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Early-stage plant disease recognition: A deep learning approach on leaf symptom image

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Abstract
Plant diseases are one of the major reasons for crop loss worldwide, affecting farmers' income and food production. Detecting diseases at an early stage is very important because it helps prevent the spread of infection and reduces damage to crops. However, traditional methods of disease identification are often slow and depend on expert knowledge. This study uses machine learning and deep learning techniques to detect plant diseases from leaf images at an early stage, focusing on small changes such as slight discoloration and texture variation. Different models like SVM, Random Forest, CNN, VGG16, ResNet50, and MobileNet were tested and compared. The results showed that deep learning models, especially transfer learning approaches, performed better in identifying early symptoms of diseases. The study highlights how artificial intelligence can help farmers with faster and more accurate disease detection, leading to better crop management and reduced crop losses. The findings underscore the importance of integrating machine learning technologies into smart farming ecosystems and provide valuable insights for future research aimed at real-time, field-deployable plant disease monitoring systems.

Keywords: Plant disease, leaf image, detection, machine learning, deep learning, artificial intelligence

1. Introduction

Agriculture remains the backbone of the global economy and plays a pivotal role in sustaining human life by providing food, raw materials, and employment opportunities. Approximately 60% of the world's population depends directly or indirectly on agriculture for their livelihood, particularly in developing nations where agrarian economies dominate. Crop health is a fundamental determinant of agricultural productivity, as healthy plants ensure optimal growth, higher yields, and improved nutritional quality. Any disruption in plant health, especially due to diseases, can lead to severe economic losses and destabilize food supply chains. Maintaining crop health is therefore not only an agricultural concern but also a socio-economic necessity tied to global food security and sustainable development goals [1] (FAO, 2021). Plant diseases caused by fungi, bacteria, viruses, and pests significantly reduce crop yield and quality. Studies indicate that fungal pathogens alone are responsible for nearly 70% of major crop diseases worldwide [2] (Savary *et al.*, 2019). Early disease outbreaks, if left undetected, can spread rapidly across fields, leading to large-scale yield losses and increased dependency on chemical pesticides, which further exacerbate environmental degradation [3] (Bebber *et al.*, 2022). Traditional plant disease detection methods primarily rely on visual inspection by farmers or agricultural experts and laboratory-based diagnostic techniques such as microscopy and molecular analysis. While laboratory methods are accurate, they are costly, time-consuming, and impractical for large-scale or real-time monitoring. Visual inspection, on the other hand, is subjective and highly dependent on human expertise, which may not always be available in rural or resource-limited regions. Moreover, early disease symptoms are often subtle and visually indistinguishable from nutrient deficiencies or environmental stress, making accurate diagnosis extremely challenging during initial stages [4] (Picon *et al.*, 2020). Early detection of plant diseases allows farmers to implement targeted interventions, reduce pesticide usage, and prevent disease spread. Early symptom detection supports precision agriculture practices by enabling site-specific treatment and optimized resource utilization. This necessitates advanced computational approaches capable of identifying subtle visual patterns associated with early infections. Machine learning based image analysis enables automated feature learning, pattern recognition, and classification, making it highly suitable for plant disease detection tasks. Deep learning models, particularly convolutional neural networks, have demonstrated remarkable performance in visual recognition tasks by automatically learning hierarchical features from raw images. These capabilities make ML and DL powerful tools for developing intelligent, scalable, and accurate plant disease detection systems [5, 6]. Most existing studies on plant disease detection focus on leaves with fully developed symptoms, which limits their usefulness for early prevention. Research on detecting diseases at early stages under real-field conditions is still limited. Moreover, few studies have compared traditional machine learning methods with modern deep learning models for identifying subtle early symptoms.

