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REVIEW ARTICLE

Advances in IoT-enabled smart diagnostics for early detection of fruit crop diseases under climate change

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Abstract

In perennial fruit crops, climate conditions play a crucial role in influencing phenological stages, fruit quality traits and particularly the occurrence and severity of pests and diseases. The predominant cause of fruit contamination is attributed to fungal and bacterial pathogens, which significantly affect crop health, yield and quality. Mitigating these impacts at an early stage requires advanced methodologies for accurate disease identification and detection. However, a major challenge in precision and smart agriculture lies in the development and availability of reliable image datasets for automated detection, visualization and classification of plant diseases. The growing adoption of the Internet of Things (IoT) has created opportunities for robust systems capable of managing large volumes of agricultural data through efficient processing, storage and transmission. The integration of image processing techniques with intelligent algorithms within IoT frameworks has emerged as a transformative approach, delivering enhanced precision and accuracy in disease monitoring and management across fruit crops. IoT-enabled smart diagnostic systems not only reduce production costs and resource wastage but also revolutionize horticultural practices through automation, leading to improved quality and yield. This review highlights advances in IoT-enabled smart diagnostics for detecting fruit crop diseases under climate conditions. The scope includes examining the interaction between climate variability and disease dynamics, analysing IoT-based frameworks for real-time monitoring and diagnostics and identifying current challenges and future opportunities for sustainable disease management in perennial fruit crops.

Keywords: climate change; disease; early detection; fruit crops; internet of things

Introduction

Horticulture plays a prominent role in the agricultural sector, which contribute enormously to the nutritional security, profitability and environment sustainability. Although, the horticulture industry across the globe encounters numerous obstacles in growth and development (1). In general, the production has been affected by market challenges induced by climate change affliction and a worldwide consumer demand pertaining to the sustainability and quality of products. The worldwide horticulture market was expected to achieve USD 40.24 billion by 2026, with a compound annual growth rate (CAGR) of 10.2 %. As per the United Nations Food and Agricultural Organization (FAO), food production demand increases by 70 % by 2050 to achieve the global requirements (2). Global fruit production is constantly increasing about 910 million metric tons with respect to the rapid growth of the population. In India, the total fruit production was about 107 million metric tonnes (3). Fruit crops demonstrate adaptability to diverse environments, requiring adjustments in light intensity, soil composition, photoperiod, chilling and heat thresholds, as well as water availability (4). The development of fruit in varied environmental conditions can be significantly influenced by a combination of biotic and abiotic stresses.

Biotic stresses in plants, which are infectious in nature, arise from bacteria, fungi, nematodes, phytoplasmas and viruses and abiotic stress, induced by non-infectious environmental factors like humidity, temperature variations and excessive rainfall (5). In recent decades, climate change plays a direct impact on fruit plants in different role such as morphological and physiological changes, pest and disease incidence, crop qualitative and quantitative composition alterations occurred (6). According to Intergovernmental panel on climate change, variations in extreme weather phenomena across all regions are factored into near to mid time projections, including changes in global temperature, rainfall, precipitation patterns, relative humidity, all of which exert a significant influence on crop production. Depending on future advancements, the average temperature in the Indian subcontinent is anticipated to increase by 0.88 to 3.16 °C by 2050 and 1.56 to 5.44 °C by 2080 (7).

The global contribution of fruit production, comprising 48 % total is affected by adaptability challenges arising from climate change (8). Approximately, 70 % to 80 % of crop losses are directly linked to plant pathogenic fungi, highlighting their significant impact on agricultural productivity. The magnitude of economic losses, falling between 30 % and 50 %, is contingent upon a combination of factors, including agricultural practices and geographic locations (9, 10). The interplay of weather parameters significantly influences the formation, dissemination and germination of inoculum across diverse disease system (11). Although the rehabilitation of high quality and increased productivity of fruit crops presents a consequential challenge, it emphasizes the necessity for extreme caution amid climatic change. The resolution of issues concerning crop production can be achieved by employing modern technology to monitor real-time climatic factors and soil characteristics.

According to modern technologies the agricultural productivity might increase while necessary manpower decreases. This provides farmers to allocate time to other aspects of agriculture, thereby increasing profit (12). The implementation of modern developing techniques in horticulture primarily focuses on monitoring the plant status, pest and disease infestation and estimation of yield (13). Smart technologies such as the big data analytics, cloud computing, digital twin (DT), IoT, data analytics, simulation, artificial intelligence (AI), drones, cyber-physical systems, precision equipment, autonomous robotic systems, GPS (Global Positioning Systems), actuators and wireless sensor networks facilitate the idea of smart farming (14). The internet functions as a worldwide network of interconnected computer networks employing the standard internet protocol for billions of users globally. It represents a network comprising millions of public, government, business, academic and private networks ranging from local to global in scope. Those networks are connected through a diverse range of wireless, electronic and optical networking technologies (15). A significant advancement in realm of smart farming is the integration of image processing and IoT due to its cohesive networked sensor data and data integration system (16). An agricultural system incorporating IoT with image processing and ecological sensing technique assists farmers in implementing preventive measures and tailoring crop management practices such as irrigation, fertilization, disease and pest management using contemporary digital, internet connected tools and smart applications (17). AI principles are utilized in developing real time programming, which is integrated into IoT devices to assist farmers to create optimal decisions (18).

