Studies in Science of Science | ISSN:1003-2053
https://doi.org/10.5281/zenodo.18851136

A Hybrid Machine Learning Algorithm to Identify Diseases of Okra Plant in South Gujarat: A Systematic Review

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Received: Jan 17, 2026 **Accepted:** Feb 17, 2026 **Published:** Mar 03, 2026

Abstract

Okra (Abelmoschus esculentus L.), an economically important vegetable in South Gujarat which faces reduced productivity due to multiple foliar diseases effected by fungal, bacterial, viral and pest-associated pathogens. Large scale field deployment is hindered by the labor-intensive and subjective characteristic of traditional disease detection. Automated image-based diagnosis is now possible by current developments in machine learning and deep learning however standalone models are frequently unreliable in real-world scenarios because of interclass similarity, backdrop complexity, illumination variations and a lack of labelled data.
This systematic review studies hybrid ML and DL approaches for plant leaf disease detection which is focusing on okra and South Gujarat agro-climatic conditions. Articles published between 2019 and 2026 were analyzed which is covering hybrid frameworks that integrate CNNs, vision transformers, handcrafted feature extraction, classical ML classifiers, ensemble learning and segmentation/localization models. The review estimate datasets, real-time applicability, model, feature fusion and performance measures. Output indicates that hybrid frameworks perform better than single models in call of accuracy and generalization however, there are still shortcomings including a dearth of okra datasets relevant to a given location, a dearth of early-stage and multi-disease detection studies, poor interpretability and a weak interaction with precision agriculture systems.

Keywords: Okra leaf disease detection, Hybrid machine learning, Deep learning (CNN, ViT), Feature fusion, Segmentation and localization, Precision agriculture.

1. Introduction

Specially in growing rural areas, plant diseases become a significant barrier to worldwide agricultural productivity, endangering in both food security and economic sustainability. Because of the foliar infections directly affect crops' photosynthetic efficiency, they are among the most harmful. If they are not detected and treated in their early stages, they can result in large losses in production and quality.
In South Gujarat, Vegetable crop okra (Abelmoschus esculentus L.) is hugely cultivated in tropical and subtropical areas. The crop is extremely vulnerable to a variety of diseases brought on by bacterial, viral, fungal, and insect-transmitted infections, all of which lower market value and productivity [28]. High humidity, erratic temperatures and the monsoon all three contribute to South Gujarat's agricultural circumstances which exacerbate disease prevalence and make efficient disease monitoring more difficult. Generally, Conventional techniques of diagnosing plant diseases rely mostly on laboratory-based pathology analysis or visual inspection by agricultural specialists. While effective to a certain extent, these approaches are time consuming, subjective, labour intensive and impractical for large-scale or real-time field deployment [13,30,31]. Due to their frequent lack of timely access to professional diagnostic services small and marginal farmers who make up a sizable segment of the agricultural

workforce in areas like South Gujarat which is often delay intervention and use excessive amounts of pesticides. These constraints have prompted the use of computer vision and artificial intelligence (AI) approaches in automated, image-based illness diagnosis systems [18,22]. Due to their capacity to directly learn unfair features from visual data by machine learning (ML) and deep learning (DL) approaches which have garnered significant attention in recent years for automated plant disease identification. Generally, Early research used handcrafted feature extraction methods such as color, texture and shape descriptors which combination with conventional machine learning classifiers like support vector machines (SVM), k-nearest neighbors (KNN) and random forests [23,24,30]. Although these methodologies showed acceptable level of performance in the controlled laboratory conditions, their reliance on manual feature engineering limited adaptability and robustness of the methodology in the real life scenarios.

Deep learning is particularly convolutional neural networks (CNNs) it has considerably enhanced the field of plant disease categorization. CNN based architectures automatically get hierarchical features from leaf pictures and give resulting in high classification accuracies across different crops and disease types [1,2,14]. Globally speaking, experimental researches have shown the usefulness of convolutional neural networks (CNNs) in plant disease diagnosis, thus showing their advantages over traditional machine learning methods for feature interpretability and quantitative measurement [5,18,19]. Despite of these gains, CNN based architecture continuously experience performance loss when subjected to complex backdrops, light fluctuations, occlusion and inter-class illness similarity. which are common in real-world agricultural settings [19,31]. To overcome the inherent drawbacks of standalone deep learning models and researchers have continuously find hybrid machine learning approaches that integrate multiple methodologies within a combine framework. Hybrid models generally combine with deep learning feature removal with classical ML classifiers, handcrafted features, ensemble strategies or multi stage processing pipelines to increase stability and adaptation [6,12,16].For example, CNN extracted deep features have been competently combined with SVM and random forest classifiers for improving classification stability, particularly when training data are within scope [9,25].