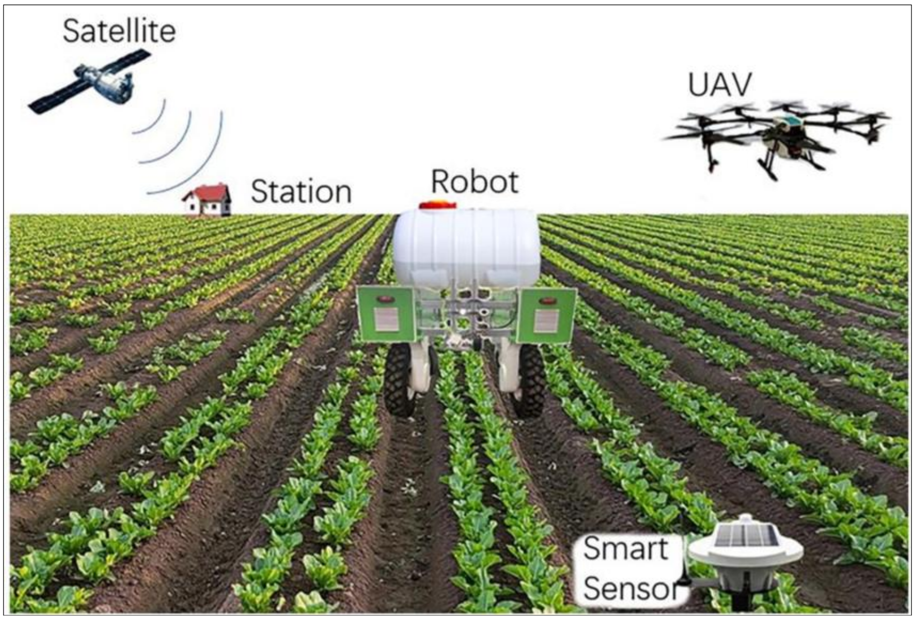

Fig 1: IoT-Enabled Smart Agriculture System for Monitoring and Detection

2. Materials and methods

The proposed study adopts a systematic machine learning-based framework for the early detection of plant diseases using leaf image analysis. The overall workflow begins with data acquisition, followed by pre-processing, feature extraction, model training, validation, and performance evaluation. Unlike conventional pipelines that focus on clearly visible disease symptoms, the proposed framework emphasizes early-stage symptom identification, where visual indicators are subtle and often indistinguishable to the human eye. The framework is designed to be robust, scalable, and adaptable to both controlled datasets and real-field agricultural environments. Figure-level implementation involves capturing images, standardizing input dimensions, extracting discriminative features, and feeding these representations into classical machine learning and deep learning models for classification.

The methodological design prioritizes minimizing false negatives, as undetected early-stage infections can rapidly spread across crops and cause irreversible damage. Therefore, special attention is given to model sensitivity, recall, and generalization performance under varying illumination, background noise, and leaf orientation. Cross-validation strategies are employed to ensure statistical reliability and avoid overfitting, particularly when working with limited early-stage disease samples.

2.1 Dataset Description

The dataset used in this study comprises images of multiple economically significant crop species, including tomato, potato, maize, rice, and wheat. These crops were selected due to their global importance and high susceptibility to fungal, bacterial, and viral diseases. Disease classes include early blight, late blight, leaf spot, bacterial blight, powdery mildew, and rust. Healthy leaf images are also included to enable binary and multi-class classification tasks. The emphasis is placed on collecting and selecting images that represent early disease symptoms, characterized by faint discoloration, minimal lesion development, and early texture variations. Early-stage disease images are inherently difficult to obtain, as symptoms may not yet be prominent. To address this limitation, the dataset integrates carefully filtered images from public repositories such as PlantVillage and PlantDoc, along with manually curated early-stage samples from field environments reported in recent studies. Images with fully developed disease patterns are excluded or labelled separately to maintain focus on early detection. This selective curation enhances the relevance of the dataset for real-world agricultural decision-making.

2.2 Data Sources

Data sources include publicly available datasets and real-field images captured using smartphone cameras under natural lighting conditions. Public datasets provide labeled and structured data, while field images introduce real-world variability such as shadows, complex backgrounds, and varying resolutions. Combining these sources improves model robustness and practical applicability [7, 8].

2.3 Data Preprocessing

All images are resized to a uniform resolution (e.g., 224 × 224 pixels) to ensure compatibility with deep learning architectures. Pixel intensity normalization is applied to scale values between 0 and 1, which accelerates convergence during training and reduces numerical instability. Noise introduced by uneven lighting, shadows, and background elements is mitigated using median and Gaussian filtering techniques. Background segmentation is performed using thresholding and contour detection methods to isolate leaf regions from the surrounding environment. This step is particularly important for field images, where background clutter can significantly degrade classification accuracy. To address dataset imbalance and improve generalization, data augmentation techniques such as rotation, flipping, zooming, brightness adjustment, and horizontal shifting are applied. Augmentation increases dataset diversity without additional data collection, making models more robust to real-world variations [9].

