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Review Article

Artificial Intelligence in Brinjal Phenotyping: A Review of Emerging Tools for Trait Characterization and Crop Improvement

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Abstract - *Over 295 million people in 53 countries experience acute food insecurity due to factors like famine, war, climate change, and conflict zones. Sustainable Development Goal 2: Zero Hunger aims to achieve food security, improve nutrition, end hunger, and promote sustainable agriculture. Balancing farming with environmental protection is crucial, especially in the face of climate change and globalization. Studying plant phenomics, which focuses on how plants grow and react to climate change, can help develop more productive and stronger crops. Advanced technology, such as High-throughput plant phenotyping, can provide detailed data for accurate predictions and better disease control. This article aims to explore the use of AI and machine learning in plant phenotyping, the integration of imaging technologies, IoT, and sensors, and the application of various technologies, including Brinjal, in vegetable phenotyping. Artificial Intelligence, IoT devices, edge computing, computer vision, and advanced sensor technologies are revolutionizing sustainable agriculture. These technologies provide real-time data, early detection of diseases, and improved nutrient, water, and pest management. Auto Machine Learning, Explainable AI, and Deep Learning enhance understanding and optimize breeding cycles. This combination of multi-omics data, machine learning, and smart tools is crucial for smart and sustainable agriculture, promoting farmer-based innovation and cross-sector collaboration.*

Keywords - *Phenotype, Genotype, Internet of Things, Artificial Intelligence, Sustainable agriculture, Sensors.*

1. Introduction

According to the 2024 report of the Food Security Information Network (FSIN), in 53 countries, over 295 million people experience acute food insecurity. It could be due to multiple factors, such as famine, war, climate change, conflicting zones, etc The only constant is the escalating world hunger [1]. Sustainable Development Goal 2: Zero Hunger was introduced as it aims to achieve food security, improve nutrition, end hunger, and promote sustainable agriculture [2]. The Brundtland Report in 1987 introduced the concept of sustainable agriculture, although the definition is not explicit, which has hindered its implementation [3]. Modern farming requires sustainable practices, but it is not an oversimplified science. Low-tech or simple farming is not always the solution; balancing farming with environmental protection by mitigating the harmful effects of modern farming is a sustainable approach. As farming is affected by numerous issues, such as climate change and globalization [4], this approach is particularly relevant. Sustainable farming is about striking a balance between not damaging nature for future generations while also producing food that meets their needs. Adding the nutrients back into the soil after farming keeps the soil fertile, and establishing alternative methods like converting farmlands into forests instead of pastureland, to meet the increasing demand, growing livestock is not a viable solution [5]. Sustainability in farming needs to be defined in a practical, scientific, and clear way because sustainable farming as an approach means following sustainable ideas and practices, and as a property, means a farming system that helps in guiding how it should change over time; neither of them is a practical and realistic approach [6] Farming is very challenging and ever-changing, as it is affected by many factors, such as nature, climate change, the economy, etc. Modern farming and farming policies should be constructed in a way that helps poor people, which is equipped to deal with real-life challenges and changes in farming styles [7].

The world's population is increasing rapidly, and feeding it while maintaining sustainability may meet present demand, but it is not enough to meet future demands. Hence, studying plant phenomics on how the plants grow and react to climate change helps in growing more productive and stronger crops [8]. The observational trait or characteristic of an organism and how its genes interact with its environment is termed the Phenotype. Though traditionally, the study of phenotypes is just physical traits, modern science and its tools have allowed us to study phenotypes and their connection with genes at a deeper and more complex level [9]. Plant phenotyping is the least researched part, and to come up with better crops to meet the harsh climate change and demands in the future, a cheaper, faster, more automated, and accurate way is required to genetically produce a better crop [10].

New technology allows scientists to study large amounts of data on plant phenotypes deeply and quickly. The High-Throughput Plant Phenotyping (HTP) uses advanced technology and sensors such as RGB camera, Thermal Infrared/Long Wave Infrared (TIR/LWIR), Light Detection and Ranging (LIDAR), Fluorescence (FLUO) Infrared (IR), AI software for image analysis, and Hyperspectral (HIS) that helps in measuring various traits of many plants on a deeper, complex level and more accurately [11]. Plant growth and quality are easily affected by their ecosystem's climate; a change in the climate affects their production. Even though we currently have strong tools to study plant phenotyping, models are less accurate on the ecosystem level due to a lack of detailed data on the species level; hence, we need better models to get detailed data to understand and make accurate predictions [12]. Traditional ways of studying plants are limited and cannot provide a deeper understanding of the plant, but with tools such as Artificial Intelligence (AI) and multi-omic data, i.e., proteomics, genomics, metabolomics, and transcriptomics, scientists can gain a wider picture and understanding that will lead to better disease control, smarter farming, stronger crops, and sustainable agriculture [13].

The objectives of this article are:

- To explore the use of AI and machine learning in plant phenotyping.
- To study the fusion of imaging technologies, IoT, and sensors in plant phenotyping.
- To examine the utilization of various technologies in vegetable phenotyping, including Brinjal.

This review is novel in providing a focused synthesis of AI applications in Brinjal phenotyping, a crop that has received limited attention in phenomics research. It uniquely consolidates insights on the fusion of Imaging, IoT, and sensor technologies for vegetable trait characterization. By centering on Brinjal within the broader context of plant phenotyping, it fills a critical gap and guides future crop improvement studies.

The manuscript organization of this article is as follows: Research Methodology is in Section 2, Overview of Plant Phenotype in Section 3, Role of Artificial Intelligence in Plant Phenotyping in Section 4, Computer vision-based plant phenotyping in Section 5, Role of IoT devices and sensors in plant phenotyping in Section 6, Recommendations are in Section 7, and Section 8 contains the Conclusion.

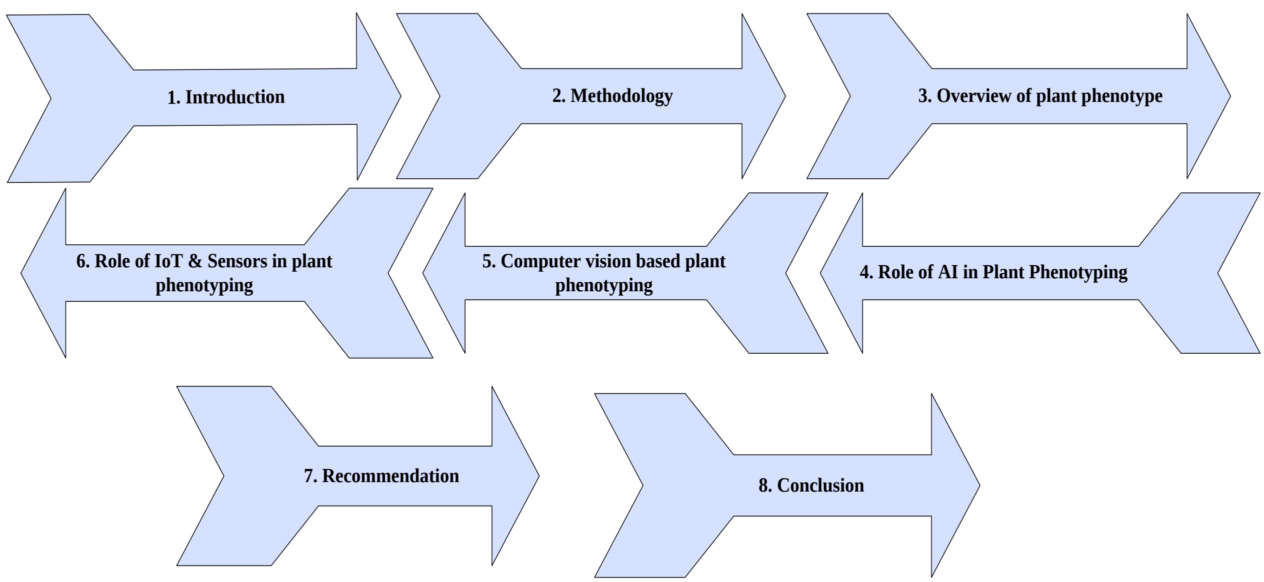

Fig. 1 Manuscript organization

2. Methodology

At the initial stage, a total of 150 articles were reviewed for this article, and out of them, 61 articles that were most suitable for our article were considered, which fall under the related categories of Artificial Intelligence, Internet of Things, Sensors, Computer Vision, and Deep Learning in Plant Phenotyping. The selection was made with an emphasis on technical depth, recency, and advancements made towards phenotyping. The articles primarily focused on the application of AI, conceptual framework, general phenotyping, sustainable farming, Computer Vision, IoT devices, and sensors from the reputed publishers like IEEE, Springer, Elsevier, MDPI, Taylore &Francis, Wiley and other specialized journals, which represent the balance of both foundational research and cutting-edge technological integration in plant phenotyping.