The combination of handcraft methods with deep learning features helps to demonstrated improve bias of visually similar disease classes for Feature level fusion methods [26]. Most of, vision transformers (ViTs) have emerged as powerful alternatives to CNNs for image-based plant disease detection because of their ability to identify long range dependencies and global contextual information [7,21]. Hybrid CNN–ViT models attached the local feature extraction ability of CNNs and the overall attention methodology of transformers and accomplish enhanced performance across diverse datasets [11,21]. Ensemble learning plan which combine guess from multiple heterogeneous architecture have advance improved detection accuracy and robustness, particularly in noisy and unbalanced datasets [10,12]. Furthermore, hybrid frameworks that utilize object detection and segmentation like YOLO and Mask R-CNN architectures have allowed similarly disease localization and classification which enabling for continuous decision support in precision agricultural applications [27]. Despite of increasing volume of literature on hybrid ML-based plant disease detection, relatively few studies focus specifically on okra crops. Existing okra related works at early stage of address disease classification using CNNs under controlled conditions or limited datasets [15,17]. Rather than computational detection methodologies it reviews on okra diseases tend to emphasize pathological aspects [28]. Furthermore, current studies used many datasets which lack regional diversity and fail to represent real field conditions prevalent in South Gujarat which is limiting the generalizability of developed models [4,31]. The unviability of the specific dataset on region and detection of early level of disease detection studies and explainable AI models remains a critical research gap. Several recent systematic reviews have pointed that plant

disease detection using ML and DL techniques. however, most used a broad crop-agnostic perspective [16,19,22]. Although these reviews provide insightful information about model designs and performance trends which they frequently only look at hybrid frameworks and region adaptive disease detection techniques. Furthermore, in the context of precision agriculture systems, comparative evaluation metrics, dataset features and real time deployment feasibility have received less attention [33].

With particular attention to agroclimatic factors relevant to South Gujarat, this systematic review tries to solve these limits by giving a thorough and coordinated investigation of hybrid machine learning algorithms for okra plant disease identification. Studies published between 2019 and 2026 have been carefully assessed to discover current trends, architectural designs, feature fusion tactics, ensemble procedures and performance evaluation methods. By integrating the state-of-the-art progress as well as defining the existing unresolved issues, this review attempts to cover the gap between algorithmic development and real field application. The findings are to be used as the basis for developing intelligent systems that can be scaled up, are robust and region-specific in their application with an aim to improve disease management and also make okra production more sustainable.

Plant diseases pose a significant problem to agricultural productivity, food security, and economic sustainability in the world, and the need to detect the diseases in time and properly demands the need to have the right disease detection means. Traditional methods of plant disease diagnostics are usually based on the manual field examination and expert knowledge, which tend to be labor intensive, subjective and ineffective in performing massive agricultural observation [67,79,80]. With the advent of computer vision and artificial intelligence, it has been possible to have automated, non-invasive and scalable solutions to detect diseases in plants, especially by image-based analysis of plant leaves [34,35,62]. The original computational methods mostly relied on manual feature extraction with classical machine learning classifiers like support vectors machines and decision trees [47,68,71,93].

However, as good as these methods were in controlled conditions, when it came to real field conditions, it failed, because of other lighting conditions, background complexity and differences in diseases.

The introduction of deep learning and specifically, convolutional neural networks (CNNs) in which automatic feature learning has been accomplished directly on raw image data resulted in an increase in disease classification accuracy and robustness [36,37,39,42,49]. Still on CNN-based models, researchers looked at the transfer learning, ensemble, and hybrid deep structures to enhance the extrapolation of diverse crops and disease categories [40,50,54,55]. The attention and vision transformer models have recently attracted increasing attention due to the fact that their conceptual functionality enables them to reason long-range dependencies and global contextual features which are especially limiting in CNNs [513,53,60,61].

Besides, clear artificial intelligence (XAI) techniques are introduced to improve interpretability of the model and to raise confidence among agriculture stakeholders [445666]. However, the drawbacks of the diversity of the datasets, their real-life variability, and computational aspects, among other points of deployment, are still present, and systematic reviews of the existing methodology and future directions of finding research about plant disease detection are needed [58,64,75].

