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A SYSTEMATIC REVIEW OF MULTI-MODAL DEEP LEARNING APPROACHES FOR HIGH-THROUGHPUT PLANT PHENOMICS

*Chandrasekhar Bhoi

Assistant Professor (TE)in Botany Buxi Jagabandhu Bidyadhar Autonomous College, Bhubaneswar, India.

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***Corresponding Author: Chandrasekhar Bhoi**
Assistant Professor (TE)in Botany Buxi Jagabandhu Bidyadhar Autonomous College, Bhubaneswar, India.

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ABSTRACT

High-throughput plant phenomics has become an essential component of modern agricultural research, supporting efficient trait analysis for crop improvement, stress monitoring, and yield estimation. Conventional phenotyping approaches are often manual, labor-intensive, and limited in scalability, which restricts their application in large field environments. Recent developments in artificial intelligence, particularly deep learning, have enabled automated analysis of complex agricultural data with improved accuracy and efficiency. The integration of multiple data sources—such as RGB and multispectral images, environmental measurements, temporal growth information, and genomic data—has further strengthened phenotypic prediction capabilities. This systematic review examines existing multi-modal deep learning approaches applied to plant phenomics, with emphasis on data integration techniques, model architectures, application areas, and evaluation practices. A structured literature search was conducted across major academic databases using predefined criteria to identify relevant peer-reviewed studies. The reviewed works indicate that advanced fusion strategies, especially attention-based and transformer-based models, enhance performance compared to single-source approaches. However, challenges remain in terms of dataset standardization, model interpretability, and cross-environment adaptability. Future research should focus on explainable models, improved generalization techniques, and practical deployment in real-world agricultural systems.

KEYWORDS: Plant phenomics; Multi-modal learning; Deep learning; Data fusion; High-throughput agriculture; Explainable artificial intelligence.

2.1 INTRODUCTION

Agriculture plays a fundamental role in global food security, economic stability, and sustainable development. With the growing world population and the increasing impact of climate change, improving crop productivity while optimizing resource use has become a critical priority. Plant phenotyping—the systematic measurement of observable plant traits—supports crop improvement, breeding programs, and stress adaptation studies. However, traditional phenotyping methods are often manual, time-consuming, labor-intensive, and limited in scalability, making them unsuitable for large-scale agricultural systems.

The increasing demand for structured evidence synthesis in scientific research further emphasizes the importance of transparent reporting methodologies in systematic reviews (Page et al., 2021a). Standardized frameworks such as PRISMA 2020 enhance reproducibility and methodological rigor in review studies (Page et al., 2021b).

2.2 Rise of Artificial Intelligence in Agriculture

Artificial intelligence has significantly transformed agricultural data analysis. Machine learning techniques have been widely applied in crop monitoring, classification, and predictive modeling. With advancements in deep learning architectures such as convolutional neural networks and transformer-based models, automated feature extraction from complex datasets has improved substantially.

Recent developments in multi-modal deep learning have enabled the integration of heterogeneous data sources, including images and non-image information, for improved predictive performance (Cui et al., 2022). Similarly, multi-modal fusion strategies have demonstrated strong potential in handling complex structured and unstructured data across domains (Zhou et al., 2020). These advances are particularly relevant for high-throughput phenotyping systems that generate large-scale imaging and sensor-based datasets.

2.3 Research Gap

Despite rapid progress, several limitations remain in current plant phenomics research. Many existing studies rely primarily on single-modal data, especially RGB imagery, with limited integration of environmental, temporal, and genomic information. This restricts the ability to capture complex plant–environment interactions.

Furthermore, several multi-modal systems suffer from limited cross-environment generalization, reducing their applicability across different geographic regions and crop varieties. Model interpretability also remains a major concern, as deep learning models often function as black-box systems, limiting transparency and practical adoption. Additionally, data scarcity and lack of standardized datasets continue to hinder robust model development.
Recent reviews highlight the need for more dynamic and predictive frameworks capable of modeling spatiotemporal plant growth and environmental interactions (Debbagh et al., 2024). These gaps justify a systematic examination of multi-modal deep learning approaches in plant phenomics.

2.4 Objectives of the Review

The primary objective of this systematic review is to provide a comprehensive and structured analysis of multi-modal deep learning approaches applied to high-throughput plant phenomics. Specifically, this study aims to:

- Systematically classify and summarize the existing machine learning and deep learning techniques utilized in plant phenotyping research.
- Examine and critically compare various multi-modal data fusion strategies adopted in current studies.
- Analyze major application domains, including plant disease detection, stress monitoring, yield prediction, and trait estimation.
- Identify prevailing limitations, methodological challenges, and research gaps in the existing literature.
- Propose future research directions to improve model robustness, interpretability, cross-domain generalization, and real-world implementation in agricultural systems.