3. Overview of Plant Phenotyping

"The Green Revolution" in the 1960s helped combat Hunger and meet the needs of the growing population, but the population boom has only doubled since then; hence, a new revolution in the name of Sustainable Agriculture is needed [8]. The modern world has brought a lot of challenges to the ecosystem, such as population growth, heat, salinity, floods, climate change, etc, which affect the plant's ability to react to stress. To understand this and make sure plants can cope with this stress, accurate genome data and phenotyping are necessary [14]. To combat this stress and improve crop production, a climate-resilient crop can be developed using a combination of modern genetic techniques and traditional breeding. These crops could have adaptive or constitutive traits, which will either only come up when stressed or be always active, respectively. However, faster and more accurate phenotyping is required to select and identify the best plant [15]. It is easy to study how plants look, that is, morphology, and that has been the traditional way, but understanding how they work and function under stress, like in drought, is called "Physiolomics". Physiolomics provides a deeper understanding by measuring the functioning of the plants, which helps select drought-tolerant plants [16]. Plant phenotyping is often combined with genotyping, which uses DNA markers to aid breeders in detecting and mixing desirable traits that produce a stronger harvest. However, analyzing and evaluating the vast data remains a challenge. Tools such as The Hordeum Toolbox (THT), which was developed for barley, solve some of these challenges, but similar tools are required for different crops [17]. Having DNA data for the plant has not yielded the expected improvements due to the lack of phenotypic data. To accurately and quickly gather the phenotypic data, phenotypic tools such as computers, sensors, robots, cameras, and analytical algorithms were developed. These tools facilitate the connection between plant genes and their traits, thereby accelerating genomics-assisted breeding through Quantitative Trait Loci Mapping (QTL) mapping and Genome-Wide Association Study (GWAS) [18], as this can be visualised in Figure 2.

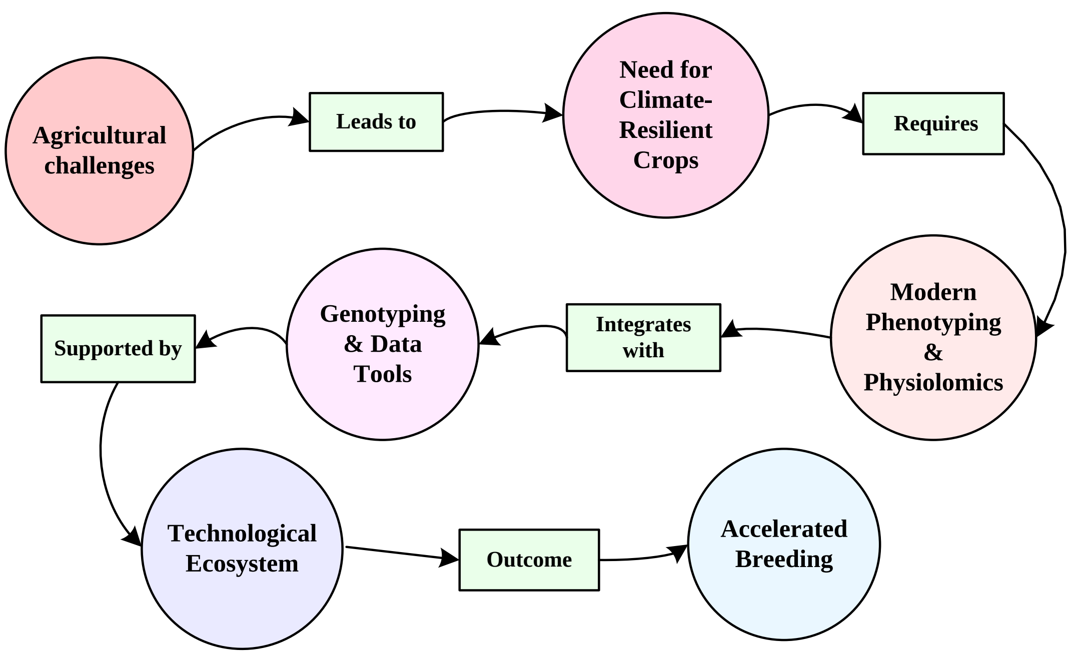

Fig. 2 Framework for plant phenotyping in climate-resilient agriculture

4. Role of Artificial Intelligence in Plant Phenotyping

The advancement in plant phenomics was achieved due to the rise of new technologies, Artificial Intelligence (AI), especially Deep Learning (DL), Machine Learning (ML), and Computer Vision. These new technologies are paired with non-invasive imaging sensors that collect and analyze plant data more accurately and efficiently. The creation of open-source tools and software for data sharing and collecting is made easier through AI [19]. Analyzing microscopic images with AI and DL has become accurate and faster, especially on a large scale. Utilising explainable

AI and automated imaging robots can now assist in identifying important biological traits [20]. To cope with the challenges provided by the traditional method, AI and advanced sensors are used to analyze and collect plant data more accurately. High-Throughput Phenotyping (HTP) is the process that uses tools like drones, Multispectral, Hyperspectral, and Thermal Infrared (TIR) cameras to track plant disease, health, stress, and growth [21].

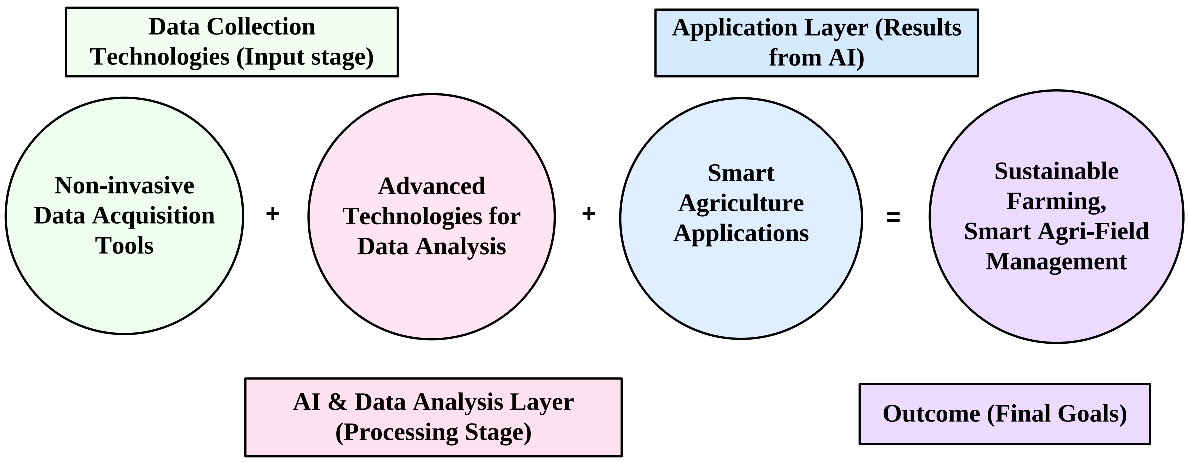

Fig. 3 High-throughput plant phenomics via AI technologies

Deep learning system, AlexNet, is adopted for crop health assessment and classification. These data are collected via IoT sensors for real-time data, drones (UAVs) for aerial crop monitoring, and computer vision for image analysis, creating a Smart Agri-Field Management System. This system yielded an F1-score of 0.98 in Growth monitoring, an F1-score of 1.0 in Health identification, and an F1-score of 0.81 in crop detection [22].