The present review highlights contemporary innovations in IoT-based smart diagnostic technologies for monitoring and detecting fruit crop diseases across different climate conditions. It particularly focuses on assessing the impact of climate variability on disease incidence and severity, while evaluating IoT -based diagnostic frameworks that integrate image processing, sensor technologies and intelligent algorithms for real-time monitoring. Furthermore, the review analyses the contribution of these systems to enhancing productivity, optimizing resource utilization and promoting sustainable horticultural practices, while also highlighting existing challenges, technological limitations and future opportunities for the effective deployment of IoT-enabled smart diagnostics in climate-stressed fruit production systems.

The dynamics of disease under climate change scenario

Climate change significantly altered pest and disease occurrences in fruit crops, leading to decreased fruit quality and production (19). The ability of temperate crops to sudden weather changes during critical growth stages in historically cultivated regions is increasingly at risk, posing imminent threats to production stability in the foreseeable future (20). Climate change poses the potential to induce shifts in geographic distribution, generation cycles, pathogen development stages, population growth rates, overwintering behaviours, developmental phases and interspecific interactions (21, 22). Plant diseases emerge as a consequence of the intricate interplay between biotic and abiotic stresses. Biotic stress emanates from infectious agents, while abiotic stress attributed to non-infectious factors within plants (23). The biotic stress induced by pathogen *viz.,* viruses, bacteria and fungi, profoundly impacts crop growth, interacting with abiotic stresses such as temperature, humidity, rainfall condition (Table 1). The inherent susceptibility of crop leaves to diseases is an intrinsic aspect, representing a natural phenomenon that occurs as an integral part of agricultural ecosystems. The progression of pathogen development, its rates, host resistance and the intricate physiological dynamics governing host-pathogen interactions in plants undergo substantial alteration as a consequence of climate change (32). Ultimately, these find-ings emphasize the need for comprehensive models that consider diverse variables to accurately predict and mitigate the impacts of climate change on disease development and their interactions with plants (33).

IoT approach in disease forecasting under climate change

The escalating impacts of climate change necessitate the development of advanced modeling approaches to effectively understand, predict and manage its complex implications for agricultural practices and plant disease management (34). The rapid advancement of IoT and AI-enabled methodologies highlights their dual capacity in disease forecasting: managing the direct consequences of climate change while dynamically restructuring their models to address specialized targets in crop health and climate resilience (35). A network of IoT devices, comprising a diverse array of components and boasting seamless data transmission to cloud storage, demonstrates the robust capability to efficiently gather real-time information. Accurate weather predictions are achieved by processing and analysing environmental data using a cloud-based algorithm, which enables the effective identification of plant diseases (36). Big data-driven AI applications are redefining strategies for managing plant diseases, particularly through the integration of climate forecasts and remote sensing information. Future hyperspectral satellite platforms, including Copernicus Hyperspectral Imaging Mission for the Environment (CHIME) and NASA's Surface Biology and Geology (SBG), promise to deliver global datasets that will enable more accurate, timely and large-scale plant health surveillance (34). Moreover, the analysis of leaf morphology, encompassing both shape and texture, emerges as a crucial diagnostic tool in discerning a multitude of diseases afflicting plants (37). Therefore, utilizing image processing of leaves enables the facile detection of disease incidences,

Table 1. Classification of fruit crop diseases in response to environmental changes

Fruit crops	Climate change	Disease/causal organism	Reference
Mango	**i)** Continuous wet weather with relative humidity 95 % **ii)** High relative humidity (above 90 %) and temperatures between 25-30 °C	**i)** Bloosom blight (*C. gloeosporioides*) **ii)** Bacterial canker (*Xanthomonas citri pv. mangifer aeidicae)*	(24)
Banana	**i)** Under high temperature and high humidity **ii)** High rainfall and humidity	**i)** Fusarium wilt (*Fusarium oxysporum*) **ii)** Black sigatoka (*Cercospora musae, Mycosphaerella musicola)*	(25,26)
Papaya	High temperature and humidity	Papaya ring spot disease	(27)
Grapes	**i)** Wet and humid **ii)** Early summer temperature followed by rainfall **iii)** High humidity and increased temperature **iv)** Highly temperature dependent with ample of moisture	**i)** Downy mildew (*Plasmopara viticola*) **ii)** Powdery mildew (*Uncinula necator)* **iii)** Botrytis Bunch Rot (*B. cinerea*) **iv)** Pierce's disease (*Xylella fastidiosa)*	(28)
Jackfruit	High rainfall or after stormy periods, fruiting season coincides with warm, humid and wet weather	Rhizopus fruit rot (*Rhizopus stolonifer, Rhizopus artocarp)*	(24)
Pineapple	**i)** Prolonged rainfall and humid weather **ii)** Rainfall during flowering period	**i)** Phytopthora root rot (*Phytophthora cinnamomic)* **ii)** Pink disease (*Pantoea citrea, Acetobacter aceti)*	(29)
Apple	**i)** Frequent warm and rainy weather during spring **ii)** Extreme summer heat	**i)** Fire blight (*Erwinia amylovora*) **ii)** Canker (*Neonectria ditissima)*	(24)
Pear	Extreme summer heat	Canker (pear blister canker viroid (PBCVd)	(24)
Durian	High rainfall	Patch canker (*P. palmivora*)	(30)
Litchi	Fluctuations in temperature	leaf and twig blight (*Colletotrichum gloeosporioides* and *Gloeosporium sp.*)	(31)

including wilt, rot, mildew, rust and virus infections in plants (38). The integration of Artificial Intelligence (AI) with advanced satellite sensing technologies provides a transformative approach for strengthening disease detection and climate change adaptation in fruit crops. When integrated with IoT-based datasets, these tools enable high-resolution monitoring and predictive modelling, allowing the identification of regional vulnerabilities shaped by both environmental stressors and pathogen pressures. Such innovations hold significant potential for safeguarding fruit production systems under increasing climate variability (33).