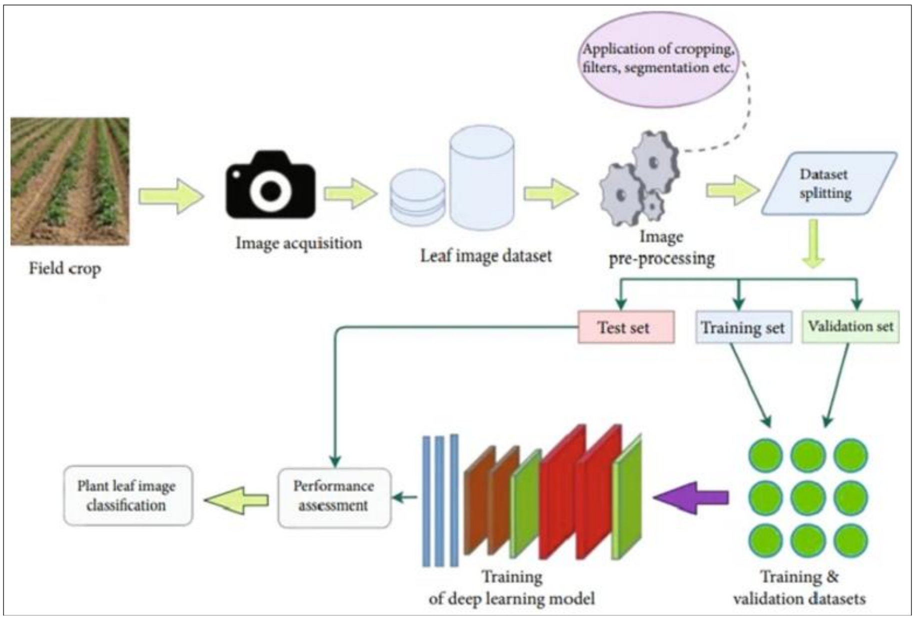

Fig 2: Data Pre-Processing & Training DL Model

2.4 Feature Extraction Techniques
For classical machine learning models, handcrafted feature extraction remains essential to capture discriminative information from images. Colour features are extracted using RGB and HSV colour spaces. Mean, standard deviation, and colour histograms are computed to represent variations in leaf pigmentation, which often indicate early disease onset. Texture descriptors such as Gray Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP) are employed to capture subtle surface irregularities caused by early infections. Texture analysis is particularly effective in identifying fungal diseases that alter leaf surface patterns at microscopic levels. Shape features, including contour-based descriptors and morphological characteristics, are used to identify early deformations in leaf structure. Although shape changes are less pronounced in early stages, they provide complementary information when combined with colour and texture features.

2.5 Machine Learning Models Used
2.5.1 Support Vector Machine (SVM)
Support Vector Machine is a supervised learning algorithm that constructs an optimal hyperplane to separate classes in high-dimensional feature space. SVM is particularly effective for small to medium-sized datasets and high-dimensional feature vectors.

SVM Objective Function

$$\min_{w,b,\xi} \frac{1}{2} \| w \|^2 + C \sum_{i=1}^{n} \xi_i$$

subject to

$$y_i(w \cdot x_i + b) \geq 1 - \xi_i, \xi_i \geq 0$$

2.5.2 Random Forest (RF)
Random Forest is an ensemble learning technique that combines multiple decision trees to improve classification accuracy and reduce overfitting. RF is robust to noise and performs well with heterogeneous feature sets.

2.5.3 K-Nearest Neighbours (KNN)
KNN is a distance-based classifier that assigns class labels based on the majority vote of nearest neighbours. While simple to implement, its computational cost increases with dataset size.