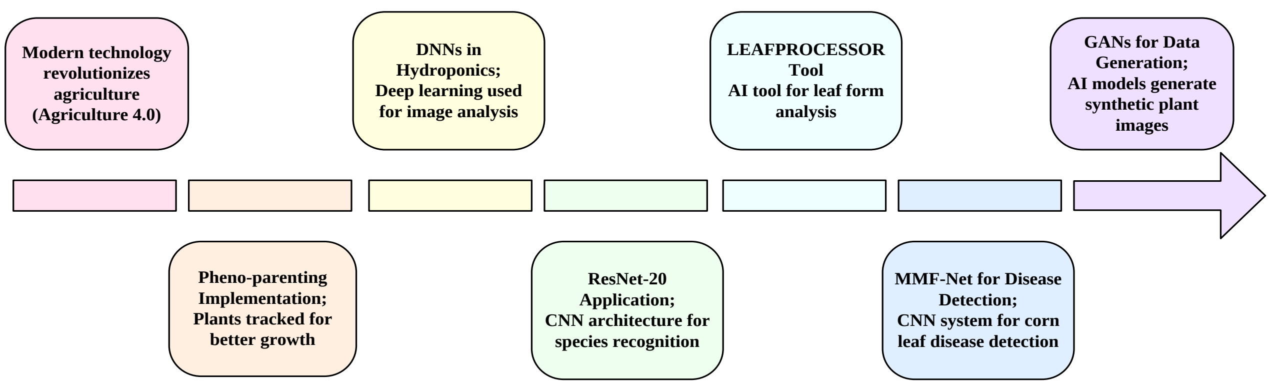

Fig. 4. The technology tree of pheno-parenting & plant disease detection

Achieving sustainable farming and food security is possible through crop improvement by adopting High-Throughput Phenotyping (HTP) and Artificial Intelligence (AI), as it measures large amounts of data of crop traits accurately and quickly. Employing HTP technologies like drones, 3D Imaging, hyperspectral cameras, and imaging sensors combined with Computer vision and machine learning yields beneficial results [23], as demonstrated in Figure 3. Modern technology has brought forth Agriculture 4.0, which analyzes and monitors a plant's growth to improve yield. Pheno-parenting is a new concept in which plants are tracked throughout their lives using sensors and tools for better growth and collecting plant phenotypes. Deep Neural Networks (DNN) are used in a hydroponic setup with cameras to capture plant images from different angles, and image analysis tools are used to detect the phenotype data of the species from the photos [24]. The contribution of ResNet-20 (V2) based CNN architecture, working with imbalanced data, employed for Species Recognition (SR) and infection detection of plants, used advanced evaluation metrics, and applied data augmentation, showed 91.49% F1 scores in SR and 83.19% F1 score in Infection Detection [25]. A smart tool, LEAFPROCESSOR, and Principal Component Analysis (PCA), an AI technique to compare and study leaf forms along with bending energy, without needing a fixed landmark, offers a better insight into plant genetics [26]. For accurately classifying and detecting diseases in corn leaves, a CNN-based deep learning system, Multi-Model Fusion Network (MMF-Net), that uses images and real-life environmental data, which is collected via IoT sensors, combines local and global image features to classify and detect corn leaf diseases. The accuracy of MMF-Net has reached 99.23% in detecting diseases [27]. Advancements in computer vision and sensor-based technology, paired with AI and Gen-AI, have enabled more accurate and faster analysis through image-based classifications and segmentations. To solve the challenges of data storage, unstructured images, high variations in plant species, and difficulty in labeling and capturing data, Generative Adversarial Networks (GANs) and deep learning models are used to generate synthetic plant images and reduce the collection of data by utilizing a digital camera and a computer vision tool to analyze them [28], as illustrated in Figure 4. A smart system built using EfficientNetB3 (a CNN model) with You Only Look Once (YOLO) architecture, a smart detector that detects each plant and its height, and another ML model, Light Gradient Boosting Machine (LightGBM), that uses data and photo info to predict how the plants will grow. This system's combination of photo and data showed improved accuracy and performance, and showed a 12% reduction in error and a 0.4783 R^2 score for predicting plant growth rates [29].

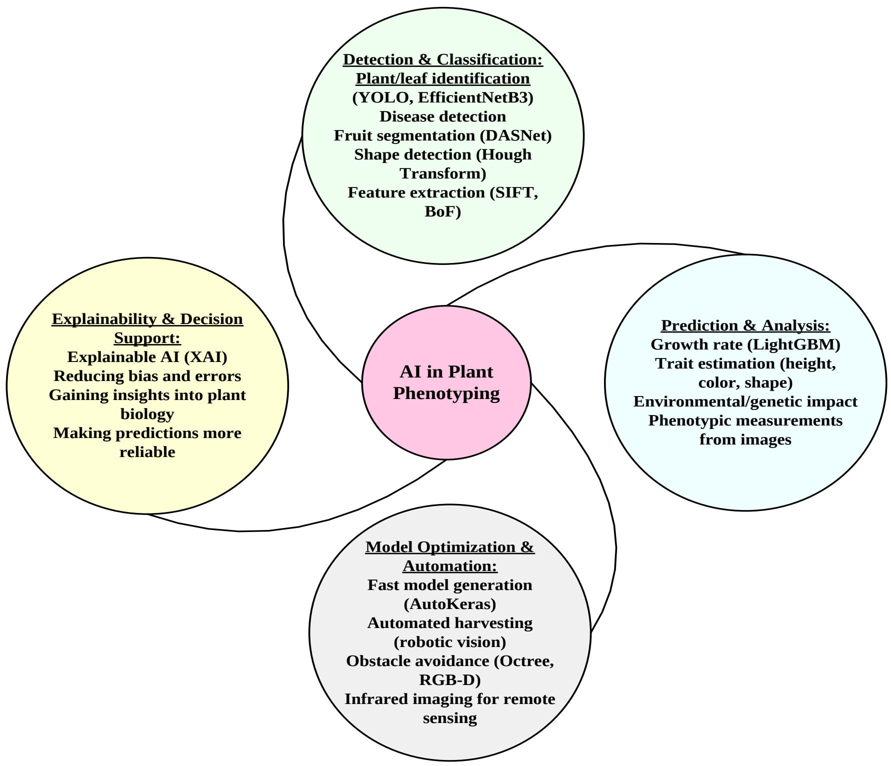

Fig. 5 AI features in plant phenotyping

An advanced open-source tool, AutoKeras, is compared with two traditional CNN models, Xception and DenseNet-201, for wheat lodging. It resulted in Autokera being up to 40 times faster than traditional CNN models, as it is much faster and easier to use to design expert-level models [30]. Leaf diseases in Brinjal cause major crop loss; to solve this, AI, image processing, sensors, and ML can detect the diseases early, resulting in a reduction of up to 56% in crop loss [31]. An automated AI-driven robotic vision system for apple harvesting, which uses a Dual Attention Segmentation Network (DASNet) for fruit detection and segmentation, and has achieved a 0.862 score in Intersection over Union (IoU) that measures object detection by comparing overlapped objects and a 0.871 F1-score. To detect shapes, like lines or circles, in images, the Hough Transform is applied and achieves an accuracy of 0.955 and 0.923, respectively. Mapping the environment to avoid any obstacles, Octree-based 3D modelling is used, and RGB-D camera sensors that support visual input [32]. Agriculture is a vital component of a country, and to protect its crops from diseases, heat-sensing cameras and AI are incorporated to spot disease more accurately. To protect crops like Brinjal, ML such as Multi-Level Twin Support Vector Machine (MLSTSVM) for classification, Scale-Invariant Feature Transform (SIFT), and Bag of Features (BoF) for feature extraction on MATrix LABoratory (Release 2018b) (MATLAB 2018b) software paired with Infrared thermal Camera for capturing thermal images and RGB camera and Thermal Imaging for Imaging, referring to Figure 5. They resulted in 87% higher accuracy from thermal processing, but it was a little time-consuming to process, and the RGB image was faster but less accurate. Hence, thermal Imaging is used in remote farming areas where accuracy is more important than speed [33], as compiled in Table 1.

