by edge computing, we aim to underscore the potential of this technology to revolutionize disease management practices in agriculture. Additionally, the introduction acknowledges the existing challenges and underscores the importance of ongoing research efforts to address these hurdles.

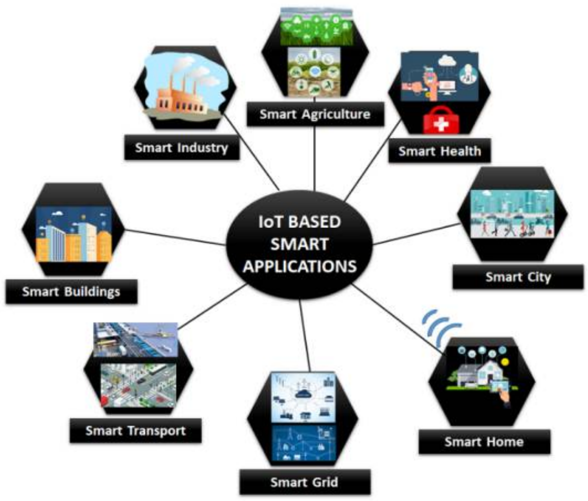

Fig 1: Block diagram showing IoT based emerging smart applications

We will briefly outline the significance of plant diseases in agriculture, the limitations of traditional disease management methods, and the potential of IoT technology to revolutionize crop health monitoring. Additionally, we will furnish readers with an overview of the structure and content of this survey, providing a roadmap of the topics we will cover.
The need for improved disease identification and prevention measures is evident in the context of global food security. As the world population is projected to surpass nine billion by 2050, agricultural systems must become more efficient and resilient. To meet this demand, we must not only increase the quantity of food produced but also ensure its quality and sustainability. Plant diseases, caused by various pathogens such as fungi, bacteria, and viruses, can devastate crops and lead to significant yield reductions, threatening food security on a global scale.
Conventional approaches for identifying plant diseases are often labor-intensive, time-consuming, and reliant on human expertise. Visual inspection of crops can be error-prone, and manual the gathering and examination of data are often limited by resource constraints. These limitations have prompted the exploration of alternative, technology-driven solutions to address plant disease challenges in agriculture.
The Internet of Things, with its capacity to interconnect devices, collect real-time data, and facilitate remote monitoring, offers a promising avenue for tackling the issues of disease identification and prevention in the agricultural sector. IoT-based systems can provide continuous, leveraging sensors, data processing, and

communication technologies, we can derive data-driven insights into the health of plants, facilitating early disease detection and timely interventions, IoT can transform traditional agriculture into a smarter, more efficient, and data-informed industry.
In essence, this survey aims to serve as a comprehensive guide for researchers, practitioners, and interested parties at the intersection of Edge-AI and smart agriculture, particularly in the realm of identifying and preventing plant leaf diseases. By navigating through the advancements, challenges, and emerging trends in this field, we hope to contribute to the ongoing dialogue surrounding sustainable and resilient agricultural practices in the era of digital transformation.