3. METHODOLOGY OF THE REVIEW

This systematic review was conducted using a structured and reproducible methodology to ensure transparency and reliability. The review process follows established systematic review practices commonly adopted in interdisciplinary research involving artificial intelligence and agriculture (Kitchenham & Charters, 2007; Snyder, 2019).

3.1 Databases Searched

A comprehensive literature search was carried out using multiple well-recognized academic databases to ensure broad and high-quality coverage of relevant studies. The selected databases include:

- Scopus
- Web of Science
- IEEE Xplore
- ScienceDirect
- Google Scholar

These databases were chosen due to their extensive indexing of peer-reviewed articles in domains such as computer science, artificial intelligence, remote sensing, and agricultural sciences (Gusenbauer & Haddaway, 2020).

3.2 Keywords Used

The search strategy was developed using a combination of keywords and Boolean operators (AND, OR) to capture relevant studies. The primary keywords included:

- “Plant phenomics”
- “Multi-modal deep learning”
- “UAV phenotyping”
- “Feature fusion in agriculture”
- “Crop yield prediction using AI”
- “Deep learning in plant phenotyping”

Search strings were adapted for each database to improve retrieval accuracy and ensure comprehensive coverage of the literature.

3.3 Selection Process

The study selection was conducted in multiple stages to ensure systematic filtering:

1. Identification: All relevant studies were collected from the selected databases using the defined search strategy.
2. Deduplication: Duplicate entries were identified and removed.
3. Screening: Titles and abstracts were reviewed to exclude irrelevant studies.
4. Eligibility Assessment: Full-text articles were evaluated based on the inclusion and exclusion criteria.
5. Final Inclusion: Studies meeting all criteria were selected for qualitative analysis.

The entire selection process will be illustrated using a PRISMA flow diagram, which presents the number of records identified, screened, excluded, and finally included in the review. This approach enhances methodological transparency and reproducibility (Moher et al., 2009).\

4. Overview of Plant Phenomics Technologies

Modern plant phenomics relies on advanced sensing technologies and automated data acquisition systems to capture large-scale, high-resolution trait information. These technologies generate high-throughput datasets that can be effectively analyzed using machine learning and deep learning methods. The major technological platforms used in plant phenomics are summarized below.

Table 1: Overview of Plant Phenomics Technologies.

Technology	Data Type	Advantages	Limitations	AI Compatibility
Ground-Based Imaging	RGB images	High resolution, controlled environment	Limited scalability	CNN, Vision Transformers
UAV-Based Monitoring	Aerial images	Large field coverage, flexible	Weather dependent	Deep learning, object detection
Satellite Remote Sensing	Multispectral data	Regional/global scale	Lower spatial resolution	ML regression, time-series models
Hyperspectral Imaging	Spectral bands	Early stress detection	High data complexity	CNN, feature fusion models
Sensor-Based Systems	Environmental data	Real-time monitoring	Requires integration	Multi-modal fusion models

4.1 Ground-Based Imaging Systems

Ground-based phenotyping systems are widely used in controlled environments such as greenhouses and experimental fields. These systems typically include fixed cameras, robotic platforms, conveyor-based imaging setups, and stationary sensor arrays. They enable detailed monitoring of plant morphology, growth dynamics, and physiological traits under controlled conditions.

Such systems are particularly useful for:

- Leaf area measurement
- Plant height estimation
- Disease detection
- Growth monitoring

Ground-based imaging provides high spatial resolution data, which is highly suitable for deep learning-based image analysis models. However, these systems may have limitations in large outdoor agricultural fields due to scalability constraints.

4.2 UAV-Based Monitoring

Unmanned Aerial Vehicles (UAVs), commonly known as drones, have become an essential tool in high-throughput plant phenotyping. UAV-based platforms allow rapid data collection over large agricultural areas with flexibility and cost efficiency.

Equipped with RGB, multispectral, or thermal cameras, UAVs enable:

- Crop health monitoring
- Stress detection
- Canopy analysis
- Yield estimation
- Field-level phenotypic mapping

The integration of UAV imagery with deep learning models significantly enhances automated trait extraction and large-scale agricultural monitoring. UAV-based systems are especially valuable for precision agriculture applications.

4.3 Satellite and Remote Sensing

Satellite-based remote sensing provides large-scale environmental and vegetation data across regional and global levels. These systems are widely used for monitoring crop growth, land use patterns, drought conditions, and seasonal variations.