Table 1. Technologies used in plant phenomics

Technology	Application
Artificial Intelligence (AI) [19, 21, 23, 31, 34]	General plant data analysis, automation, Imaging, and modelling
Deep Learning (DL) [19, 22, 24, 25, 27]	Large-scale image analysis, trait detection, disease classification
Machine Learning (ML) [19, 21, 31, 33, 34]	Crop trait prediction, disease classification, and environmental response prediction
Computer Vision [22, 24, 28, 32]	Image-based trait detection, segmentation, and disease monitoring
Explainable AI (XAI) [20, 34]	Interpretation of model decisions, reducing bias, and improving reliability.
Automated Imaging Robots [20]	Identify biological traits from images.
High-Throughput Phenotyping (HTP) [21, 23]	Tracking plant stress, health, and growth
Drones (UAVs) [21, 23]	Aerial plant monitoring and data collection for phenotyping
Multispectral Cameras [21]	Tracking disease and stress in plants
Hyperspectral Cameras [21, 23]	Crop health and trait analysis
Thermal Infrared Cameras [21]	Detecting plant stress through heat patterns
IoT Sensors [22, 27, 34]	Real-time environmental and plant data
Smart Agri-Field Management System [22]	Integrated data + image + AI for precision agriculture
3D Imaging [23]	Structural phenotyping
Pheno-Parenting [24]	Lifelong plant monitoring and phenotype tracking
Deep Neural Networks (DNN) [24]	Analyzing plant traits from images
Data Augmentation [25]	Improving model performance
LEAFPROCESSOR Tool [26]	Leaf form analysis using bending energy
Principal Component Analysis (PCA) [26]	Leaf structure comparison
Generative Adversarial Networks (GANs) [28]	Generating synthetic plant images
Digital Camera + Computer Vision (CV) [28]	Image-based trait analysis
EfficientNetB3 (CNN) [29]	Plant detection and height estimation
You Only Look Once (YOLO) [29]	Object detection in phenotyping
Xception, DenseNet-201[30]	Traditional CNNs for phenotyping
Sensors + ML [31]	Disease detection in crops like Brinjal
Octree-based 3D Modeling [32]	Obstacle mapping
RGB-D Camera [32]	Visual-depth sensing
Multi-Level Twin Support Vector Machine (MLSTSVM) [33]	Classification of thermal images
Scale-Invariant Feature Transform and Bag of Features (SIFT + BoF) [33]	Feature extraction from images
(MATLAB 2018b) [33]	Image processing environment
ML + IoT + Sensors [34]	Trait prediction and phenotyping

Machine learning, paired with IoT and sensors, quickly and accurately measures plants' traits and features through images and predicts whether the plants are affected by their environment and genes. Although these AI models are like a “black box” because how they conclude is unknown, to combat that gap, Explainable AI (XAI) shows why the model made that prediction, which helps in reducing errors and bias, gives insight into plant biology, and makes the model more reliable [34], as evident in Table 2.

Table 2. Recorded results of the mentioned technologies

Technology	Application	Performance matrix
Smart Agri-Field Management System (AlexNet + IoT + CV) [22]	Crop health monitoring and classification	F1-Score: 0.98 (Growth monitoring), 1.0 (Health identification), 0.81 (Crop detection)
ResNet-20 (V2) CNN [25]	Species and infection identification	F1-Score: 91.49% (Species Recognition), 83.19% (Infection Detection)
MMF-Net (CNN-based System) [27]	Corn leaf disease classification using image + environmental data	Accuracy: 99.23%
YOLO + EfficientNetB3 + LightGBM [29]	Plant growth rate prediction using image and data	R^2 Score: 0.4783, 12% reduction in prediction error
AutoKeras vs. CNN (Xception, DenseNet-201 [30]	High-throughput wheat lodging detection	Up to 40x faster than traditional CNNs
AI for Brinjal Disease Detection [31]	Early detection of Brinjal leaf disease	Up to 56% reduction in crop loss
DASNet (Robotic Vision for Apple Harvesting) [32]	Fruit detection and segmentation	IoU: 0.862, F1-Score: 0.871
Hough Transform (Shape Detection) [32]	Shape detection in images for automated harvesting	Accuracy: 0.955 (Lines), 0.923 (Circles)
Thermal Imaging + MLSTSVM + SIFT + BoF [33]	Disease detection in Brinjal using thermal and RGB Imaging	87% accuracy (thermal); Faster but less accurate with RGB

5. Computer Vision-Based Plant Phenotyping

Plants' traits, appearance, behavior, and features are affected by their environment and genes. Traditionally, they were costlier and time-consuming, but due to technologies such as UAVs, 2D/3D Imaging, Volumetric Imaging, Image analysis algorithms, and cameras, tools such as Machine learning to recognize plant traits, Public benchmark datasets to compare results, computer vision to analyze plant images, template matching for leaf segmentation, and Computer Vision Problems in Plant Phenotyping (CVPPP), Image Analysis Methods for the Plant Sciences (IAMPS) workshops to share and improve research. These technologies together analyze roots and shoots, segment leaves, track plant growth, classify plant species, and improve food production and crop breeding [35].

Replacing the older, manual, time-consuming, and costlier method with computer vision for plant phenotyping. Adopting AI and ML technology, combined with depth and optical sensors utilizing LiDAR, Thermal, Multispectral, Hyperspectral, and RGB cameras, enables more efficient measurement of plant features [36]. High-tech tools and AI are being used to study plant growth, environmental responses, and genetic relationships. These tools, including High-Throughput Phenotyping (HTP), thermal Imaging, software sensors, fluorescence imaging, and hyperspectral Imaging, are used to monitor plant environment and improve crop sustainability and yield. Supported by smart lighting systems and CRISPR, these methods aim to enhance plant growth, reduce chemical usage, and increase crop productivity, promoting sustainable and precise agriculture [37]. A combination of AI with smart technology that does precision agriculture by monitoring crops and improving yields in real-time. Plant phenotyping through AI, image analysis, and 2D/3D Imaging, which identifies top-performing crops, growth issues, and yields. It combines it with high-throughput Imaging that performs robot harvesting, canopy monitoring, and root analysis, improving accuracy and yielding faster results. Smartphone-based phenotyping and time series data used in ML is the future of phenotyping [38]. A Gantry-robot with 3-D scanners that are powered by a computer vision algorithm that moves around the plants, capturing detailed scans over time from seedling to maturity, especially under controlled light/dark cycles [39], as illustrated in Figure 6.

For a faster and more reliable crop analysis, and improving technicality and economy in farming, computer vision and deep learning, such as Visual Geometry Group (VGG), You Only Look Once (YOLO), and Faster Region-based Convolutional Neural Network (Faster R-CNN) with an imaging system that helps detect stress, plant parts, diseases, pests, and sort weed [40].

Computer vision and AI models, such as DANet (Dual Attention Network), Real-Time Multi-task Detection (RTMDet), and Real-Time Multi-person Pose Estimation (RTMPose), are used in technologies, DL, Cluster analysis, and Image processing. Also, the Mobile Segment Anything Model (MobileSAM) is a user-friendly, automated software that works on mobile/edge devices. These technologies and tools combined aimed to speed up and improve melon breeding and detect and measure physical traits like size, shape, and stem to select high-quality melon varieties [41].