Internet of things (IoT) based technology and application

Internet of things (IoT) technology

In the realm of agriculture, recent year witnessed remarkable strides propelled by the pervasive integration of cutting-edge technologies such as the Internet of Things and deep learning (39). The Internet of Things collects real-time data, which involves in the identification of non visual information. The term "Internet" and "Things" signifies a globally interconnected network, potentially representing an evolved iteration of communication systems, networking infrastructure, sensor technology and information processing techniques (Fig. 1). Multiple supporting technologies contribute to shaping the IoT, encompassing barcodes, intelligent sensing, RFID (Radio Frequency Identification Devices), low energy wireless communications and cloud computing. IoT devices are equipped with advanced intelligence and seamless interconnectivity through sensors and software, comprising both mechanical and digital elements. The integration of physical applications into computer or network - based systems enhances efficiency and accuracy across a wide array of field (40). In the domain of IoT, RFID bears the capability of an advanced technology, facilitating the automatic identification of devices with limited resources constraints communicating over network devices. It plays a significant role in identifying and tracking data associated with objects as sensors collect and process data to discern changes in physical applications, thereby enhancing the network capabilities (41).

An IoT, powered by AI algorithms enhances an efficiency and improves the quality of decision-making through rapid data analysis. Innovative method in IoT, including machine vision/ robotics, machine learning, deep learning and natural language processing significantly elevating the automation process in agriculture majorly in disease diagnosis and meteorological monitoring (42). Machine learning techniques in disease diagnosis, *viz.,* Ada boost, Logistic regression, decision tree, K-Nearest Neighbor (KNN), Naive Baye (NB) and support vector machine (SVM) (43). Multiple systems are available for image processing in deep learning *viz.,* convolutional neural network (CNN), artificial neural network (ANN), graph neural network (GNN), probabilistic neural network (PNN) and recurrent neural network (RNN). These systems utilize algorithms to detect patterns in large datasets and achieve high accuracy in identifying different diseases through the utilization of multiple layers of artificial neurons (44). IoT devices accomplished with high intelligence and interconnectivity through the integration of embedded sensors, actuators and processors.

Design and architecture of IoT

The architectural framework of an IoT network serves as the cornerstone for the development of an agricultural IoT network, incorporating specific principles and techniques. The widespread adoption of a layered architecture in most IoT applications underscores its popularity and interoperability, thereby enhancing capabilities for sustainable production and resource management

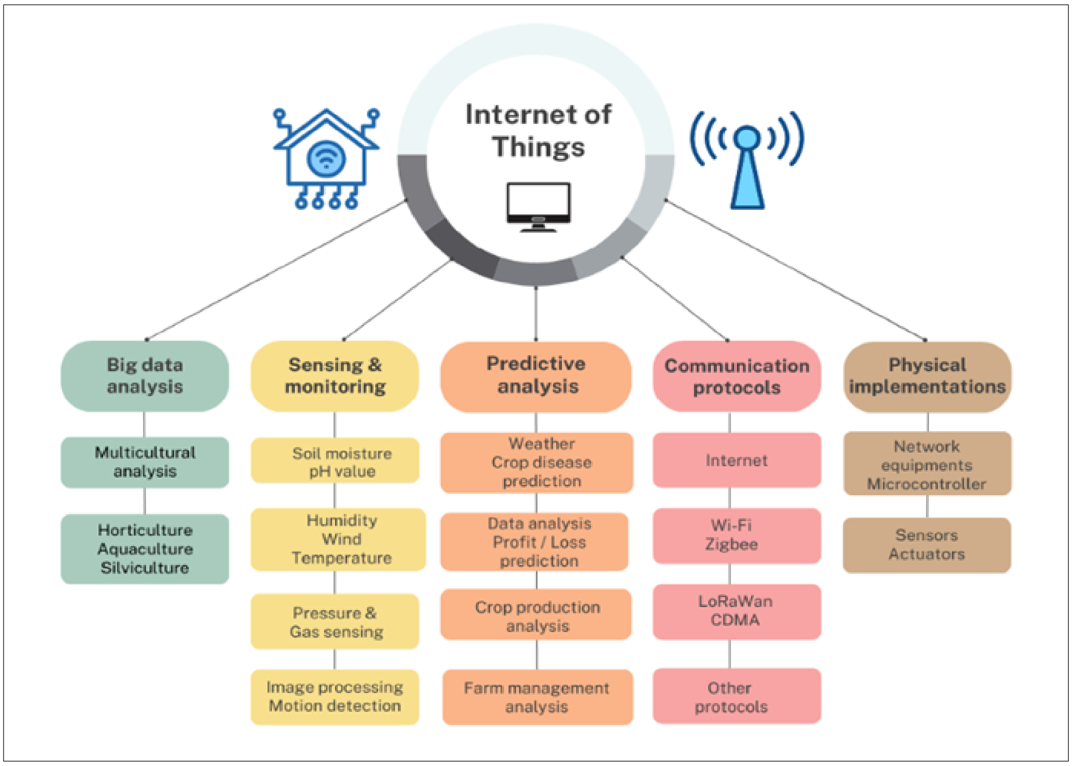

Fig. 1. Internet of things.