Common satellite-derived data include:

- Vegetation indices (e.g., NDVI)
- Land surface temperature
- Crop classification maps

Although satellite imagery may have lower spatial resolution compared to UAV data, it offers extensive temporal coverage and supports long-term agricultural monitoring. When integrated with AI models, remote sensing data enhances predictive capabilities for yield estimation and environmental analysis.

4.4 Hyperspectral and Multispectral Imaging

Hyperspectral and multispectral imaging technologies capture data across multiple spectral bands beyond the visible range. These imaging techniques provide detailed spectral signatures of plants, enabling early detection of physiological changes, nutrient deficiencies, and stress conditions.

Key applications include:

- Disease diagnosis
- Nutrient status assessment
- Abiotic stress monitoring
- Trait differentiation

Hyperspectral data is particularly suitable for multi-modal deep learning frameworks because it contains rich information that can be fused with spatial and environmental features for improved prediction accuracy.

4.5 Sensor-Based Data Collection

Sensor networks play a crucial role in capturing environmental and physiological parameters in real-time.

These sensors may measure:

- Soil moisture
- Temperature
- Humidity
- Light intensity
- Soil nutrient levels

Sensor-based systems are commonly integrated with Internet of Things (IoT) frameworks to enable continuous monitoring of crop conditions. When combined with imaging data, sensor information enhances multi-modal learning models by providing contextual environmental variables that improve prediction robustness and cross-environment generalization.

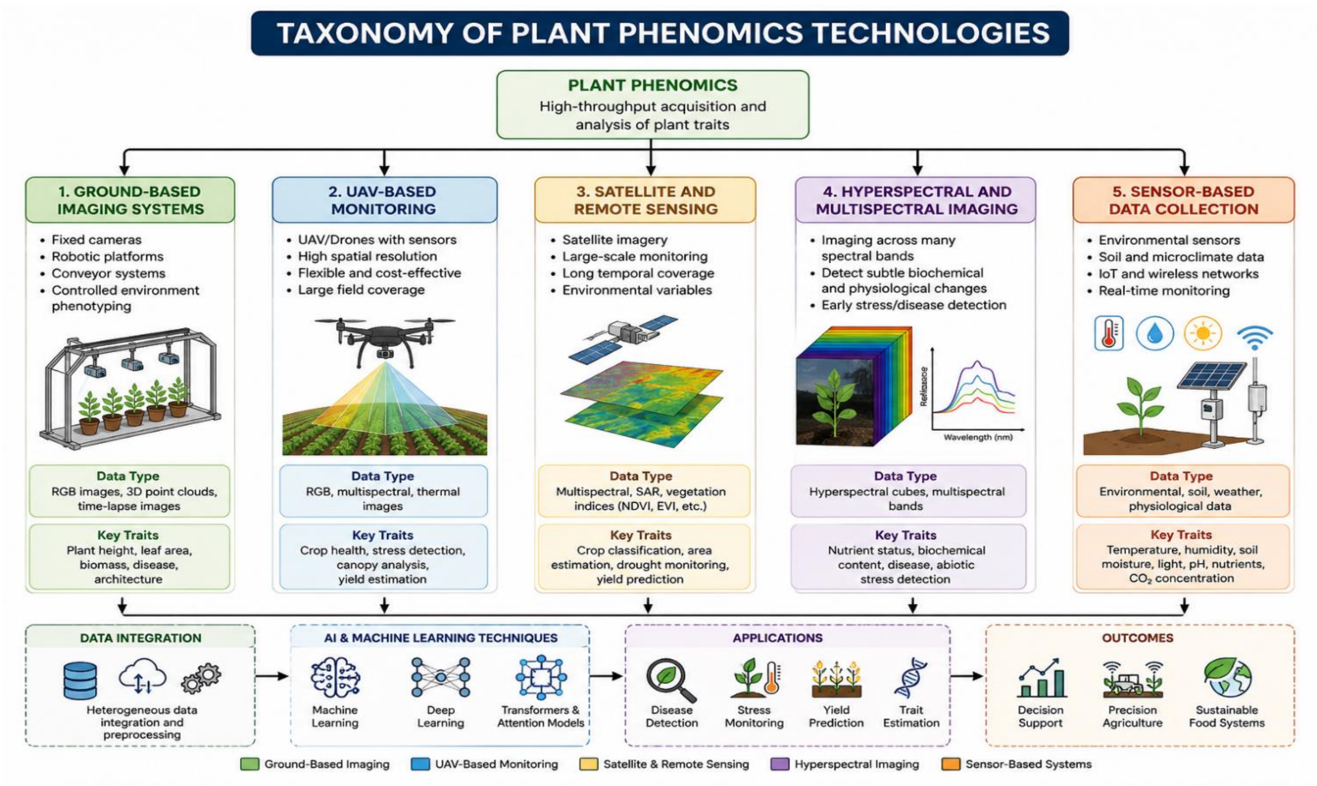

Figure 1. Taxonomy of plant phenomics technologies.