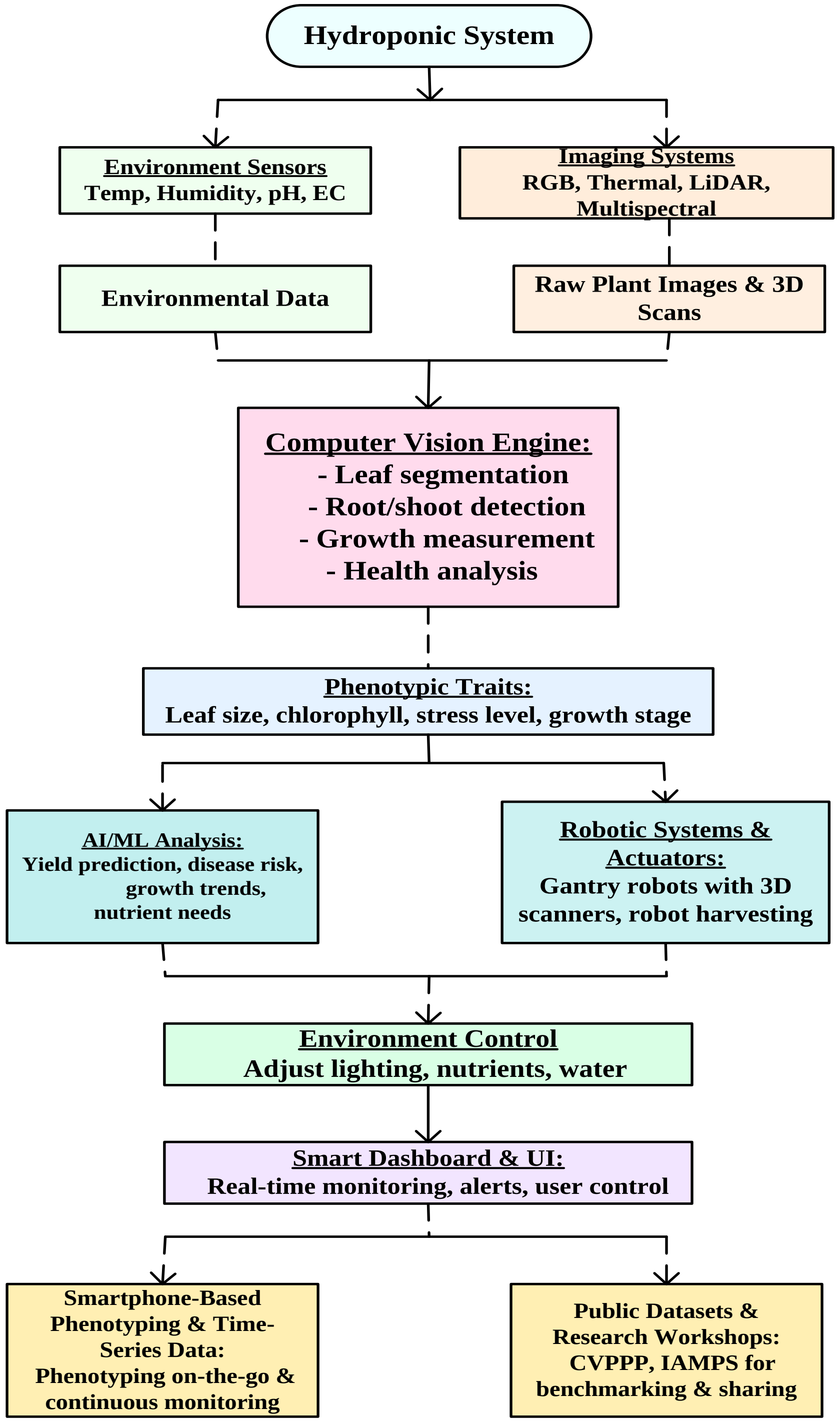

Fig. 6 Process of computer vision in a hydroponic system for plant phenotyping

To detect plant diseases, especially in apple trees, multispectral Imaging, machine learning, and computer vision are used to scan the fields, analyze leaf health, and identify infected or stressed trees [42]. The images captured by the RGB camera used for plant phenotyping, mutant identification, and leaf segmentation contain both annotated and raw images, which enhance computer vision algorithms for plant analysis. It aims to fill the gap in methods across high-quality, standardized datasets for fair comparison [43]. Segmenting an individual leaf is challenging because of lighting issues, shape variations, and overlapping leaves. Leaf Segmentation Challenge (2014) tested 4 methods and showed high accuracy in separating plants from the background, but still had a long way to go in counting and separating overlapping or young leaves accurately [44], as reflected in Figure 7.

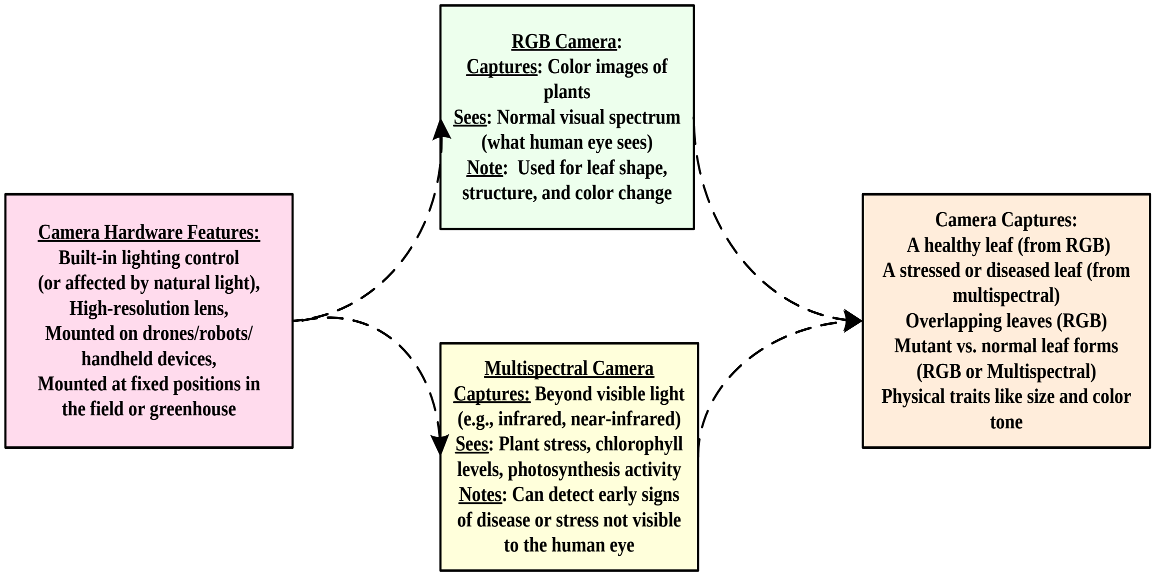

Fig. 7 Process of data capturing in plant phenotyping via cameras

Brinjal harvesting is facing a labor shortage. To combat these difficulties, a computer vision-based algorithm that detects and identifies moderately mature KKM-1 brinjals suitable for harvesting is needed. These processes involve clustering (ML algorithm) that handles shading and segments the interested regions, followed by shape filtering and contour detection to isolate brinjals. This method resulted in 79% precision and 85% F1-score in brinjal detection and 96% in precision with 91% F1-score in maturity prediction [45], as detailed in Table 3.