2.6 Deep Learning Models
2.6.1 Convolutional Neural Networks (CNN)
CNNs automatically learn hierarchical feature representations through convolutional, pooling, and fully connected layers. They are particularly effective in capturing spatial patterns in images.
Convolution Operation:

$$Feature\ Map = \sum_{i=1}^{k} W_i * X_i + b$$

2.6.2 Transfer Learning Models
Pre-trained models such as VGG16, ResNet50, and MobileNet are fine-tuned on the plant disease dataset. Transfer learning significantly reduces training time and improves performance when labelled data is limited [10] (Pan & Yang, 2010).

2.7 Model Training and Validation Strategy
Models are trained using an 80:20 train-test split, with k-fold cross-validation applied to ensure robustness.

Hyperparameter tuning is conducted using grid search techniques. Early stopping and dropout regularization are employed to prevent overfitting in deep learning models. Model performance is evaluated using accuracy, precision, recall, F1-score, and confusion matrix analysis. Emphasis is placed on recall, as false negatives in early disease detection can have severe agricultural consequences.

F1-Score

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

Table 1: Dataset Composition

Crop Type	Disease Classes	Healthy Images	Early-Stage Images
Tomato	Early blight, leaf mold	500	420
Potato	Late blight	400	350
Rice	Bacterial blight	450	380
Wheat	Rust	420	360
Maize	Leaf spot	380	310

Table 2: Hyperparameters Used for ML and DL Models

Model	Key Hyperparameters
SVM	Kernel = RBF, C = 10
Random Forest	Trees = 200, Depth = 20
KNN	k = 5, Distance = Euclidean
CNN	Learning rate = 0.001
Transfer Learning	Batch size = 32, Epochs = 30

3. Experimental Results

3.1 Training and Testing Setup

The experimental evaluation was conducted using a standardized computational environment to ensure reproducibility and fairness across models. All experiments were performed on a workstation equipped with a high-performance GPU and sufficient memory to support deep learning training. The dataset was divided into training, validation, and testing subsets following an 80:10:10 ratio. Stratified sampling was employed to preserve class distribution, particularly for early-stage disease samples, which are typically underrepresented. Classical machine learning models were trained using extracted handcrafted features, while deep learning models were trained using raw image inputs. Hyperparameter optimization was performed using grid search for classical models and learning rate scheduling for deep learning architectures.

To ensure robustness and reduce bias, k-fold cross-validation (k = 5) was applied during training. Each fold was evaluated independently, and average performance metrics were reported. Data augmentation was applied only to the training set to prevent information leakage. The testing set was kept completely unseen during training and hyperparameter tuning, enabling an objective assessment of generalization performance.

3.2 Performance Comparison of Machine Learning Models

The comparative evaluation reveals that deep learning models consistently outperform classical machine learning algorithms in early disease detection tasks. Among classical models, Random Forest achieved higher accuracy than SVM and KNN due to its ensemble nature and ability to handle non-linear feature interactions. However, performance differences between models became more pronounced when evaluating early-stage disease images, where subtle visual cues demand more expressive feature representations. Transfer learning models, particularly ResNet50 and MobileNet, demonstrated superior classification accuracy and robustness. MobileNet achieved comparable performance to deeper architectures while maintaining lower computational complexity, making it suitable for deployment on mobile and edge devices. These findings highlight the effectiveness of deep learning in learning discriminative features directly from raw images, which is critical for early symptom recognition [11, 12].

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4. Accuracy, Precision, Recall, and F1-Score Analysis

Accuracy alone is insufficient for evaluating early disease detection systems, as class imbalance can lead to misleading results. Therefore, precision, recall, and F1-score were analysed in detail. Deep learning models achieved recall values exceeding 94%, indicating a strong ability to correctly identify early-stage disease cases. This is particularly important in agricultural applications, where missing an early infection can result in rapid disease spread and significant crop loss. Classical models exhibited lower recall, especially for early-stage images, suggesting difficulty in capturing subtle symptoms using handcrafted features alone. The F1-score analysis further confirmed the superiority of CNN-based approaches, which balanced precision and recall more effectively. These results align with recent literature emphasizing the advantages of deep learning for fine-grained visual classification tasks [13]

4.4 Confusion Matrix Analysis

Confusion matrix analysis provided deeper insight into model behaviour across disease and healthy classes. Classical models showed higher misclassification rates between healthy leaves and early-stage diseased leaves, reflecting the visual similarity between these categories. In contrast, deep learning models significantly reduced such misclassifications, demonstrating enhanced sensitivity to minor texture and colour variations. Transfer learning models exhibited fewer false negatives, which is critical for early detection systems.