II. Related Work

A novel, lightweight convolutional neural network (CNN) structure (DLMC-Net) [1] is proposed for plant-leaf disease detection across multiple crops in real-time agricultural applications. The model addresses the vanishing gradient problem and decreases the count of trainable parameters through the utilization of collective blocks, passage layers, point-wise, and separable convolution blocks. The efficacy of the model is validated on four datasets: citrus, cucumber, grapes, and tomato. Empirical findings indicate that the proposed model outperforms seven cutting-edge models exhibit elevated accuracy, precision, recall, sensitivity, specificity, F1-score, and Matthews correlation coefficient. The model attains an accuracy of 93.56%, 92.34%, 99.50%, and 96.56% on citrus, cucumber, grapes, and tomato, respectively, making it a promising solution for plant-leaf disease detection across multiple crops.
A simplified CNN model [2] with 8 hidden layers is proposed for identifying diseases in tomato crops. The model surpasses traditional machine learning methods and pretrained models, boasting an impressive accuracy of 98.4%. It is trained using the PlantVillage dataset, comprising 39 distinct classes of different crops including 10 classes of tomato diseases. Image pre-processing techniques, such as changing image brightness and data augmentation, are utilized to enhance the performance of the model.
Two potential disadvantages of the proposed simplified CNN model include its computational burden stemming from the substantial number of parameters involved, and its reliance on image pre-processing methods that might introduce added complexity and computational overhead.
This study [3] investigates the utilization of Few-Shot Learning (FSL) algorithms [3] to classify plant leaf diseases using small datasets. The FSL method, using Siamese networks and Triplet loss, outperformed classical transfer learning techniques. With as few as 15 images per class, the FSL method achieved a 90% reduction in training data needs while maintaining high accuracy.
Some potential disadvantages of the Few-Shot Learning (FSL) algorithm for plant leaf classification include the requirement for extensive labeled datasets during the initial training phase and the potential for diminished accuracy when dealing with extremely limited training data.
A study [4] concentrated on plant disease classification employing deep learning models, notably the EfficientNet architecture. Training encompassed the PlantVillage dataset, involving both original and augmented images. Among the EfficientNet variants, B5 and B4 models demonstrated superior accuracy and precision compared to alternative deep learning models, registering high accuracy values of 99.91% and 99.97%, and precision values of 98.42% and 99.39% respectively. The study highlights the potential of computer-aided diagnostic systems in improving the efficiency and accuracy of plant disease diagnosis.
One potential disadvantage of computer-aided diagnostic systems for plant disease classification is the reliance on accurate and representative datasets for training the models. Another disadvantage is the need for computational resources and computing power to effectively implement deep learning models.
The study [5] centers on employing deep learning techniques, particularly transfer learning with pre-trained models, for plant leaf disease identification. The VGGNet and Inception module, trained on ImageNet, serve as the foundation for their approach. By initializing weights with these pre-trained networks, they attain a validation accuracy of no less than 91.83% on a public dataset. Even in the presence of intricate background conditions, the proposed approach achieves an average accuracy of 92.00% for classifying rice plant images. In summary, the study underscores the effectiveness and efficiency of their approach in plant disease detection.
While the approach proposed in the study achieves high accuracy, it comes with a few drawbacks to take into account. One disadvantage is that transfer learning with pre-trained models may not be suitable for all types of plant diseases, as the model may struggle to capture specific nuances or variations. Moreover, the study does not delve into the computational and resource demands associated with implementing deep learning algorithms for plant disease identification.

This paper [6] introduces a framework for plant disease recognition using deep learning, proposing a deep feature descriptor based on transfer learning and integrating it with traditional handcrafted features. The framework also incorporates center loss to enhance the discriminative ability of the fused feature. Experimental results showcase high classification accuracies on three publicly available datasets, highlighting the effectiveness of the proposed method in distinguishing plant leaf diseases.

However, there are a couple of potential disadvantages to consider. Firstly, the paper does not outline any limitations or weaknesses of the framework. Secondly, the method's effectiveness may vary based on the specific plant species and disease types, potentially impacting its applicability in diverse scenarios.

Climate change is impacting crop production in Latin America and the Caribbean, affecting both the quantity and quality of food. Deep learning in [7] is proposed as a solution for plant disease detection, but uncertainty in predictions on unseen samples is a challenge. This article introduces a probabilistic programming approach utilizing techniques from Bayesian deep learning to address uncertainty and misclassification measurement. Results show comparable performance to standard optimization procedures while quantifying uncertainty in predictions for out-of-sample instances.

One disadvantage of the complexity of utilizing a probabilistic programming approach for plant disease detection and computational requirements associated with Bayesian deep learning techniques. Additionally, the need to approximate the posterior density for the plant disease detection problem adds additional computational overhead.