(Source: Authors owns creation)

Summary of Technologies

Together, these technologies form the foundation of high-throughput plant phenotyping systems. The integration of ground imaging, UAV platforms, remote sensing, hyperspectral data, and environmental sensors generates heterogeneous datasets. Multi-modal deep learning frameworks are particularly well-suited to analyze such complex data, enabling improved accuracy, scalability, and adaptability in agricultural applications.

5. Machine Learning Techniques in Plant Phenomics

Machine learning and deep learning techniques have significantly enhanced automated trait extraction and predictive modeling in plant phenomics. These approaches enable efficient analysis of high-dimensional data generated from imaging systems, remote sensing platforms, and sensor networks. The methods used in the literature can be broadly categorized into traditional machine learning, deep learning, and transfer learning approaches.

5.1 Traditional Machine Learning

Traditional machine learning algorithms have been widely applied in plant phenomics, particularly for classification and regression tasks using handcrafted features extracted from images or sensor data.

Support Vector Machines (SVM)

SVM is a supervised learning algorithm commonly used for classification tasks such as disease detection and stress identification. It performs well in high-dimensional feature spaces and is effective when the dataset size is moderate.

Random Forest (RF)

Random Forest is an ensemble learning method that constructs multiple decision trees and aggregates their outputs. It is widely used for crop classification, yield prediction, and feature importance analysis due to its robustness and interpretability.

K-Nearest Neighbors (KNN)

KNN is a simple instance-based learning algorithm used for classification based on similarity measures. It has been applied in early-stage phenotypic classification studies.

Gradient Boosting Methods

Algorithms such as Gradient Boosting Machines (GBM) and Extreme Gradient Boosting (XGBoost) have demonstrated strong performance in predictive modeling tasks, including yield estimation and trait prediction, due to their high accuracy and ability to handle complex nonlinear relationships.

Although traditional methods are computationally efficient and interpretable, their performance depends heavily on manually engineered features, limiting scalability for large and complex datasets.

5.2 Deep Learning Approaches

Deep learning methods automatically learn hierarchical feature representations from raw data, making them highly suitable for high-throughput phenotyping applications.

Convolutional Neural Networks (CNNs)

CNNs are the most widely used architecture in image-based plant phenomics.

They are highly effective in tasks such as:

- Plant disease detection
- Leaf segmentation
- Stress classification
- Trait estimation

CNNs automatically extract spatial features from images, reducing the need for manual feature engineering.

Recurrent Neural Networks (RNNs)

RNNs are designed for sequential data analysis and are useful in modeling temporal plant growth patterns and time-series environmental data.

Long Short-Term Memory (LSTM) Networks

LSTM networks, a specialized form of RNNs, are capable of learning long-term dependencies.

They are applied in:

- Growth prediction
- Seasonal yield forecasting
- Temporal phenotypic analysis

Transformer-Based Models

Transformers have recently gained attention due to their attention mechanisms, which allow models to capture long-range dependencies effectively. In plant phenomics, transformer architectures are increasingly used for:

- Multi-modal data integration
- Large-scale image analysis
- Cross-domain learning

Deep learning approaches generally outperform traditional methods when large annotated datasets are available, though they require significant computational resources.

5.3 Transfer Learning Approaches

Transfer learning has become an important strategy in plant phenomics due to limited labeled datasets. In this approach, models pre-trained on large-scale datasets (such as ImageNet) are fine-tuned on plant-specific data.

Advantages include:

- Reduced training time
- Improved accuracy with small datasets
- Better generalization performance

Transfer learning is particularly effective in plant disease detection and image-based classification tasks, where collecting large labeled agricultural datasets is challenging.
This approach enhances model performance while reducing data dependency, making it highly suitable for real-world agricultural applications.

Table 2. Overview of machine learning and deep learning techniques used in plant phenomics with representative studies.