(45). It efficiently facilitates the monitoring, recognition and transmission of agricultural data. The four-layer architecture permits the development of multiple user application i.e. perception layer, network layer, cloud layer and application layer (Fig. 2). The perception layer is recognizing the physical state of the properties *viz.,* crop, soil, disease, livestock, machinery. The layer consists of sensing technology image processing RFID, sensor, controller, actuators and GPS (Global positioning systems) to collect and transmit data in the real environment (46). The collected data are uploaded to the upper layer through the network layer for construction of database and subsequent big data analysis (47). The network layer serves as a communication module, leveraging microprocessor to transfer the data to the cloud and application layer through different transporting media (48). The cloud layer, also referred to as data pre-processing layer provides the infrastructure for processing, storage and analysis. It empowers farmers with real-time data driven decision making capabilities, thereby strengthening the reliability and scalability required for deploying large scale IoT system (49). At the pinnacle of the IoT architecture, the application layer employs smart data processing to manage, control, diagnose disease infection, provides early warning, address pest infestation and operates autonomous machinery. Anticipating future trends relies on analysing past datasets through system evaluation and decision-making support, aiming to proactively address agricultural issues and optimize production efficiency (50).

Application of IoT in horticulture

Smart Horticulture represents a profound fusion of advanced breeding technology, engineering, biotechnology and information technology. Actively ensuring precise perception, intelligent operation and effective control throughout the cultivation and transportation of horticultural products, it contributes to sustainable improvement by enhancing resource use efficiency, productivity and minimizing labour input (51). In smart horticulture, an innovative technology development is driven by the integration of next-generation communications, big data analytics, cloud computing and blockchain (52). In the diverse agro-climatic conditions of horticultural crops, a smart and dynamic monitoring system is essential for assessing environmental and soil data, detecting plant disease outbreaks and evaluating plant phenotypes to maintain optimal plant growth (53) (Fig. 3). The optimization of resource utilization and the enhancement of crop yields are achieved through the real-time monitoring and control of agricultural operations, made possible by integrating sensors, data analytics and the Internet of Things. A several proposed prediction techniques were discussed in Table 2. The primary focus of the most significant IoT application in horticulture revolves around different aspects specifically i.e. monitoring and control, sustainable farming, climate condition monitoring, crop health monitoring, precision irrigation, remote management and decision support system.

A range of multiple monitoring and control systems are implemented, including tracking and tracing of climate conditions, surveillance of crop health, evaluation of soil characteristics, smart irrigation and identification of optimal harvesting period (59). IoT applications contribute to sustainable farming, which enables to enhance agricultural productivity and transforming cropping system into more efficient and smarter (66). In recent times, environmental hazards pose potential problems, necessitating an automated prompt response to prevent agricultural losses (67). A various type of sensors is utilized to gather real-time environmental data, including temperature, humidity, carbon dioxide levels, moisture and oxygen levels, for plant growth maintenance purposes (68). The sensor based cognitive monitoring system and image processing techniques plays a crucial role in automated disease detection, providing substantial advantages over manual observations by utilizing real time data (69). Water resources management in horticulture, facilitated by IoT leads 60 % water saving usage (70). Remote security management is essential for monitoring, diagnostics, configuration updates, validation and analysis of devices or sensor features. It serves as a protective measure against potential threats in IoT (71). The decision support system within the