In this study [8], a multi-convolutional neural network (CNN) model named MergeModel was employed to automatically detect tea leaf diseases in limited samples. The model combined diseased leaf segmentation and a weight initialization method for improved accuracy. MergeModel's integration of multiple CNN modules allowed for the extraction of various discriminative features. The model also employed data augmentation techniques to enhance the training samples. The experimental results demonstrated that MergeModel outperformed existing methods in accurately identifying common tea leaf diseases in small samples.

A potential drawback of employing the MergeModel for identifying tea leaf diseases is its potential demand for substantial computational resources, attributed to the utilization of multiple CNN modules. Furthermore, the model's efficacy in recognizing rare or less common tea leaf diseases might be constrained due to the limited number of available training samples.

Researchers in [9] have developed a computer vision approach to diagnose and treat plant diseases, focusing on soybean plants. The approach includes two modules: one for extracting the leaf part from the image and another for the application of a deep learning convolutional neural network (CNN) named SoyNet to recognize soybean plant diseases. The proposed method achieves an impressive identification accuracy of 98.14% and outperforms nine other state-of-the-art methods/models.

One potential disadvantage of the proposed computer vision approach is that it may rely heavily the effectiveness of the segmentation process is contingent on the quality of the input images, as intricate backgrounds can pose challenges for accurate segmentation. Furthermore, the dependence on deep learning models such as SoyNet may necessitate substantial computational resources to ensure efficient processing.

A research paper [10] proposes a method for recognizing and classifying diseases in paddy leaf images using an optimized deep neural network. The images are acquired from rice plant leaves in the farm field. Pre-processing involves converting RGB images to HSV and extracting binary images based on hue and saturation. Clustering is applied to segment diseased, normal, and background areas, while classification is carried out using an optimized deep neural network with the Jaya Optimization Algorithm. This approach attains high accuracy across various disease types.

The suggested method for recognizing and classifying diseases in paddy leaf images through optimized deep neural networks offers several advantages, such as achieving high accuracy for different disease types. However, it is necessary to evaluate potential disadvantages or limitations to offer a comprehensive perspective. Without specific information, it is challenging to outline these disadvantages in just two lines. In order to offer a substantial response, could you please provide additional details or specify particular aspects you would like me to emphasize when discussing the potential limitations of the approach presented.

In this paper [11], The paper introduces a method for identifying diseases in tea leaves using low-shot learning, employing support vector machines (SVM) for disease spot segmentation through the extraction of color and texture features. The approach employs enhanced conditional deep convolutional generative adversarial networks (C-DCGAN) to generate new training samples through data augmentation. Training the VGG16 deep learning model with augmented disease spot images results in an average identification accuracy of 90%, surpassing the performance of traditional low-shot learning methods.

A potential disadvantage of the low-shot method for identifying diseases in tea leaves is that it heavily relies on the quality and diversity of training data. Additionally, the utilization of deep learning models, such as VGG16, can be computationally expensive and require significant computational resources.
A novel deep learning approach is suggested to enhance the detection and severity analysis of tea leaf blight (TLB) disease [12]. The technique incorporates a Retinex algorithm to mitigate the impact of light variation and shadows in TLB images. Employing the Faster Region-based Convolutional Neural Networks deep learning framework enables the detection of TLB leaves, even in situations involving blurriness, occlusion, and small fragments. Subsequently, the identified TLB leaves undergo severity analysis using trained VGG16 networks, demonstrating heightened accuracy compared to traditional machine learning methods.
However, potential drawbacks of this method may include the intricacy and computational demands associated with deep learning algorithms, potentially limiting its practicality for certain applications. Additionally, the requirement for a substantial amount of labeled data for training the deep learning models could pose a challenge in certain scenarios.
The paper in [13] proposes a deep learning-based algorithm for accurately detecting multi-scale apple leaf spots in unconstrained environments. The algorithm incorporates a Bole convolution module, cross-attention module, and bidirectional transposition feature pyramid network (BCTNet) to improve accuracy and efficiency. The proposed method outperforms other state-of-the-art methods, providing decision information for growers and pesticide spraying robots to optimize pesticide usage and reduce crop yield losses.
One potential disadvantage of the proposed method is that it relies on a high-quality labeled dataset, which may be time-consuming and expensive to create under the guidance of agricultural experts. Additionally, the algorithm's The method's performance might be susceptible to fluctuations in unconstrained environmental conditions, potentially resulting in false detections or diminished accuracy.
Efficient early detection of diseases and pests in apple trees is essential to prevent further spread and mitigate economic losses in the apple industry [14]. However, identifying diseases can be challenging due to various factors such as multiple symptoms on the same leaf, non-homogeneous background, and differences in leaf color. Accurate and timely diagnosis is essential for controlling infections and ensuring better productivity. Sophisticated methods and instruments are required to tackle these obstacles and enhance the identification of diseases in apple trees.