Table 3. Technology implemented in plant pheromonic

Technologies	Application
Unmanned Aerial Vehicles (UAVs) [35]	Remote sensing and monitoring plant traits from above
Two-dimensional/Three-dimensional Imaging (2D/3D Imaging) [35, 38]	Capturing structural traits like leaf shape, plant height, and canopy structure
Volumetric Imaging [35]	Captures 3D plant architecture for phenotypic analysis
Image Analysis Algorithms [35]	Automated extraction of features from plant images (e.g., shape, texture)
Red-Green-Blue Cameras (RGB Cameras) [35, 42, 43]	Capturing visual plant data for phenotyping and segmentation
Computer Vision Problems in Plant Phenotyping (CVPPP) Workshops [35]	Collaborative events for advancing plant phenotyping using imaging techniques
Template Matching [35]	Identifying and segmenting plant parts (especially leaves) from images
Image Analysis Methods for the Plant Sciences (IAMPS) Workshops [35]	Workshops focused on developing and sharing image-based plant analysis methods
Depth and Optical Sensors [36]	Capturing plant depth information and optical traits (e.g., reflectance)
Light Detection and Ranging (LiDAR) [36]	Scanning plant height, volume, and architecture in 3D
Multispectral Imaging [36, 42]	Measures plant stress, health, and nutrient levels via wavelength bands
Thermal Imaging [37]	Detects plant water stress and transpiration by measuring temperature
Hyperspectral Imaging [37]	Analyzes plant pigments and biochemical composition

High-Throughput Phenotyping (HTP) [37]	Automated large-scale phenotyping using imaging and sensing systems
Software Sensors [37]	Monitor environmental variables like temperature, light, and humidity.
Fluorescence Imaging [37]	Measures photosynthesis efficiency by detecting fluorescence emissions
Smart Lighting Systems [37]	Optimized lighting in hydroponics for controlled plant growth
Clustered Regularly Interspaced Short Palindromic Repeats (CRISPR) [37]	Genetic editing for enhancing desired plant traits
High-Throughput Imaging [38]	Enables tasks like robot harvesting, canopy analysis, and root monitoring
Smartphone-based Phenotyping [38, 46]	Portable plant data collection for disease detection and classification
Time-Series Data [38]	Tracking plant growth and development over time
Gantry-Robot with 3D Scanners [39]	Moves around plants, capturing 3D scans from seedling to maturity
Visual Geometry Group Network (VGG) [40]	Deep learning model used for disease/stress detection in plants
Faster Region-based Convolutional Neural Network (Faster R-CNN) [40]	Detects plant diseases, pests, and weeds from images
Dual Attention Network (DANet) [41]	Measures melon size, shape, and other features for breeding
Real-Time Multi-task Detection (RTMDet) [41]	Identifies multiple traits of melon plants in real time
Real-Time Multi-person Pose Estimation (RTMPose) [41]	Adapted for estimating plant pose or orientation in images
Mobile Segment Anything Model (MobileSAM) [41]	Edge-device compatible tool for easy leaf/plant segmentation
Public Benchmark Datasets [43]	Standard datasets used to evaluate and compare phenotyping algorithms
Annotated Image Datasets [43, 46]	Provides labeled data for training phenotyping models

4,098 labeled images across 6 categories, insect pest, leaf spot, mosaic virus, wilt, healthy, and white Mold, of brinjal leaves taken by smartphones in a natural and controlled environment to be used in computer vision-based disease detection, to learn to classify and detect leaf diseases [46], as represented in Table 4.

Table 4. Performance metrics of the technologies used

Technology	Application	Results
Leaf Segmentation Challenge [44]	Evaluated segmentation methods for leaf counting	High background separation accuracy, limited by overlapping leaves
Clustering Algorithm [45]	Used to isolate regions of interest in brinjal detection	79% Precision, 85% F1-Score (Detection); 96% Precision, 91% F1-Score (Maturity)
Contour Detection [45]	Used to isolate fruit shapes like Brinjal from the background	79% Precision, 85% F1-Score (Detection); 96% Precision, 91% F1-Score (Maturity)
Smartphone-based Phenotyping [46]	Used for capturing brinjal leaf diseases in the field	4,098 labeled images across 6 categories for classification

6. Role of IoT Devices and Sensors in Plant Phenotyping

Processing a large amount of data constantly without sharing it all on the cloud, which enhances privacy, saves bandwidth, extends battery life, and enhances response time, is possible with the use of IoT sensors creating Edge computing. Technologies like Edge Nodes/Gateways manage, filter, and process the data from IoT sensors, creating a collaborative edge where devices work together for faster and more efficient data handling [47]. To collect and analyze data from the plant without harming the plants, technologies need to be non-invasive and more accurate. The sensors, such as thermal cameras, multispectral sensors, LiDAR, which are non-evasive, handheld sensors, cameras that are for proximal sensing, and drones, satellites for remote sensing, these sensors identify traits like yield, quality, and stress resistance to help in plant breeding and precision farming [48]. Plant stress can be detected using a camera and environmental sensors to monitor humidity, temperature, etc., by capturing leaf images and processing them through the Support Vector Machine (SVM) algorithm, an AI model, to classify healthy and unhealthy leaves. Afterwards, the Grey Level Co-occurrence Matrix (GLCM) method extracts leaf features and sends them to the agriculture experts for review and suggestions [49]. Plant Phenotyping requires advanced technologies like LiDAR, Red Green Blue-Depth (RGB-D) cameras, structured light sensors, and multi-view stereo systems. These IoT-enabled sensors collect high-resolution leaf area, biomass, and height data, which are then processed through computer vision, 3D modelling Techniques, and AI. The processed images are then analyzed for improving crop breeding and management, and complex plant structure [50]. Thermal sensors for imaging have proved to be a powerful tool for detecting pests, water stress, diseases, freezing damage, assessing nutrient levels, and predicting crop and seed viability without harming the plant [51]. To protect the crops from pest and disease issues and maintain a favourable condition for the crops to get better yields, modern technologies and tools like Chlorophyll Fluorescence Imaging, Thermal Imaging, and Hyperspectral Imaging track plant humidity, temperature, health, etc, combined with AI. These technologies control and detect problems early [52], as represented in Figure 8.