2. Literature Review

The recent improvements in artificial intelligence have made a major impact on the image-based detection of plant diseases as machine learning (ML) and deep learning (DL) have become the core of precision agriculture. The early literature sources mainly assumed image processing with the help of conventional classifiers based on ML. Halder et al. [30] and Mohammed and Yusoff [13] emphasized that handcrafted features (color histograms, texture

descriptors (GLCM, LBP), and shape features) with the help of support vector machines (SVM) and the k-nearest neighbors (KNN) classifiers were good at identifying basic disease, although with low levels of robustness and scalability.

Likewise, Raju et al. [23] and Alyas and Mohammed [24] have also reported similar results, as they have shown that the classical ML-based pipelines were vulnerable to background noise and change in illumination. The invention of convolutional neural networks (CNNs) led to the paradigm shift in the industry of detection of plant diseases since it allowed automatic learning of the pecked features. Among other crops and types of diseases, several detailed studies have confirmed the excellent performances of CNN-based models relative to conventional techniques [1,2,5,14,18,19]. According to Upadhyay et al. [1] and Pacal et al. [19], the incredible taxonomy of CNN models, including AlexNet, VGG, ResNet, DenseNet, and EfficientNet, are reported and emphasized by the authors as effective in controlled and semi-controlled environments. However, they also discovered that there was a deterioration in performance in real-field conditions in inter-class similarity, occlusion and environmental variability. To overcome the limitations of standalone CNNs, researchers have been exploring an increasing number of hybrid machine learning systems which entail a mixture of deep learning and traditional ML classifiers or feature engineering procedures. Valarmathi and Laurence Aroquiaraj proposed a hybrid pipeline of CNN-based feature extraction and statistical feature analysis and classical ML classifiers [6], which is more stable in classification and explainable.

Similarly, Bhowmik et al. [9] as well as Piska et al. [25] observed that the deep feature using SVM and random forest classifier increased the performance in situations where the training data was limited, which was an inherent problem with agricultural data. Another efficient hybrid approach of enhancing the accuracy of plant diseases detection has been found in ensemble learning. Zubair et al. [12] came up with a strong framework of ensemble prediction, which is an amalgamation of conclusions of various deep learning frameworks, and attains excellent generalization abilities to varied datasets. Gohil et al. [10] also expanded the idea of ensemble to real-time disease localization, by combining detection and classification modules, indicating their relevance to precision agriculture systems. These experiments affirm that model bias and variance is minimized through the application of ensemble-based hybrid models especially in heterogeneous agricultural settings. Vision transformers (ViTs) have been a topic of increasing interest in the recent years as a substitute and/or complement to convolutional neural networks (CNNs) for plant disease detection.

Aboelenin et al. [7] introduced a framework of CNN-ViT that can utilize both convolutional layers and transformer attention models to extract local features (local cycle) and the global context (global cycle), respectively, and achieves better classification outcomes. ViT-based models were shown to be more effective in detecting far-range dependencies of leaf imagery than standard CNNs due to Murugavalli and Gopi [21]. Mehnaz and Islam [11] made the comparative analysis of CNNs, transformers, and non-neural networks to detect the rice leaf diseases and finally concluded that hybrid CNN-transformer models provide more robustness and adaptability. The automated disease diagnosis has also been extended by the use of object detection and segmentation-based hybrid frameworks.

Chen et al. [27] have offered a better YOLOv8-based framework to detect soybean leaf diseases in natural field, which has successfully resulted in an accurate localization and classification of the disease. Hybrid methods based on such detection allow real-time tracking and decision support, which are required in large-scale agricultural implementations. In the area of crop-specific disease detection Sowmiya and Thenmozhi [4] provided publicly accessible okra disease data to be classified and segmented, which is urgently needed to have structured datasets in crop-specific disease detection studies. Okra-specific studies are not so numerous even though substantial literature has been written on plant disease detection. Shraddha et al.

[15] and Hridoy et al. [17] dedicated their attention to the classification of okra disease using CNN-based models, and they provided promising outcomes in the controlled settings. Nevertheless, these researches were based on small-scale databases and lacked hybrid learning approaches as well as on real-field variation. Nichat and Yedey [26] considered disease detection in plants of Malvaceae family with enhanced deep learning based on color-level descriptors, which has indicated that hybrid colors feature representation is relevant to okra disease detection.