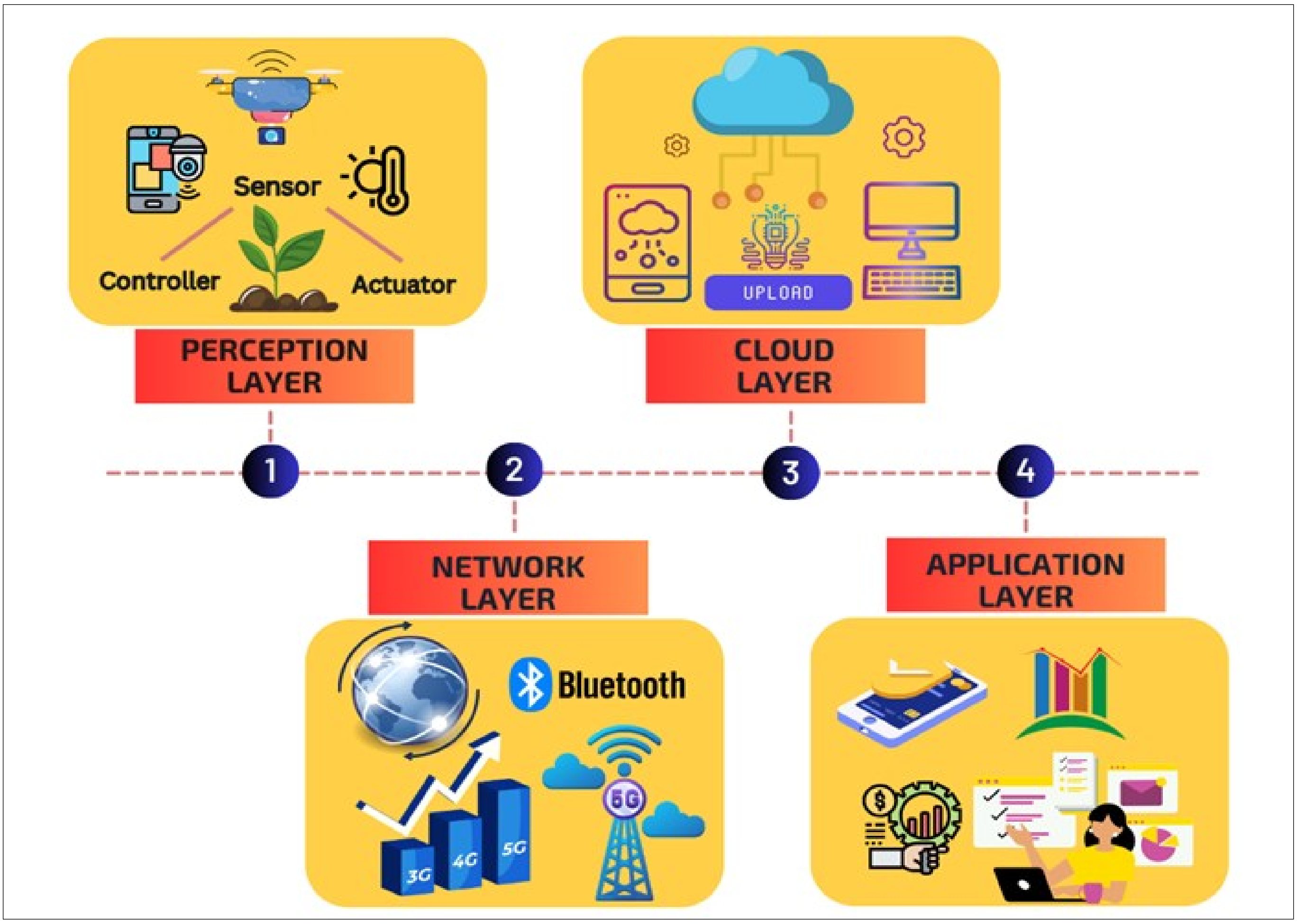

Fig. 2. Architecture of IoT.

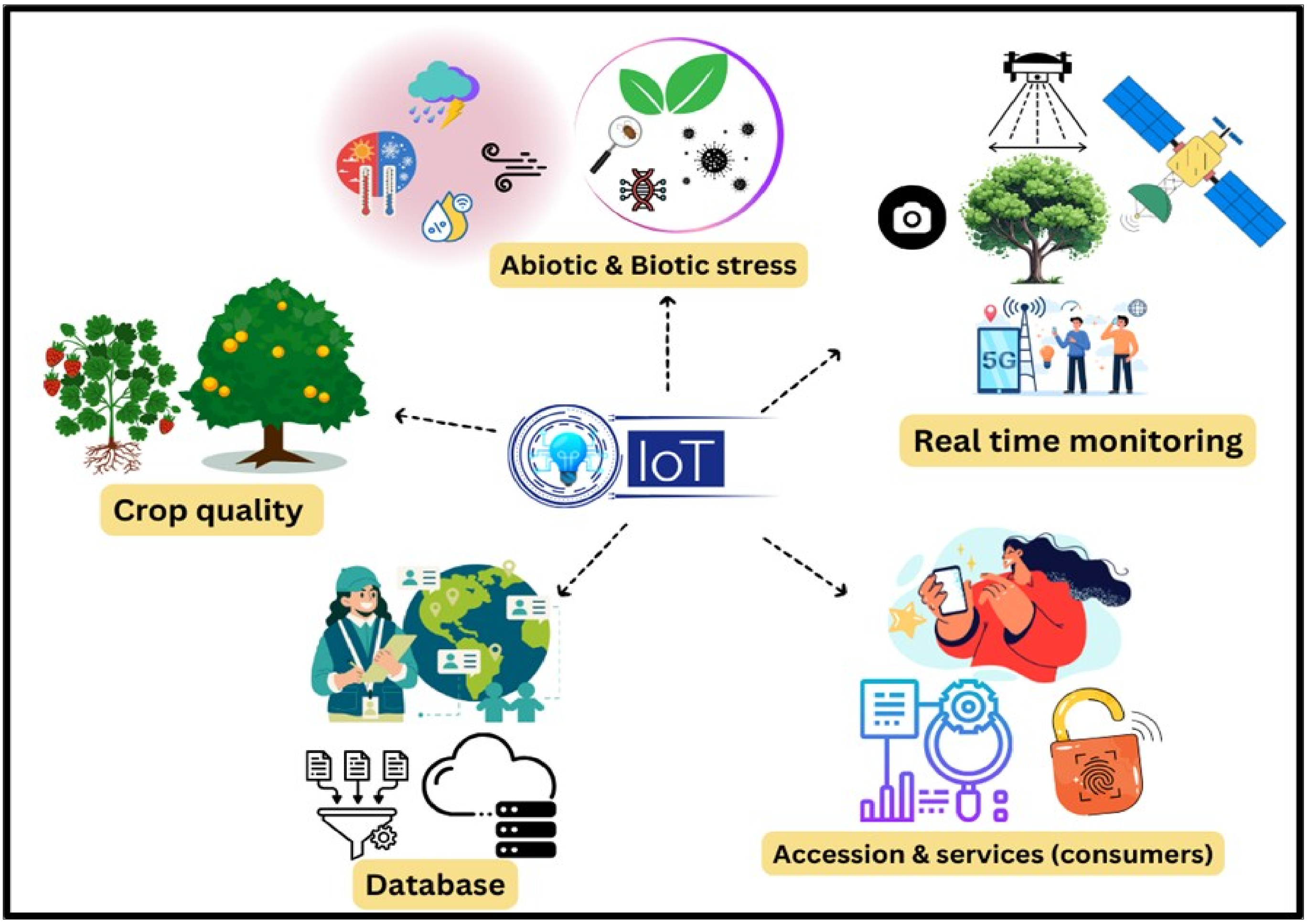

Fig. 3. Internet of things in horticulture.