Category	Method	Key Application in Phenomics	Strengths	Representative Citation (APA)
Traditional ML	Support Vector Machine (SVM)	Disease classification, trait prediction	Effective in high-dimensional data	Liakos et al., 2018
Traditional ML	Random Forest	Yield prediction, feature importance	Robust, interpretable	Liakos et al., 2018
Traditional ML	Gradient Boosting / XGBoost	Crop yield modelling	High predictive accuracy	Kamilaris & Prenafeta-Boldú, 2018
Deep Learning	Convolutional Neural Networks (CNNs)	Image-based disease detection	Automatic feature extraction	Barbedo, 2018
Deep Learning	CNN-based models	General agricultural vision tasks	High accuracy with large datasets	LeCun et al., 2015
Deep Learning	Multi-modal Fusion Models	Image + sensor integration	Improved robustness	Cui et al., 2022
Deep Learning	Transformer-based Models	Attention-based phenotyping	Captures long-range dependencies	Vaswani et al., 2017
Transfer Learning	Pre-trained CNN fine-tuning	Small dataset disease detection	Works with limited data	Barbedo, 2018

6. Multi-Modal Deep Learning Frameworks

Multi-modal deep learning frameworks have emerged as an effective approach for integrating heterogeneous agricultural data in high-throughput plant phenomics. Unlike single-modal systems that rely only on image data, multi-modal frameworks combine complementary information from multiple sources such as imaging, environmental measurements, genomic information, and temporal growth records. This integration improves predictive accuracy, robustness, and adaptability across varying agricultural environments (Kamilaris & Prenafeta-Boldú, 2018).

6.1 Types of Data Used

Images

Image-based data are the most widely used modality in plant phenomics. RGB, thermal, multispectral, and hyperspectral images provide detailed information regarding plant morphology, canopy structure, disease symptoms, and physiological conditions. Deep learning architectures, particularly convolutional neural networks (CNNs), are commonly employed for automated feature extraction and classification tasks (LeCun et al., 2015).

Environmental Data

Environmental variables such as temperature, humidity, rainfall, soil moisture, and nutrient availability play a critical role in plant growth and stress response. Integrating environmental information with imaging data enhances contextual understanding and improves prediction reliability under varying field conditions.

Genomic Data

Genomic data provide valuable insights into genotype-to-phenotype relationships. The integration of genomic information with phenotypic observations supports crop breeding programs, trait selection, and genetic improvement studies. Multi-modal frameworks enable simultaneous analysis of biological and environmental interactions.

Temporal Growth Data

Temporal growth data consist of sequential observations collected over time during different growth stages. Such data are useful for modeling developmental patterns, seasonal changes, and long-term crop behavior. Recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) networks are commonly applied for temporal sequence analysis.

6.2 Fusion Strategies

Fusion strategies are essential components of multi-modal frameworks because they determine how information from different modalities is integrated within the learning model.

Early Fusion

Early fusion combines raw data from multiple modalities before feature extraction. This method is relatively simple and computationally straightforward; however, it may be sensitive to noisy or incomplete data.

Feature-Level Fusion

Feature-level fusion independently extracts features from each modality and merges them into a unified representation. This approach is widely used in plant phenomics because it preserves modality-specific information while enabling integrated learning.

Late Fusion

Late fusion combines outputs or predictions from separate models trained on different modalities. This strategy offers modularity and flexibility but may fail to capture complex interdependencies among modalities.

Attention-Based Fusion

Attention-based fusion employs attention mechanisms to dynamically assign importance to different modalities and features. Transformer-based architectures have significantly improved multi-modal integration by effectively modeling long-range dependencies and complex feature interactions (Vaswani et al., 2017). These methods have shown promising performance in large-scale phenotyping applications.

6.3 Comparative Analysis of Fusion Methods

Different fusion strategies offer distinct advantages and limitations depending on the application, data complexity, and computational requirements.

Table 4. Comparative Analysis of Multi-Modal Fusion Strategies.

Fusion Strategy	Description	Advantages	Limitations	Common Applications
Early Fusion	Combines raw data before feature extraction	Simple implementation	Sensitive to noise and missing data	Small-scale phenotyping
Feature-Level Fusion	Merges extracted features from multiple modalities	Preserves modality-specific information	Moderate computational complexity	Disease detection, yield prediction
Late Fusion	Combines outputs from separate models	Flexible and modular	Limited cross-modal interaction	Ensemble learning systems
Attention-Based Fusion	Uses attention mechanisms for adaptive integration	High accuracy and adaptability	Computationally expensive	Large-scale multi-modal phenomics

Feature-level fusion remains the most commonly adopted strategy in current plant phenomics studies due to its balanced performance and implementation flexibility. However, recent research indicates that attention-based fusion and transformer architectures provide superior adaptability and improved generalization across diverse environmental conditions (Kamilaris & Prenafeta-Boldú, 2018).