A number of recent surveys have also tried to summarize the progress in plant disease detection with the help of ML and DL [16,18,20,22,33]. Although such reviews give general descriptions of algorithms, datasets, and metrics of evaluation, they all follow a crop-neutral approach and do not analyze hybrid frameworks or region-adaptive modeling approaches specifically. Furthermore, less attention has been paid to explainability, detection of diseases early and region-specific agro-climatic issues. The necessity to use hybrid intelligent systems was reinforced by the fact that okra viral diseases have complicated visual signs, which demand powerful and versatile detection frameworks (Sastry et al. [28]). To conclude, the reviewed literature shows that hybrid machine learning methods, such as CNNs with transformers or other classical machine learning classifiers, or just ensemble strategies, or feature fusion, are consistently more effective in plant disease detection. Nevertheless, there are still major gaps in research, such as the unavailability of region-specific okra data, poor comparison of hybrid models under the field conditions, and lack of interaction with precision agriculture systems. These gaps demonstrate the need to conduct a targeted systematic review of an okra disease detection based on hybrid ML, especially in agro-climatic regions, like South Gujarat.

Several studies have been conducted on the image-based plant disease detection, which progressed through the conventional machine learning algorithms to the advanced deep-learning frameworks. A majority of the earlier studies relied on manual attributes, like colour, texture and shape characters and classifier such as support vector machine, decision trees and artificially neural networks with mediocre quality in controlled laboratory environments and alternate results in the field environments [67,68,71,73,79,81]. Convolutional neural network (CNN) has contributed a lot to the identification of the disease by automatically identifying hierarchical properties of the leaf image that led to a dramatic enhancement of the performance based on tomato, rice, cucumber and apple among others [34,36,37,39,42,49,56]. In order to enhance further the accuracy and generalization, the scholars adopted the transfer learning and fine-tuning of the existing pre-trained deep models, reducing the training time and mitigating the issue of the lack of data [35,40,50,87,95].

Subsequent research explored ensemble learning and hybrid models, to learn a large number of deep models or include CNNs and attention mechanisms to improve the accuracy of a classification [43,54,55,72,75]. Also, vision transformers raised global feature modelling facilities, which were found to deliver with CNN based techniques in intricate disease recognition tasks [51,53]. Despite these advances, the question of diversity of datasets, environmental variability, and computational efficiency, as well as model interpretability, still remains, which encourages the implementation of explainable artificial intelligence approaches to achieve increased transparency and realistic applicability of precision agriculture platforms [44,58,66].

Research Matrix:

Author(s)	Model / Approach	Reported Accuracy / Performance	Key Contribution
Upadhyay et al. [1]	CNNs, Hybrid DL frameworks (Review)		introduce a comprehensive review of convolutional neural networks and hybrid deep learning architectures on plant disease detection with a focus on new hybrid and ensemble approaches in computer vision.
Ngugi et al. [2]	ML & DL models (CNN, SVM, RF)		Perform a performance-based comparative analysis of different machine learning and deep learning models, such as CNNs, support vector machine and random forest, to assess their relative efficacy for the diagnosis of crop diseases.
Mustofa et al. [3]	CNN-based DL models (Review)		Survey of deep learning techniques for leaf disease detection with dataset and model comparison
Sowmiya & Thenmozhi [4]	CNN, Segmentation models	Dataset contribution	Introduced an okra disease dataset for classification and segmentation applications
Jackulin & Murugavalli [5]	ML, DL, Hybrid models (Review)		review the machine learning (ML) and deep learning (DL) methodology, in particular with a focus on feature extraction techniques and the setup of classification pipelines.
Valarmathi & Laurence Aroquiaraj [6]	CNN + ML hybrid with statistical analysis	95%	Proposed a novel hybrid framework integrating deep features with statistical and ML analysis
Aboelenin et al. [7]	CNN + Vision Transformer (Hybrid)	98.1%	Developed a hybrid CNN–ViT framework for enhanced plant leaf disease classification
Yao et al. [8]	Multi-prediction DL models	96–98%	Present multi-task prediction approaches with 96-(arb.) 98 (%) accuracy in plant identification and classifying diseases.
Bhowmik et al. [9]	CNN + SVM (Review-focused)		Provide a review of the machine system approaches of jamun leaf disease diagnosis, especially the CNN and SVM system.
Gohil et al. [10]	Hybrid DL + Detection (YOLO-based)		Propose a hybrid scheme that combines deep learning and YOLO based detection for achieving the real time disease detection and localization.
Mehnaz & Islam [11]	CNN vs Transformer comparison	97%	Comparative study showing transformers outperform CNNs in rice disease detection
Zubair et al. [12]	Ensemble DL architectures	99.2%	Developed a robust ensemble deep learning model for plant disease detection
Mohammed & Yusoff [13]	Image processing + ML (Review)		Reviews application of digital image processing and machine - learning technique to plant disease detection.
Shoaib et al. [14]	Advanced DL models (Review)		Advanced DL models (Review) extensively reviewed state of the art (SOTA) deep