Limitations in [14] identified listed below
1. The presence of multiple symptoms on the same leaf makes it difficult to accurately diagnose specific diseases, leading to potential misidentification or missed detection.
2. non-homogeneous background and variations in leaf color due to age of infected cells can further complicate disease identification, increasing the risk of false positives or negatives.

In this paper [15], a method is introduced for the identification of plant diseases utilizing image processing and convolutional neural network (CNN) models. The application of this technique focuses on analyzing unhealthy leaf symptoms in potato and tomato leaves, demonstrating notable success with high accuracy rates of 97% and 96.1% for ResNet-50, and 96.5% and 95.3% for AlexNet in classifying healthy-unhealthy leaves and leaf diseases, respectively. Additionally, a preventive measures technique and graphical layout are provided to promote plant health awareness.
Some disadvantages of using digital farming practices for plant disease detection include the requirement for advanced technical knowledge and equipment, which may be difficult for farmers in remote areas to access and implement. Additionally, there could be a high initial cost involved in setting up the infrastructure for digital farming practices.
This paper [16] focuses on the early detection of leaf diseases in tomato plants, which is crucial for the agricultural economy in India. The suggested system employs image processing methods, incorporating image segmentation techniques and clustering, to accurately identify and classify tomato plant leaf diseases. The implementation of this system aims to provide a reliable and effective means of disease detection, contributing to the overall health and productivity of tomato plants.
A potential drawback associated with employing image processing techniques for detecting plant leaf diseases is the requirement for high-quality and accurately captured images, which may not always be readily attainable in real-world scenarios. Additionally, the reliance on open-source algorithms may limit the customization and adaptability of the system to specific local environments or unique disease patterns.
This study [17] aimed to detect diseases on tomato plants using deep learning algorithms. The researchers tested two architectures, AlexNet and SqueezeNet, on tomato leaf images from the PlantVillage dataset. The trained

networks were able to detect various diseases on the leaves, and the algorithms were intended to be implemented on a robot for real-time disease detection in tomato fields or greenhouses.

Using deep learning techniques for detecting diseases in tomato plants has drawbacks, namely the necessity for extensive labeled training data and the risk of overfitting, where the model excels on training data but falters on new, unseen data.

In Indian agriculture, the incorporation of technology is essential to enhance crop yield and mitigate plant diseases [18]. The adoption of integrated systems that blend IoT devices with machine learning algorithms is gaining traction for automated disease identification and prevention. Various sensors, including thermal, moisture, and color sensors, are employed to monitor vital plant health parameters. The implementation of automated processes for spraying medicinal solutions contributes to disease control and optimizes overall plant growth.

Some potential disadvantages of the automated disease identification and prevention system in Indian agriculture include the initial cost of implementing the technology and the need for technical expertise to operate and maintain the system. Additionally, reliance on technology may make farmers more dependent on external factors and could potentially lead to a reduction in traditional farming practices and knowledge.

In the research approach outlined in reference [19], deep learning methods, particularly Convolutional Neural Networks (CNN), were employed to autonomously identify and categorize diseases in both potato and citrus leaves. The study involved the creation of a database comprising 1700 photos of potato leaves for model training, and 600 images for testing. The results indicated that the suggested architecture, particularly the ResNet model, achieved an impressive accuracy score of 99.62%, outperforming other current models. Nonetheless, a constraint of this methodology might be the necessity for an extensive and varied dataset to guarantee the resilience and generalizability of the model. Moreover, challenges could arise in extending this approach to various types of plant diseases and diverse environmental conditions. Furthermore, the performance of the model in authentic agricultural settings and its practical applicability may require additional assessment and validation.