Table 2. Types of IoT based technology approach

IoT Technology	Assessment/Contribution	Objectives/Description	References
Machine learning algorithms			
Random forest regression	Predict extreme rainfall	Predict random values and classifies individual trees	(54)
K-Nearest Neighbour (KNN)	Categorization of nano parametric data	Determines distance between data samples with nearest value	(43)
Support vector machine (SVM)	Climate & satellite data analysis	Classifies unlabelled data in the clustering dataset	(55)
Deep learning			
Convolutional Neural Network (CNN)	Plant diseases diagnosis	Real-time analysis of plant images for disease detection	(56)
Artificial Neural Network (ANN)	Image recognition & tracking accuracy	Analyse complex environmental datasets using wireless networks	(57)
Wireless Federated Learning (WFL)	Multi-objective optimization	Enhances communication efficiency	(58)
Sensors			
Passive sensors			
Zigbee/Bluetooth /Wi-Fi/LoRaWAN	Weather & real-time data	Low-cost, low-power communication for efficient data transfer	(59)
GPS	Location-based data	Real-time navigation and personal data analysis	(60)
Active sensors			
LiDAR	Three-dimensional environmental mapping	Generates dense elevation points for precise localization	(61)
RADAR (radio detection and ranging)	Three-dimensional environmental mapping	Real-time object detection using radio waves	(61)
Temperature sensor	Monitoring temperature range	Aids in reducing energy expenditure and enhancing overall growth	(62)
Soil Moisture sensor	Water availability monitoring system	Measurement of moisture content at various soil depth	(63)
Soil NPK sensor	Soil nutrient levels	To improve crop productivity, aiming to minimize fertilizer waste	(64)
Humidity Sensor	Humidity monitoring	Improves growth and protecting against pests and diseases,	(62)
Light Sensor	Light intensity management	Optimizes crop quality by regulating illumination and providing shading	(65)

IoT employs advanced data collection and analysis techniques to proactively address traffic regulation challenges, optimize data load balancing and generate detailed information reports (72).

IoT and fruit crops

IoT disease detection method

In pursuit of heightened economic and environmental sustainability, the strategic deployment of intelligent systems is employed to discern between diseased and healthy plants, ensuring precision in the application of targeted fungicides. The challenges associated with visually identifying plant diseases are continually evolving, concomitant with a diminishing level of observational accuracy. The meticulous deployment of an accurate and real-time disease detection system serves as a cornerstone in facilitating robust mitigation strategies, which in turn play a vital role in guaranteeing cost-effective crop protection at a local level and strengthening food security on a global scale (73). The image processing method can be utilized to identify the infected areas of the plant. Image segmentation is the process of partitioning an image into distinct regions or segments, each representing different parts of the image (74). Image segmentation stands as a robust model utilized to distinguish between various forms of image alterations, enhancing the precision of disease quantification (75). The diagnosis and analysis of foliage diseases significantly contributes a vital role in image processing. The discernment of diseases across diverse plant components is achieved through the application of advanced techniques, including image processing within internet of things (76). In the Internet of Things, the comprehensive integration of image, parametric and genomic datasets form the overarching data infrastructure. In the realm of IoT methodologies, the cornerstone techniques include image processing, image pre-processing, object identification, pattern matching and classification (77).

IoT system for disease recognition in fruit crops

An information pertinent for decision-making in traditional agricultural practices is unsuitable for managing vast crop fields (78). It is imperative to ensure the precise detection of pathogens in infected crops (79). The current agricultural sector experienced a profound revolution, evolving into a highly data-centric domain through the integration of cutting-edge technologies, including computer vision, machine learning and remote sensing. These technologies stand as indispensable pillars in fruit disease detection, demonstrating their paramount significance by proficiently analyzing crop images, categorizing disease instances and identifying symptoms with remarkable precision and efficiency. A type of cameras or sensors serve as integral components within these systems, adeptly capturing high-resolution images of fruit crops. Utilizing extensive datasets and algorithms derived from the Internet of Things, the images undergo thorough processing to discern between healthy and diseased crops (80). The deep learning architectures offer a wide array of diverse feature extraction methods, empowering them to effectively analyse complex problems (Fig. 4).

Advanced training models like VGG (Visual geometry group), SVM (Support Vector Machine) and GoogleNet are integrated into the architecture, preloaded with preset weights to mitigate the high computational costs associated with their usage (81). A robust disease detection methodology harnessing the power of neural networks (82). Low-resolution images, along with processed ones using principal components analysis, are systematically fed into a neural network as part of their algorithmic approach for disease detection. The rapid convergence of cutting-edge technologies for precise image detection, classification and activity prediction is greatly expedited by the utilization of pretrained networks. The pre-trained network 'AlexNet' for disease identification in the majority of plant leaves (83). A CNN-based approach enables precise feature extraction and classification, ensuring robust and accurate identification of plant diseases and pests (84). This advanced technique integrates such as Support Vector Machine (SVM) and Long Short-Term Memory (LSTM) are employed to enhance the model's effectiveness. An extended processing time is imperative for the LSTM classifier, particularly when trained with high-dimensional feature vectors. The integration of fully conventional neural network (F-CNN) and segmented convolutional neural network (S-CNN) forms a powerful hybrid model, significantly boosting the robustness of plant disease detection while achieving highest accuracy (85, 86) (Fig. 5.). An accurate disease detection in fruit crops is achieved through IoT models employing a variety of machine learning and deep learning methods, including CNN, DNN, SVM, decision trees, k-nearest neighbor and random forest algorithms are mentioned below in Table 3. Collectively, these technologies function as practical problem-solving tools by ensuring easy adoption through IoT-enabled automation, enabling early recognition of both disease incidences and climate-induced stress and offering cost-effective monitoring solutions by minimizing manual inspections and reducing economic losses. In this way, they not only strengthen disease diagnostics but also provide scalable and adaptive solutions to address the dual challenges of climate variability and plant health management in fruit crops (33).