7. Applications in Plant Phenomics

Artificial intelligence and multi-modal deep learning techniques have significantly expanded the applications of plant phenomics in modern agriculture. By integrating imaging systems, environmental sensing, and predictive modeling, AI-driven phenomics supports accurate crop monitoring, early stress identification, and data-driven breeding decisions. The major applications of AI-based plant phenomics are discussed below.

7.1 Disease Detection

Plant disease detection is one of the most widely studied applications of deep learning in agriculture. Early identification of diseases is essential for reducing crop losses and improving productivity. Convolutional Neural Networks (CNNs) have demonstrated strong performance in recognizing disease symptoms from leaf and canopy images.

Deep learning models are commonly applied for:

- Leaf disease classification
- Lesion segmentation

- Pathogen identification
- Disease severity estimation

The integration of UAV imagery and hyperspectral data further improves large-scale disease monitoring under field conditions. Transfer learning approaches are also widely used to overcome limitations associated with small labeled agricultural datasets (Barbedo, 2018).

7.2 Stress Detection (Drought, Salinity, Heat)

Abiotic stresses such as drought, salinity, and heat significantly affect crop growth and yield. AI-based phenomics systems enable early stress detection through the analysis of physiological and spectral changes in plants.

Commonly used data sources include:

- Thermal imaging
- Hyperspectral imagery
- Soil moisture sensors
- Environmental monitoring systems

Machine learning and deep learning models can identify subtle stress patterns before visible symptoms appear, enabling timely intervention and precision management. Multi-modal frameworks integrating environmental and imaging data improve stress prediction accuracy under diverse climatic conditions.

7.3 Yield Prediction

Accurate yield prediction is critical for agricultural planning, supply chain management, and food security assessment. AI-driven phenomics integrates temporal growth patterns, environmental variables, and imaging data to estimate crop yield more accurately.

Traditional machine learning methods such as Random Forest and Gradient Boosting are widely used for yield forecasting, while deep learning approaches improve prediction performance for complex datasets. UAV-based monitoring and remote sensing technologies provide large-scale field information that enhances predictive capability.

Multi-modal models combining weather data, spectral imagery, and crop growth records have shown improved robustness and generalization compared to single-modal systems (Kamilaris & Prenafeta-Boldú, 2018).

7.4 Trait Estimation

Trait estimation involves the quantitative measurement of plant characteristics such as:

- Plant height
- Leaf area
- Biomass
- Canopy structure
- Chlorophyll content

Deep learning methods enable automated extraction of phenotypic traits from high-resolution imagery and sensor data. CNN-based segmentation models are particularly effective for image-based trait analysis.

Hyperspectral imaging and LiDAR technologies further enhance the precision of non-destructive trait estimation. These approaches support large-scale phenotyping and reduce manual labor requirements.

7.5 Breeding Support Systems

AI-based phenomics plays a vital role in modern plant breeding programs by enabling efficient genotype-to-phenotype analysis. Multi-modal frameworks integrating genomic, environmental, and phenotypic data assist breeders in selecting high-performing crop varieties.

Applications include:

- Genomic prediction
- Trait association analysis
- Stress-tolerant variety identification
- Accelerated breeding cycles

Machine learning models improve the identification of complex trait relationships and support data-driven breeding decisions. Such systems contribute to the development of climate-resilient and high-yield crop varieties.

Table 5. Major Applications of AI-Based Plant Phenomics.

Application Area	Common Data Sources	AI Techniques Used	Major Benefits
Disease Detection	RGB images, hyperspectral data	CNN, Transfer Learning	Early disease identification
Stress Detection	Thermal imaging, environmental sensors	Deep learning, multi-modal fusion	Early stress monitoring
Yield Prediction	UAV imagery, weather data	Random Forest, LSTM	Improved yield estimation
Trait Estimation	RGB images, LiDAR, hyperspectral imaging	CNN, segmentation models	Automated trait extraction
Breeding Support Systems	Genomic + phenotypic data	Multi-modal learning	Faster crop improvement

8.1 Classification Metrics

Classification metrics are commonly used in applications such as disease detection, stress classification, and crop type identification.

Accuracy

Accuracy measures the proportion of correctly classified samples among the total observations.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Several deep learning studies in plant disease detection have reported classification accuracies exceeding 95% under controlled conditions (Barbedo, 2018). CNN-based models trained on large image datasets have achieved accuracy values ranging from 90% to 99% depending on crop type and disease complexity.