This study [20] examines computer vision-based techniques for automated identification and categorization of crop diseases in India using technology. It reviews recent research studies, categorizing them based on parameters such as crop type, architecture used, dataset, disease types, and accuracy. The research reveals that employing deep learning in conjunction with real-field and laboratory-conditioned images results in superior accuracy (98.8%) compared to machine learning-based methods (92.2%). However, certain drawbacks are associated with computer vision-based approaches for crop disease detection and classification. These include a dependence on high-quality images and the requirement for extensive training data to ensure precision. Moreover, these methods may encounter challenges in accurately identifying diseases under real-field conditions due to factors such as variations in lighting, background, and other environmental factors.

III. USE OF IOT IN SMART AGRICULTURE

Wireless sensor technologies for smart agriculture

A. Temperature Sensors

Functionality:

Measure the ambient temperature in the agricultural environment.

Provide real-time data for climate monitoring.

Types:

Thermocouples: Based on the Seebeck effect, using two different metals to produce a voltage proportional to temperature.

Resistive Temperature Devices (RTDs): Exploit the change in electrical resistance with temperature, commonly using platinum.

Thermistors: Thermally sensitive resistors with resistance varying significantly with temperature.

Applications:

Climate control in greenhouses.

Frost prediction and protection.

Monitoring temperature-sensitive crops.

B. Humidity Sensors

Functionality:

Measure the moisture content in the air.
Contribute to understanding the water vapor levels in the environment.

Types:
Capacitive Humidity Sensors: Measure changes in capacitance caused by water absorption.
Resistive Humidity Sensors: Utilize changes in electrical resistance due to moisture absorption.
Thermal Hygrometers: Measure the cooling effect of water evaporation.

Applications:
Precision irrigation based on humidity levels.
Disease prediction, as some plant diseases thrive in specific humidity conditions.
Prevention of excessive moisture, which can lead to mold and fungal growth.

C. Soil Sensors

Functionality:
Monitor various soil parameters crucial for plant growth.
Provide data on soil moisture, pH levels, and nutrient concentrations.

Types:
Soil Moisture Sensors: Measure the water content in the soil.
Soil pH Sensors: Determine the acidity or alkalinity of the soil.
Soil Nutrient Sensors: Measure the concentration of nutrients like nitrogen, phosphorus, and potassium.

Applications:
Precision farming for optimized irrigation and fertilization.
Early detection of nutrient deficiencies.
Monitoring soil health and preventing overwatering or drought stress.

D. Fluid Level Sensors

Functionality:
Measure the level of liquids in tanks, reservoirs, or irrigation systems.
Ensure efficient use of water resources and prevent overflows or shortages.

Types:
Ultrasonic Sensors: Emit ultrasonic waves to measure the distance to the liquid surface.
Float Sensors: Use a floating device to detect the liquid level.
Pressure Sensors: Measure the pressure exerted by the liquid to determine the level.

Applications:
Automated irrigation control for precise water delivery.
Management of fluid reservoirs to prevent wastage.
Integration with IoT for real-time monitoring and control.
In smart agriculture, the integration of these sensors contributes to data-driven decision-making, optimizing resource usage, and ultimately enhancing crop yields and sustainability. The use of wireless communication technologies allows for real-time monitoring and control, making these sensors integral components of modern precision agriculture systems.

IV. How do Sensors Convey Information? Utilizing Wireless Communication Technologies at the Physical Layer

Fig. 2 shows the smart agriculture architecture from the viewpoint of wireless communication strategies to communicate between field devices and Internet Gateways at various abstraction levels. The capabilities of these wireless technologies vis-a-vis their practical use cases are discussed in different sections below.
Sensors communicate through various physical layer wireless communication technologies, each with its own set of advantages and limitations. Here are some common physical layer wireless communication technologies used by sensors.