Conclusion

The accelerating impacts of climate change, together with the rising incidence of plant diseases, threaten the stability and sustainability of fruit crop production. Conventional monitoring and management practices are insufficient to handle the complexity of climate-driven variability and pathogen outbreaks. In this context, IoT-enabled diagnostic systems provide a practical solution by combining sensors for continuous environmental monitoring, real-time data acquisition and integration with artificial intelligence, convolutional neural networks (CNNs) and machine learning models for accurate disease detection and predictive risk assessment. These frameworks enable early diagnosis, improve decision support for farmers and can be scaled effectively across diverse agro-climatic regions. By linking traditional horticultural practices with IoT-based sensors, image processing and intelligent algorithms, smart diagnostic systems strengthen disease management, optimize resource use and support the long-term sustainability of fruit production.

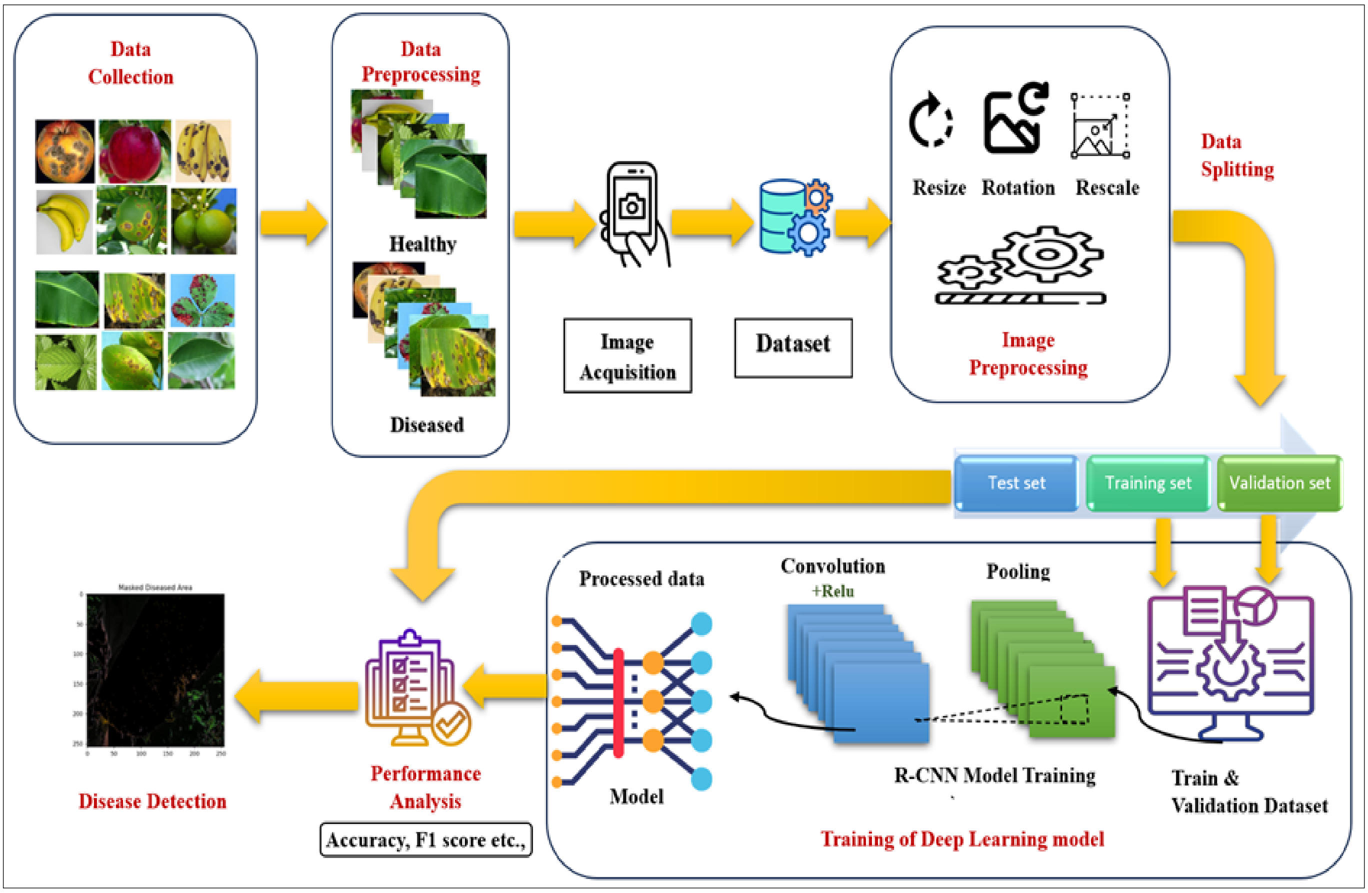

Fig. 4. Deep learning architecture for disease detection.