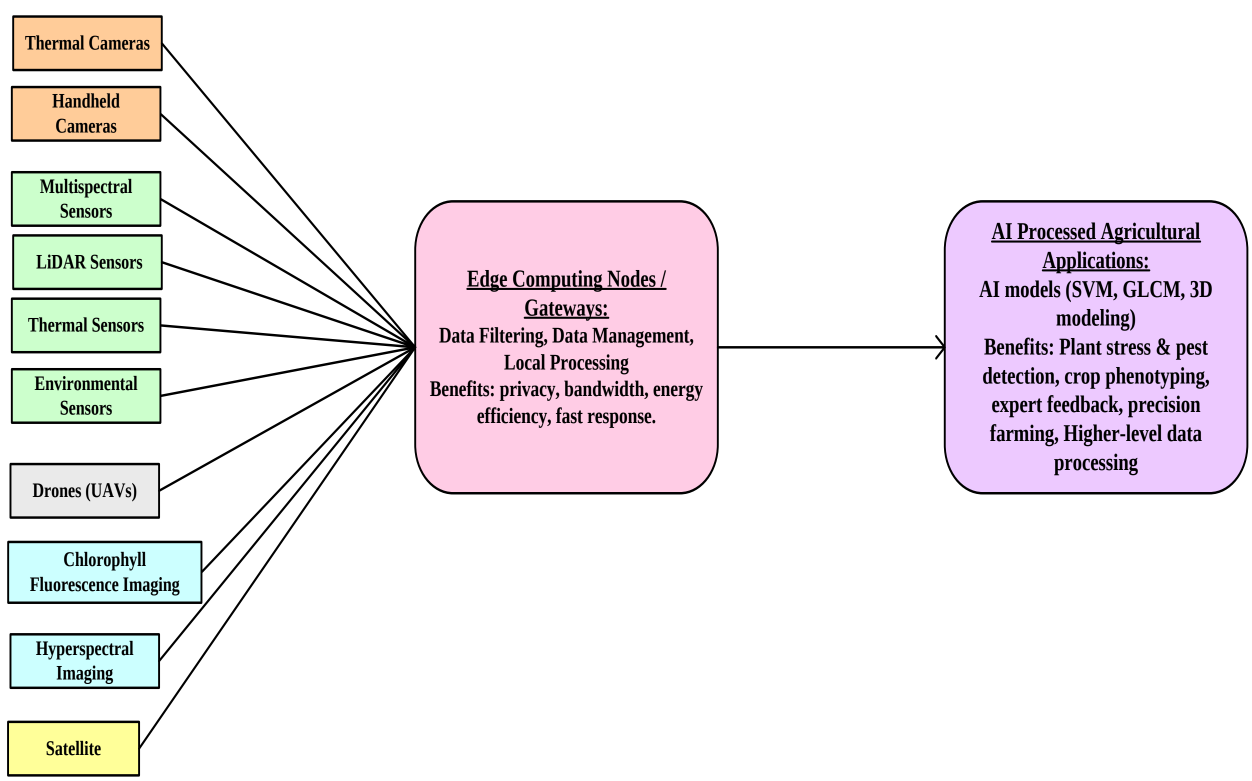

Fig. 8 Smart agriculture via sensors and IoT devices

Modern farming faces issues like environmental concerns, a labour shortage, and an increase in food demand. Therefore, 62 robot systems are used to overcome these challenges and perform agricultural tasks, where 80% are in the research stage, 32% use RGB cameras, 64% lack robotic arms, and 35% use computer vision algorithms. These robotic systems use a Multispectral sensor and an RGB camera for plant health, soil sensors, and GPS paired with IoT tech for communication and real-time monitoring. This robotic system has improved harvest success rates by 23%

and reduced harvesting time from 2014 to 2021 by 43% [53]. An AI technology combined with non-invasive imaging sensors, Multispectral, Hyperspectral imaging, Thermal Imaging, 3D Imaging, Chlorophyll fluorescence imaging (CFIM), Red Green Blue (RGB) camera (visible Imaging), and Environmental monitoring sensors (IoT) and statistical analysis enables precise analyses of plants' roots and leaves through feature extraction, classification, and segmentation [54]. A 3D plant canopy structure analysis includes imaging technologies, such as RGB cameras for visual sensors, sensors, Time-of-Flight (ToF) Cameras, Light Detection and Ranging (LiDAR), and Structured Light Cameras for depth, paired with Multi-View Stereo (MVS) and Structure from Motion (SfM) techniques that are supported by AI-based segmentation on the Center for Machine Perception Multi-View Stereo (CMPMVS) software, which helps to extract traits like canopy shape and leaf area [55].

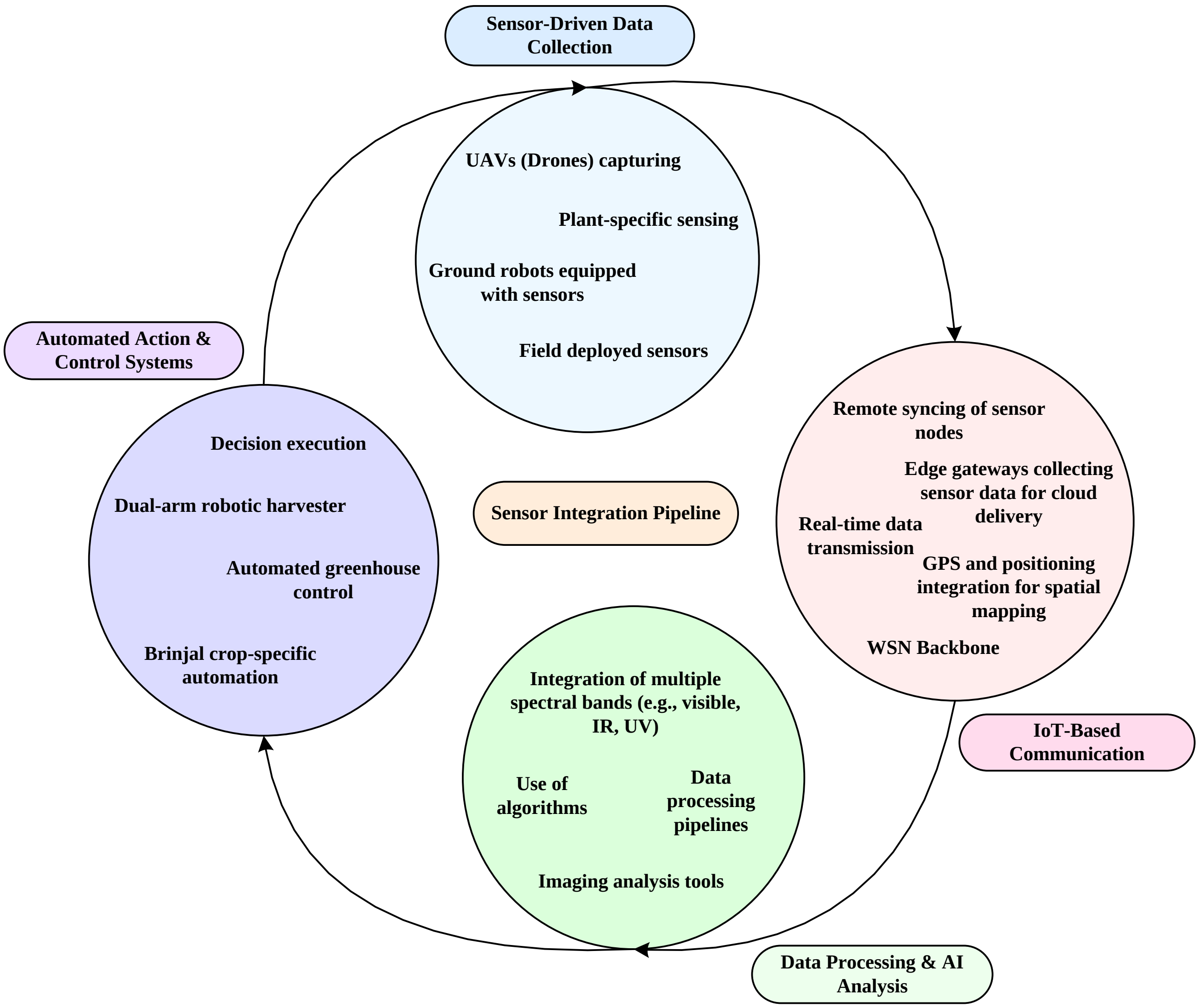

Fig. 9 Smart farming workflow via IoT and sensor technologies

Collecting accurate data on a large scale and fast High-Throughput Phenotyping (HTP) using drones (UAVs) and AI-based image analysis is a strong solution. This solution uses Unmanned Aerial Vehicles (UAVs), Multispectral / Hyperspectral sensors, and RGB cameras to capture plant health data. Data Processing Pipelines that extract traits from images and Image Analytics Software to process drone images, ML, and DL AI models [56]. A mobile sensing platform that is equipped with various non-contact optical sensors, Near-infrared (700-1000 nm), Full-spectrum (350-2500 nm), Ultraviolet (280-400 nm), Visible light (400-700 nm), Chlorophyll fluorescence, and Thermal (infrared) enables consistent and quick monitoring of the plant growth [57]. For modernizing the farming of the vegetable brinjal, by using Long Range Wide Area Network (LoRaWAN)-based in an environment where devices like fans and heaters are automatically adjusted to maintain optimal conditions for brinjal crop growth, and using a Wireless Sensor Network (WSN) to control and monitor brinjal growth. CupCarbon simulator is where this setup is being tested, as it enables remote automated climate control that is efficient in greenhouses [58]. Modernized farming has evolved to utilising robotics instead of manual labour, as a dual-arm robotic system designed to automatically harvest aubergines in complex farm environments has shown 91.67% success rates, and 26 seconds per fruit is its average picking time. This dual-arm robotic system uses an Occlusion algorithm for handling hidden fruits, a Dynamic planning algorithm for arm movement, and a Support Vector Machine (SVM) for image classification. The dual arm coordination is flexible for fruit picking, employing depth sensors for 3D mapping for point cloud generation and Vision sensors (cameras) for detecting fruit and obstacles [59], as shown in Figure 9. Technologies like IoT, sensors, AI, drones, Smart Irrigation Systems (SIS), remote sensing, and big data combined make up digital agriculture. In eggplant farming, key tools, sensors such as soil moisture, temperature, humidity, and optical sensors that collect real-time data on plant and soil health, UAVs, and yield monitors collect data, which is analyzed on AI and machine learning to optimize irrigation and fertilization, detect pests and diseases, and predict yields for better eggplant crop management [60], referring to Table 5.