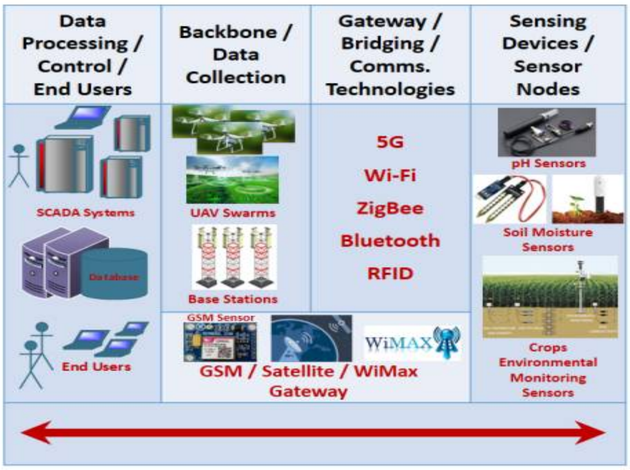

Fig 2: Wireless physical layer standards for communication between IoT based sensors and smart farming machinery at edge to agriculture database servers at core

A. Radio Frequency Identification (RFID)

Description: RFID technology uses electromagnetic fields to transmit data between a reader and RFID tags attached to objects.
Use Cases: Asset tracking, inventory management, and livestock monitoring in agriculture.

B. Bluetooth

Description: Bluetooth is a wireless communication standard with limited range, facilitating the exchange of data between devices over short distances.
Use Cases: Sensor networks in precision agriculture, connecting sensors to a centralized control system.

C. Wi-Fi

Description: Wi-Fi provides high-speed wireless connectivity over a local area network (LAN).

Use Cases: High-data-rate sensor applications in smart agriculture, connecting sensors to a central server or cloud.

D. Zigbee

Description: Zigbee is a low-power, a wireless communication standard for short-range applications with low data rates and complexity.
Use Cases: Sensor networks in precision agriculture, especially in scenarios where low power consumption is critical.

E. LoRa (Long Range)

Description: LoRa is a low-power, long-range wireless communication technology developed for Internet of Things (IoT) applications.
Use Cases: Agricultural sensor networks covering large areas, such as crop fields or orchards.

F. NB-IoT (Narrowband IoT)

Description: NB-IoT is a cellular communication standard optimized for low-power, wide-area IoT applications.
Use Cases: Remote sensor deployments in agriculture, leveraging existing cellular infrastructure.

G. Sigfox

Description: Sigfox is a low-power, wide-area network (LPWAN) technology developed for low-data-requirement IoT applications.
Use Cases: Low-cost, low-power sensor networks for agriculture applications with limited data transmission needs.

H. 5G

Description: 5G is the latest generation of cellular network technology, which provides high data speeds, minimal latency, and widespread device connection.

Use Cases: High-data-rate sensor applications, real-time monitoring, and control in smart agriculture.

I. Infrared (IR)

Description: Infrared communication uses infrared light to transmit data between devices.
Use Cases: Short-range communication between sensors in controlled environments.

J. UWB (Ultra-Wideband)

Description: UWB uses a broad spectrum of frequencies for short-range, high-bandwidth communication.
Use Cases: Precision ranging and positioning applications in agriculture.
The communication technology used is determined by considerations such as the desired range, data rate, power consumption, and cost. A mix of these technologies may be used in sensor networks in smart agriculture to suit the system's different communication demands.

V. Coordination of Sensors and Actuators on Microcontroller Platform for IoT based Smart Agriculture Systems

The study explores the intricacies of how sensors and actuators collaborate within the framework of microcontroller platforms to establish efficient communication in IoT-based smart agriculture systems. The discussion encompasses the integration of various sensors and actuators, the role of microcontrollers in orchestrating their interactions, considering the influence of these technologies on agricultural precision and automation.