Precision

Precision evaluates the proportion of correctly predicted positive observations.

$$\text{Precision} = \frac{TP}{TP + FP}$$

High precision is important in agricultural diagnostics to minimize false disease alarms. Precision values between 0.88 and 0.97 have been reported in image-based disease classification systems.

Recall

Recall measures the model's ability to correctly identify positive cases.

$$\text{Recall} = \frac{TP}{TP + FN}$$

In stress detection applications, recall values above 90% are often considered effective for early intervention systems.

F1-Score

The F1-score combines precision and recall into a single metric.

$$\text{F1-score} = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Recent multi-modal deep learning frameworks have reported F1-scores ranging from 0.91 to 0.98 in disease and stress classification tasks.

Area Under the Curve (AUC)

AUC evaluates the discriminatory capability of classification models across different thresholds. Advanced transformer-based phenotyping systems have achieved AUC values above 0.95, indicating strong classification reliability.

8.2 Regression Metrics

Regression metrics are widely used for yield prediction, biomass estimation, and trait quantification.

Root Mean Square Error (RMSE)

RMSE measures prediction error magnitude.

$$RMSE = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Lower RMSE values indicate better predictive performance. UAV-based yield prediction studies commonly report RMSE values between 5% and 15% depending on environmental variability**.**

Mean Absolute Error (MAE)

MAE calculates the average absolute difference between predicted and actual values.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$$

Deep learning regression models in crop yield forecasting have demonstrated MAE reductions of approximately 10–20% compared to conventional statistical approaches.

Coefficient of Determination (R^2)

R^2 measures the proportion of variance explained by the model.

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

Many recent phenomics studies report R^2 values above 0.85 for biomass estimation and yield prediction using multi-modal frameworks.

8.3 Segmentation Metrics

Segmentation metrics are primarily used in image-based plant phenotyping tasks such as leaf segmentation, canopy extraction, and disease lesion identification.

Intersection over Union (IoU)

IoU evaluates the overlap between predicted and ground-truth segmentation regions.

$$IoU = \frac{Area\ of\ Overlap}{Area\ of\ Union}$$

Advanced segmentation models such as U-Net and Mask R-CNN have achieved IoU scores between 0.80 and 0.95 in leaf and canopy segmentation tasks.

Dice Coefficient

The Dice coefficient measures similarity between predicted and actual segmented regions.

$$Dice = \frac{2 | A \cap B |}{| A | + | B |}$$

Recent deep learning segmentation studies have reported Dice scores exceeding 0.90, indicating highly accurate plant structure segmentation.

Table 6. Common Evaluation Metrics in Plant Phenomics Studies.

Task Type	Metric	Purpose	Typical Reported Range
Classification	Accuracy	Overall classification performance	90%–99%
Classification	Precision	Positive prediction reliability	0.88–0.97
Classification	Recall	Detection sensitivity	0.90–0.98
Classification	F1-score	Balanced precision and recall	0.91–0.98
Classification	AUC	Model discrimination ability	>0.95
Regression	RMSE	Prediction error magnitude	5%–15%
Regression	MAE	Average prediction deviation	10%–20% improvement
Regression	R^2	Variance explanation capability	>0.85
Segmentation	IoU	Segmentation overlap quality	0.80–0.95
Segmentation	Dice Coefficient	Segmentation similarity	>0.90

9. Comparative Analysis of Existing Studies

A comparative analysis of recent studies highlights the growing importance of AI and deep learning in plant phenomics. Most studies focus on disease detection, yield prediction, stress monitoring, and trait estimation using image-based and multi-modal datasets. Deep learning models generally outperform traditional machine learning approaches due to their ability to automatically learn complex features from high-dimensional data.

9.1 Summary of Reviewed Studies

Table 7. Summary of Existing Studies in Plant Phenomics.

Study	Model Used	Application	Performance	Limitation
Barbedo (2018)	CNN + Transfer Learning	Disease Detection	Accuracy: 95%–99%	Limited field data
Liakos et al. (2018)	SVM, RF	Precision Agriculture	Accuracy >90%	Small datasets
UAV-Based Studies	Random Forest, LSTM	Yield Prediction	R^2 >0.85	Weather sensitivity
U-Net Models	CNN Segmentation	Trait Estimation	Dice >0.90	High computation
Transformer Models	Vision Transformers	Multi-modal Learning	AUC >0.95	Computational cost

9.2 Model and Dataset Comparison

Traditional machine learning methods such as SVM and Random Forest are effective for structured agricultural datasets, whereas deep learning models perform better in image-based applications. CNNs are widely used for disease detection and segmentation, while LSTM and transformer-based models are preferred for temporal and multi-modal analysis.