Table 5. Sensors and IoT technologies used in plant pheromone

Technology	Application
Edge computing, Edge nodes/gateways [47]	Local processing for enhanced privacy, lower latency
Thermal Cameras, Multispectral Sensors, Light Detection and Ranging (LiDAR), Red Green Blue Camera (RGB), Drones, Satellites [48]	Non-invasive sensing for trait analysis
Light Detection and Ranging (LiDAR), Red Green Blue-Depth Camera (RGB-D), Structured Light Sensors, Multi-View Stereo (MVS), Structure from Motion (SfM) [50]	3D imaging and modelling for plant phenotyping
Thermal Imaging Sensors [51]	Detect water stress, disease, freezing, and nutrient levels.
Chlorophyll Fluorescence Imaging (CFIM), Thermal Imaging, Hyperspectral Imaging, Artificial Intelligence (AI) [52]	Track humidity, temperature, and plant health to detect early issues
Multispectral Imaging, Hyperspectral Imaging, 3D Imaging, Chlorophyll Fluorescence Imaging (CFIM), Red Green Blue Camera (RGB), Environmental Monitoring Sensors, Artificial Intelligence (AI) [54]	Extract and classify root and leaf features.
Red Green Blue Camera (RGB), Time-of-Flight Camera (ToF), Light Detection and Ranging (LiDAR), Structured Light Camera, Multi-View Stereo (MVS), Structure from Motion (SfM) [55]	Analyze canopy structure and extract traits.
Unmanned Aerial Vehicles (UAVs), Multispectral Sensors, Hyperspectral Sensors, Red Green Blue Camera (RGB), Artificial Intelligence (AI) [56]	High-Throughput Phenotyping (HTP) and image analytics
Near-Infrared (NIR), Ultraviolet (UV), Visible Light, Full-Spectrum Sensors, Chlorophyll Fluorescence Imaging (CFIM), Thermal Imaging [57]	Mobile sensing platform for fast, non-invasive monitoring
Long Range Wide Area Network (LoRaWAN), Wireless Sensor Network (WSN), CupCarbon Simulator [58]	IoT-based automated brinjal crop monitoring system
Internet of Things (IoT), Soil Moisture Sensors, Temperature and Humidity Sensors, Smart Irrigation System (SIS), Red Green Blue Camera (RGB), Unmanned Aerial Vehicles (UAVs), Artificial Intelligence (AI), Machine Learning (ML) [60]	Optimize irrigation, fertilization, pest detection, and yield prediction.

Weed is also an enemy of healthy crops, and manual weed control is risky and time-consuming due to pesticide exposure. To save time, reduce pesticide exposure, and reduce labour in a brinjal farm, a U-Net with Inception-ResNetV2, a deep learning AI model, paired with an RGB camera that captures images under ambient lighting with over 96% accuracy, as depicted in Table 6, easily detects and classifies weeds. This Semantic Segmentation method accurately identifies different species of weeds under natural light [61].

Table 6. Performance results of the applied Sensors

Technology	Purpose	Results
Support Vector Machine (SVM), Grey Level Co-occurrence Matrix (GLCM) [49]	Detect and classify plant stress from leaf images	Classification performed by SVM; features extracted by GLCM; no specific accuracy provided
Agricultural Robotics, Computer Vision (CV), Red Green Blue Camera (RGB), Internet of Things (IoT) [53]	Perform tasks like harvesting, monitoring, and plant health analysis	- 23% increase in harvest success - 43% reduction in harvest time (2014-2021) - 32% use RGB cameras - 64% lack robotic arms - 35% use CV algorithms
Dual-Arm Robotic System, Support Vector Machine (SVM), Occlusion Algorithm, Depth Sensors, Vision Sensors [59]	Automate aubergine harvesting in complex environments	- 91.67% picking success rate - 26 seconds per fruit
U-Net with Inception-ResNetV2 (Deep Learning), Red Green Blue Camera (RGB), Semantic Segmentation [61]	Detect and classify weed species in brinjal fields	Over 96% accuracy in weed detection under ambient/natural light

7. Recommendation

Advancement in plant phenotyping is achieved when we combine technology with knowledge. Artificial Intelligence, Computer vision, Internet of Things (IoT), and smart sensors have all made it very possible to understand the complexities of plant and their response to their surroundings and environment. Food demand has increased over the past decade, and to meet this demand, a strong and climate-resistant crop is a must. Due to the population rise and the spread of urbanization, agriculture has been the least advanced industry among others. Advanced technology in farming is the solution for smart and sustainable farming, as by leveraging these advanced tools and technology, farmers can enhance productivity, resilience, and resource efficiency.

- Aligning with SDG 2 - Zero Hunger calls for simultaneously addressing the food security challenges, minimizing environmental impact, and promoting sustainable agricultural practices combining IoT, AI, and Phenomics.
- To accelerate crop improvement through linking genotypes to phenotypes by integrating AI-driven high-throughput phenotyping, utilizing advanced computer vision and deep learning algorithms for automation to yield prediction, enhancing stress tolerance, detecting diseases, and leaf segmentation, accurately and efficiently, with reduced manual labour.
- For a deeper understanding of plant traits, their stress responses, and for precision breeding by their stress response, a real-time, precise monitoring of plant health and the environmental surroundings is achieved by deploying IoT sensors and remote sensing technologies, and adopting multi-omics and explainable AI frameworks.
- Especially high-value vegetables, like Brinjal, can implement robotic systems and autonomous harvesting technologies, improving crop production efficiency.

8. Conclusion

Integrating Artificial Intelligence with IoT devices, edge computing, computer vision, and advanced sensor technologies without harming the environment presents a promising future in sustainable agriculture. These advanced innovations provide real-time, precise data by non-evasively monitoring crops through thermal and 3D vision, and UAV imaging technologies detect diseases and stress early, saving the crops and increasing productivity.

To gain field-level insight on optimising nutrients, water, and pest management, implementing IoT sensors and edge computing has proven to be successful. The advancement of Auto Machine Learning, Explainable AI, and Deep Learning has enhanced the understanding and overcoming of the complexities in accelerating breeding cycles, predicting diseases, and mapping Genotype-Phenotype. Deploying the fusion of these innovations, even in a protected environment, by making it a smart agri-field system, optimizes disease control and yields. These advanced plant phenotype technologies, which are powered by high-throughput Imaging, computer vision, AI, IoT, and sensors, together make it the most viable and crucial for smart and sustainable agriculture. The amalgamation of multi-omics data, machine learning, and smart tools and technologies provides a versatile path forward by prioritising and realizing their full potential, farmer-based innovation, inclusive access, and cross-sector collaboration.

Author Contributions Statement

Conceptualization: A.B.; Methodology: A.B. and C.D.E.; Data Collection: C.D.; Formal Analysis: A.B. and C.D.E.; Writing-Original Draft: A.B.; Writing-Review & Editing: A.B.E. and C.D. All authors have read and approved the final manuscript.

Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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