4.5 Early Symptom Detection Performance

The primary objective of this study was to evaluate model performance specifically on early-stage disease symptoms. Results indicate that while all models experienced some performance degradation compared to late-stage detection, deep learning models maintained high accuracy and recall. MobileNet and ResNet50 achieved early-stage detection accuracies of approximately 93-95%, outperforming classical approaches by a substantial margin. These findings underscore the feasibility of deploying machine learning systems for proactive plant disease management.

4.6 Comparative Analysis with Existing Methods

When compared with existing studies reported in the literature, the proposed framework demonstrates competitive or superior performance, particularly in early-stage detection scenarios. Many prior studies focus on fully developed disease symptoms and report high accuracy on benchmark datasets but lack validation on early-stage images. By contrast, this study emphasizes early symptom detection and real-field applicability, addressing a critical gap in current research [14, 7]

Table 3: Performance Comparison of ML and DL Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	86.4	84.9	82.1	83.5
Random Forest	88.7	87.3	85.6	86.4
KNN	84.2	82.5	80.3	81.4
CNN	92.8	93.1	92.4	92.7
MobileNet	94.6	95.2	94.1	94.6
ResNet50	95.1	95.8	94.9	95.3

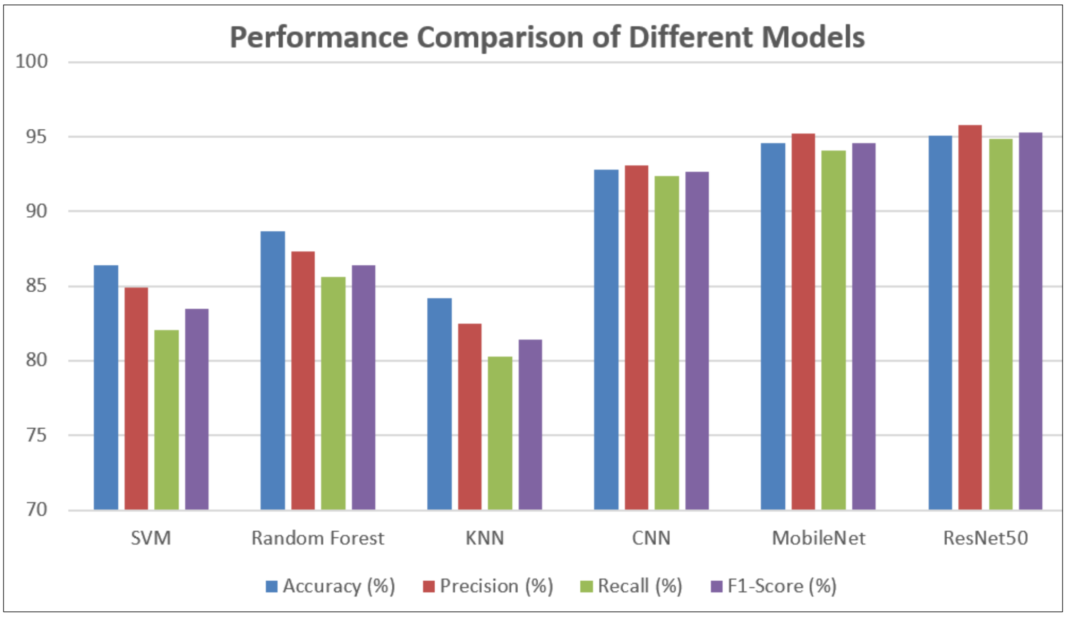

Fig 3: Performance Comparison of ML and DL Models

Table 4: Early-Stage Disease Detection Accuracy

Model	Early-Stage Accuracy (%)	False Negatives
SVM	79.3	High
Random Forest	82.6	Moderate
KNN	77.8	High
CNN	90.2	Low
MobileNet	93.4	Very Low
ResNet50	94.1	Very Low