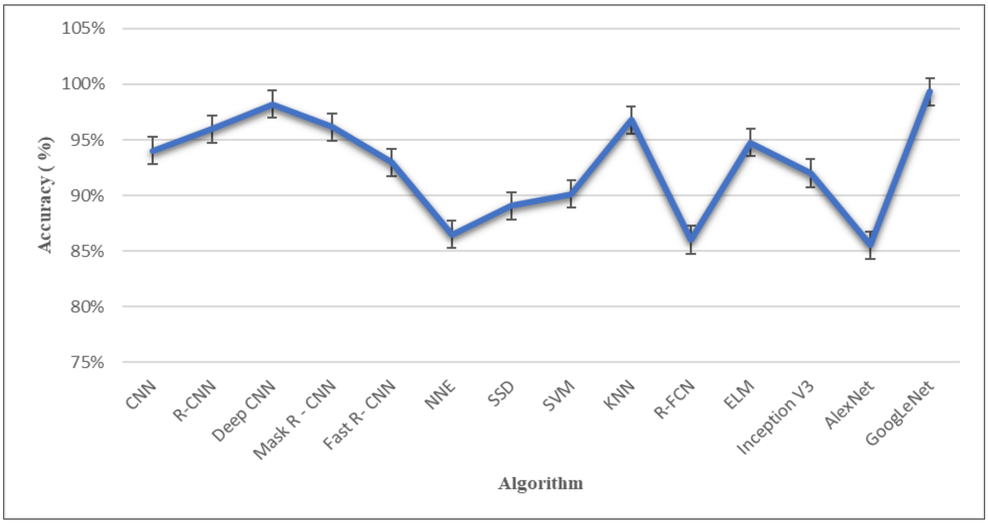

Fig. 5. Fruit disease detection accuracy level on different algorithm.

Table 3. Types of IoT model applied for disease recognition in fruit crops

Crops	Disease	Parts	Model/techniques	Accuracy	Reference
Mango	Anthracnose	Leaves	ML- AlexNet, GoogleNet, DenseNet	98.33 %	(87)
			CNN	70 %	(88)
	Sooty mould	Leaves	neural network ensemble (NNE)	86.5 %	(89)
Grapes	Leaf blight	Leaves	AlexNet	99.03 %	(81)
Orange	spot	Fruit	SSD, Mask R-CNN	89.05 %, 96.14 %	(90)
	Brown rot	Fruit	Fast R-CNN, Mask R-CNN	92.97 %, 95.76 %	(90)
	Greening and scab	Fruits	CNN	94.00 %	(91)
	Huanglongbing (HLB)	Leaves	SPA-STD-SVM	97.46 %	(92)
Apple	Alternaria leaf spot, brown spot, mosaic and rust.	Leaves	Rainbow Single-Shot Detector,	98.80 %	(93)
	grey spot	Fruit	SSD, Mask R-CNN	88.42 %, 95.42 %	(90)
	Rot	Fruit	Fast R-CNN, Mask R-CNN	92.31 %, 96.86 %	(90)
Banana	Fusarium wilt,	Leaves	Faster R-CNN, R-FCN and SSD	86.00 %	(94)
	Sigatoka	Leaves	SVM	90.1 %	(94)
	Banana streak virus	Leaves	KNN	96.8 %	(95)
Peach	*Monilia laxa* (disease)	Fruit	SVM	95.5 %	(84)
	Powdery mildew	Leaves	Deep CNN	98.21 %	(96)
Apricot	*Monilia laxa* (disease)	Fruit	ELM	94.74 %	(84)
Papaya	Powdery mildew	Leaves	SVM	91.47 %	(97)
	Black spot	Fruits	SVM	90.22 %	(97)
Guava	Anthracnose, Fruit rot and canker	Fruit	CNN	95.61 %	(98)
Plum	Brown rot	fruit	Inception-V3	92 %	(99)
Pear	Rot	Fruit	SSD, Mask R-CNN	88.46 %, 95.96 %	(90)
	spot	Fruit	Fast R-CNN, Mask R-CNN	92.34 %, 95.72 %	(90)
Cherry	Powdery Mildew,	Leaves	AlexNet	85.53 %	(79)
Strawberry	Leaf Scorch	leaves	GoogLeNet	99.34 %	(79)

Future trends and opportunities

Despite the widespread use of IoT-based technologies in disease detection, the implementation of these technologies in plant protection poses a significant challenge. Farmers face difficulties in accessing the latest advancements, highlighting the pressing need for improved integration and accessibility in agricultural practices. The installation of IoT-tagged sensors and equipment across extensive areas presents a major challenge due to the considerable financial costs involved (100). A standardized feature extraction is imperative, accomplished through the cross -training integration of diverse IoT network intrusion datasets (40). In a concerted effort to significantly enhance agricultural profitability and markedly reduce labor-intensive tasks, the proposal involves for the pioneering integration of solar-powered smart agriculture systems with predictive models for crop diseases (101). The adverse environmental conditions, including heavy rainfall, strong winds and dust, present a significant obstacle to the outdoor installation of IoT devices, often leading to mechanical failures. To mitigate these effects effectively, the utilization of exceptionally durable raw materials in the fabrication of IoT devices for smart farming significantly enhances their longevity, leading to more reliable output. The government's endorsement of specific policies offering financial aid to farmers, guaranteeing data encryption and fostering digital literacy is imperative for the widespread adoption of IoT devices in smart farming across farmlands (102). The study is dedicated to discerning and categorizing diseases affecting fruits by employing diverse classification methodologies within the Internet of Things framework. In the synergistic utilization of machine and deep learning algorithms a diverse array of techniques for systemic feature extraction, discerning selection and precise classification is dynamically applied to fruit disease dataset. The implementation of image processing techniques, coupled with advanced algorithms, consistently achieves remarkable precision accuracy levels, ranging between 80 % to 100 %, in detecting numerous leaf disease infections. The immense potential lies in the development of power-efficient IoT devices, seamlessly integrating IoT-based systems into mobile applications to enhance disease detection capabilities for more effective crop protection and management.

Authors' contributions

SD carried out methodology, writing original review draft, review and editing, visualization and validating, KPS carried out conceptualization, methodology, supervision and validation of the experiments, SP contributed in methodology, supervision and visualization, MI contributed in conceptualization, methodology and supervision, SA contributed in review and editing, validation, KS contributed in supervision and visualization and VG assisted in review and editing. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interests to declare.

Ethical issues: None

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