Most studies use:

- RGB images
- UAV imagery
- Hyperspectral data
- Environmental sensor data

However, many datasets are small and collected under controlled conditions, limiting generalization in real-world agricultural environments.

9.3 Performance Analysis

Recent studies report:

- Classification accuracy above 95% for disease detection
- R^2 values greater than 0.85 for yield prediction
- Dice coefficients above 0.90 for segmentation tasks

Multi-modal frameworks consistently show better performance than single-modal approaches due to improved feature integration and contextual understanding.

9.4 Strengths and Weaknesses

Strengths

- High prediction accuracy
- Automated feature extraction
- Efficient large-scale phenotyping

Weaknesses

- Limited annotated datasets
- High computational requirements
- Poor model interpretability
- Limited cross-environment adaptability

10. Challenges and Limitations

Despite significant advancements in AI and multi-modal deep learning for plant phenomics, several challenges continue to limit their large-scale adoption and practical implementation. The integration of heterogeneous data sources such as imaging, environmental, and genomic data increases preprocessing complexity and affects model consistency. Many studies rely on small labeled datasets, which can lead to overfitting and reduced generalization across different crops and environmental conditions. In addition, deep learning models often lack interpretability, making their predictions difficult to explain in real-world agricultural decision-making. High computational requirements and expensive hardware infrastructure further restrict deployment in resource-limited farming environments. These limitations highlight the need for robust, interpretable, and computationally efficient AI frameworks for future plant phenomics applications (Barbedo, 2018; Kamilaris & Prenafeta-Boldú, 2018).

Table 8. Major Challenges in AI-Based Plant Phenomics.

Challenge	Impact
Data heterogeneity	Difficult integration of multi-source data
Small labeled datasets	Reduced model robustness and accuracy
Overfitting	Poor performance on unseen data
Limited generalization	Reduced adaptability across environments
Model interpretability	Limited transparency and user trust
Computational complexity	High processing and hardware requirements
Deployment challenges	Limited large-scale field implementation

11. Future Research Directions

Future research in AI-based plant phenomics should focus on developing more scalable, interpretable, and adaptive learning systems for real-world agricultural applications. Several emerging technologies and research directions have the potential to significantly improve the efficiency and robustness of high-throughput phenotyping systems (Kamilaris & Prenafeta-Boldú, 2018).

- **Self-supervised learning:** Enables models to learn meaningful representations from unlabeled agricultural data, reducing dependency on manually annotated datasets.
- **Foundation models for agriculture:** Large-scale pre-trained models can improve transferability, scalability, and generalization across crops, environments, and phenotyping tasks.
- **Federated learning:** Supports collaborative model training across multiple institutions or farms without centralized data sharing, improving privacy and data security.
- **Edge AI deployment:** Allows real-time inference directly on UAVs, mobile devices, and field sensors with lower latency and reduced internet dependency.
- **Explainable Artificial Intelligence (XAI):** Improves model transparency and interpretability, increasing user trust and supporting better agricultural decision-making.

- **Climate-resilient phenotyping systems:** Integration of environmental, genomic, and temporal data can support the development of crop varieties adapted to changing climatic conditions.

Overall, future AI-driven phenomics systems should emphasize robustness, computational efficiency, scalability, and sustainability for practical deployment in precision agriculture.

12. CONCLUSION

This systematic review examines recent advancements in artificial intelligence (AI) and multi-modal deep learning approaches in high-throughput plant phenomics. The study highlights the increasing role of machine learning, deep learning, UAV-based monitoring, hyperspectral imaging, and sensor-integrated systems in improving agricultural analysis and crop management. Deep learning models such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and transformer-based architectures have shown strong performance in disease detection, stress monitoring, yield prediction, and trait estimation.

The review emphasizes the importance of multi-modal AI frameworks that integrate heterogeneous data sources including imaging, environmental, genomic, and temporal information. Compared with single-modal systems, multi-modal approaches provide improved prediction accuracy, robustness, and adaptability under diverse agricultural conditions. Feature-level and attention-based fusion strategies were identified as effective methods for multi-source data integration.

Several challenges remain, including small labeled datasets, overfitting, limited generalization, computational complexity, and poor model interpretability. The lack of standardized large-scale agricultural datasets also affects benchmarking and reproducibility. Future research should focus on scalable and explainable AI systems using self-supervised learning, foundation models, federated learning, and Edge AI technologies to support sustainable and climate-resilient precision agriculture.

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