The examination begins by looking at the importance of sensors for data acquisition and actuators for effecting changes in the physical environment. It delves into the diverse types of sensors used in smart agriculture, ranging from environmental sensors to plant health monitoring devices, and investigates the many actuators used for functions like as irrigation, fertilizing, and pest control.

The focus then shifts to microcontroller platforms, pivotal components that serve as the brain of IoT-based systems. The paper investigates the capabilities of microcontrollers in processing sensor data, making informed decisions, and coordinating the activation of actuators. It delves into popular microcontroller systems like as Arduino, Raspberry Pi, and ESP8266, emphasizing their strengths and uses in the context of smart agriculture.

Key aspects of coordination, such as data fusion, decision algorithms, and communication protocols, are discussed to provide insights into the seamless integration of sensors and actuators.

Several case studies and real-world examples showcase the practical implementation of sensor-actuator coordination on microcontroller platforms in smart agriculture. These applications range from automatic irrigation systems that respond to soil moisture levels to agricultural health monitoring systems that use drones.

VI. Conclusion

This survey comprehensively explores the landscape of Edge-AI-based plant leaf disease identification and prevention, shedding light on the transformative potential application of this technology in the field of smart agriculture. The integration of Edge-AI marks a significant leap forward in addressing the challenges posed by plant diseases, offering real-time, localized decision-making capabilities at the edge of the agricultural ecosystem.

The survey has provided a thorough examination of various Edge-AI models, Algorithms and strategies used to manage plant leaf disease. The merits and limits of many methodologies, ranging from Convolutional Neural Networks (CNNs) to ensemble learning methods, have been clarified, providing useful insights for both researchers and practitioners.

Furthermore, the discussion has underscored the importance of edge computing in revolutionizing disease identification and prevention. By processing data locally, Edge-AI mitigates latency issues and reduces dependence on centralized systems, thereby enhancing the responsiveness and resilience of smart agriculture systems.

As we navigate through the challenges, including data privacy concerns, model robustness, and the need for standardized datasets, it becomes evident that collaborative efforts and ongoing research are crucial for the continued advancement of Edge-AI in plant disease management. The emergence of trends such as federated learning and blockchain highlights the industry's commitment to addressing these challenges and fostering secure, collaborative solutions.

Looking ahead, the survey provides a forward-looking perspective, recognizing emerging themes that will determine the future of Edge-AI in smart agriculture. Federated learning, blockchain, and other innovations hold the promise of further improving plant disease identification and prevention security, cooperation, and efficiency.

In essence, this survey is a useful tool for researchers, practitioners, and stakeholders navigating the intersection of Edge-AI and smart agriculture. By understanding the current state-of-the-art, challenges, and emerging trends, the community is empowered to contribute to the development of robust, scalable, and intelligent solutions for ensuring the health and productivity of crops in an increasingly dynamic agricultural landscape.

REFERENCES

[1] Vivek Sharma a, AshishKumar Tripathi a, Himanshu Mittal, "DLMC-Net: Deeper lightweight multi-class classification model for plant leaf disease detection", 2023, Ecological Informatics , Volume 75, July 2023, 102025

[2] Mohit Agarwal, Suneet Kr. Gupta, K.K. Biswas, "Development of Efficient CNN model for Tomato crop disease identification "2020, Sustainable Computing: Informatics and Systems. Volume 28, December 2020, 100407

[3] David Argüeso a b, Artzai Picon a, Unai Irusta b, Alfonso Medela a, Miguel G San-Emeterio a, Arantza Bereciartua a, Aitor Alvarez-Gila, "Few-Shot Learning approach for plant disease classification using images taken in the field", Computers and Electronics in Agriculture, Volume 175, August 2020, 105542

[4] Umit Atila A, Murat Ucar B, Kemal Akyol C, Emine Ucar, "Plant leaf disease classification using Efficient Net deep learning model" 2021, Ecological Informatics, Volume 61, March 2021, 101182