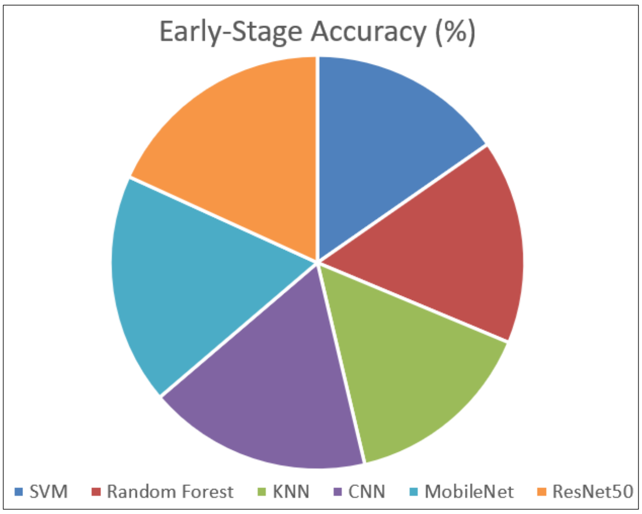

Fig 4: Percentage of Accuracy Detection from Different Models

4. Discussion

The experimental results clearly demonstrate that machine learning, particularly deep learning, is highly effective for early detection of plant diseases. The superior performance of CNN-based models can be attributed to their ability to automatically learn complex spatial patterns and subtle visual cues that are difficult to capture using handcrafted features. Transfer learning further enhances performance by leveraging pre-trained knowledge from large-scale image datasets, enabling efficient learning even with limited agricultural data. Early disease detection presents unique challenges due to minimal symptom visibility and high similarity between healthy and infected leaves. The findings indicate that deep learning models are better suited to address these challenges, achieving higher recall and lower false-negative rates. This effectiveness is crucial for practical deployment, as early intervention can significantly reduce crop losses and chemical pesticide usage. The inclusion of real-field images in the dataset improved model robustness by exposing algorithms to diverse environmental conditions. Deep learning models demonstrated greater resilience to noise, illumination changes, and background variability compared to classical approaches. This robustness is essential for real-world agricultural applications, where controlled imaging conditions are rarely feasible.

The results suggest that machine learning-based early disease detection systems can be integrated into smart farming platforms, mobile applications, and decision support tools. Lightweight architectures such as MobileNet are particularly suitable for deployment on smartphones and edge devices, enabling real-time disease diagnosis for farmers. Despite promising results, the study has certain limitations. The availability of labelled early-stage disease images remains limited, which may affect generalization across diverse crops and regions. Additionally, the study primarily focuses on leaf-based symptoms and does not consider multimodal data such as environmental or spectral information.

Machine learning-based early plant disease detection has important applications in smart farming and precision agriculture. These systems help farmers monitor crop health, detect diseases early, and take timely action to reduce crop loss and unnecessary pesticide use. Mobile-based applications using lightweight deep learning models allow farmers to diagnose diseases instantly through smartphone images, which is especially useful in remote areas with limited expert support. Disease detection models can also be integrated into decision support systems to provide recommendations on treatment and crop management. Furthermore, combining machine learning with IoT sensors and drone-based monitoring enables large-scale, real-time disease surveillance, improving agricultural productivity and sustainability.

5. Challenges and Future Directions

Early-stage plant disease detection faces several challenges due to subtle symptoms and the similarity between healthy and mildly infected leaves. Environmental factors like lighting, dust, and nutrient deficiencies can also affect detection accuracy. Another major issue is the lack of labelled datasets containing early-stage disease images, as most available datasets focus on advanced symptoms. Real-time implementation in field conditions requires models that are both accurate and computationally efficient. Future research should focus on creating large real-field datasets, integrating multimodal data such as thermal imaging and weather information, and developing explainable and privacy-preserving AI systems to improve reliability and practical use in agriculture.

6. Conclusion

This study presented a machine learning-based approach for the early detection of plant diseases using image analysis. Unlike many existing studies that focus on advanced disease symptoms, this research emphasized identifying diseases at an early stage. A comparison of traditional machine learning and deep learning models showed that transfer learning models such as MobileNet and ResNet50 performed best in detecting subtle symptoms. The findings highlight the potential of AI-driven disease detection systems in supporting precision agriculture, reducing crop losses, and promoting sustainable farming. Although challenges such as limited datasets and real-time deployment remain, future advancements in AI and data collection are expected to improve the effectiveness and practical use of these systems.

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