[5] Junde Chen a, Jinxiu Chen a, Defu Zhang a, Yuandong Sun b, Y.A. Nanehkaran, "Using deep transfer learning for image-based plant disease identification", Computers and Electronics in Agriculture, Volume 173, June 2020, 105393

[6] Xijian Fan a 1, Peng Luo b c 1, Yuen Mu a, Rui Zhou a, Tardi Tjahjadi d, Yi Ren, "Leaf image based plant disease identification using transfer learning and feature fusion", 2022, Computers and Electronics in Agriculture, Volume 196, May 2022, 106892

[7] Hernández a b, Juan L. López, "Uncertainty quantification for plant disease detection using Bayesian deep learning", 2020, Applied Soft Computing, Volume 96, November 2020, 106597

[8] Hu Gensheng, Fang Min, " Using a multi-convolutional neural network to automatically identify small-sample tea leaf diseases", 2022, Sustainable Computing: Informatics and Systems, Volume 35, September 2022, 100696

[9] Aditya Karlekar a, Ayan Seal, "SoyNet: Soybean leaf diseases classification", 2020, Computers and Electronics in Agriculture, Volume 172, May 2020, 105342

[10] Ramesh, D. Vydeki, "Recognition and classification of paddy leaf diseases using Optimized Deep Neural network with Jaya algorithm", 2020, Information Processing in Agriculture, Volume 7, Issue 2, June 2020, Pages 249-260.

[11] Hu Gensheng a, Wu Haoyu a, Zhang Yan a, Wan Mingzhu, "A low shot learning method for tea leaf's disease identification", 2019, Computers and Electronics in Agriculture, Volume 163, August 2019, 104852

[12] Gensheng Hu a, Huaiyu Wang a, Yan Zhang a, Mingzhu Wan b, "Detection and severity analysis of tea leaf blight based on deep learning", 2021, Computers & Electrical Engineering Volume 90, March 2021, 107023

[13] Yukai Zhang a, Guoxiong Zhou a, Aibin Chen a, Mingfang He a, Johnny Li b, Yahui Hu c, "A precise apple leaf diseases detection using BCTNet under unconstrained environments", 2023, Computers and Electronics in Agriculture, Volume 212, September 2023, 108132

[14] Asif Iqbal Khan B, S.M.K. Quadri B, Saba Banday C, Junaid Latief Shah , "Deep diagnosis: A real-time apple leaf disease detection system based on deep learning", 2022, Computers and Electronics in Agriculture, Volume 198, July 2022, 107093

[15] Husnul Ajra; Mst. Khairun Nahar; Lipika Sarkar; Md. Shohidul Islam, "Disease Detection of Plant Leaf using Image Processing and CNN with Preventive Measures", 2020 Emerging Technology in Computing, Communication and Electronics (ETCCE)

[16] Surampalli Ashok; Gemini Kishore; Velpula Rajesh; S. Suchitra; S.G. Gino Sophia; B. Pavithra, "Tomato Leaf Disease Detection Using Deep Learning Techniques", 2020, 5th International Conference on Communication and Electronics Systems (ICCES)

[17] Halil Durmuş; Ece Olcay Güneş; Mürvet Kırcı, "Disease detection on the leaves of the tomato plants by using deep learning", 2017, 6th International Conference on Agro-Geoinformatics

[18] R. Gowtham and Dr. R. Jebakumar , "AN IOT BASED PLANT LEAF DISEASE DETECTION USING MACHINE LEARNING AND AUTO SPRAYING MECHANISM", 2022, Journal of Positive School Psychology , 2022, Vol. 6, No. 4, 283-297

[19] Gulbir Singh, "Performance evaluation of plant leaf disease detection using deep learning models" , 2023, Archievs of Phytopathology and Plant Protection, Volume 56, 2023 – Issue 3.

[20] Raj Kumar, "A Systematic Analysis of Machine Learning and Deep Learning Based Approaches for Plant Leaf Disease Classification: A Review",2022,Volume 2022 | Article ID 3287561 | https://doi.org/10.1155/2022/3287561