			learning architectures along with their associated challenges.
Shraddha et al. [15]	CNN-based classifier	94%	Implemented CNN for okra disease detection under controlled conditions
Nyawose et al. [16]	ML & DL approaches (Review)		ML & DL approaches (Review) study machine-learning and deep-learning methods with special attention to the classification accuracy.
Hridoy et al. [17]	Deep CNN	96.3%	Early recognition of okra diseases and pests using deep CNNs
Murugavalli & Gopi [21]	Vision Transformers	98%	Demonstrated effectiveness of ViTs in precision agriculture
Raju et al. [23]	SVM + image processing	90%	Classical ML-based disease detection using handcrafted features
Alyas & Mohammed [24]	Image processing + ML	92%	Demonstrated ML-based disease detection using image processing
Piska et al. [25]	ML-based hybrid approaches	95%	Showed improved agricultural productivity using ML models
Nichat & Yedey [26]	Enhanced DL + color descriptors	97%	Disease detection in Malvaceae family plants using hybrid features
Chen et al. [27]	Improved YOLOv8	98.6%	Real-field disease detection and localization in natural environments
Kumar et al. [32]	Image processing + ML	93%	Proposed ML-based plant leaf disease classification framework

3. Inference from current research studies

As a result of the review of the literature at hand, one can say that machine learning and deep learning approaches have achieved an extraordinarily high level regarding the field of automated plant disease detection, to be more specific, image-based initiatives. The first researches based on the use of traditional image processing and traditional machine learning classifiers, which were proved to be comparatively weak in terms of their reaction to changes in illumination, background, and similarity of symptoms of diseases, which were sensitive to the background [13,23,24,28,30,31]. These techniques were the foundation of automated diagnosis but they are limited by the ability to mine features manually that limits their scalability as well as generalization. All the recent works specify the increased precision of deep learning models especially the convolutional neural networks (CNNs) in the extracting of the discriminative features in the images of the plant leaves [1,2,14,18]. However, the artificial CNN models do not perform very well in uncontrolled agricultural environments, which highlights the problem of data and class imbalance, and regionality [19,28,31]. These limitations have required a direct change towards hybrid machine learning systems. Combination Hybrid models combining deep learning feature extractors and classical machine learning classifiers, feature-level fusion, ensemble methods, or vision transformers have performed better in terms of classification accuracy, robustness, and generalization [6,7,12,21]. Specifically, CNN -transformer hybrid models and ensemble learning techniques prove to be highly resistant against tricky backgrounds and dissimilarity of one disease to another and, hence, find application in practice in real fields [10,11,27]. The hybrid schemes based on object recognition and segmentation go further to increase the practical use with the ability to localize the disease in addition to classification needed by a precision agriculture system [4,27]. In spite

of these developments, the research on okra-specific detection of disease is restricted and mostly relegated to controlled experimental set-ups using small-scale data [15,17]. Also, geographical factors like the agro-climatic situational factors in South Gujarat are never considered in the model construction or assessment and the gaps of generalization could arise in the practical application [28,31]. Literature also does not provide enough focus on detecting disease at an early stage, explainability of the model, and connecting it to farmer-centric decision-support systems.

Overall, the available literature suggests that hybrid machine learning solutions are the most promising in achieving the objective of getting the right, robust and scalable plant disease detection. However, the research should be transformed in the future with region-adaptive framework, normalized data, explicable artificial intelligence, and real-time deployment systems to bridge the gap between the output of the algorithm and the results of agriculture. These inferences indicate a necessity to perform a focused systematic review of machine-assisted okra disease detection using hybrid MLs to identify the disease in region-specific agricultural contexts.

The recent developments in the field of plant disease detection have been focused on the methods of improving the model accuracy, stability, and practicality in the real world by implementing the use of the latest, i.e., advanced, deep learning and hybrid methodologies. Deep convolutional neural networks are so popular due to the fact that they have good feature extraction capacities and they have recorded good performance in the detection of diseases in different crops [36,37,39]. Recent studies have also emphasized the transfer learning and ensemble techniques to avoid such issues of either limited annotated data or environmental variety, and is more likely to be effective than single-model counterparts [35,40,50]. More recently, CNNs have been shown to be complementary with attention mechanisms and vision transformer models to hold potential in capturing global contextual information, and therefore offer more reliability in classification in complex field conditions [51 53]. At the same time, explainable AI approaches continue to increase in popularity to make such models more understandable and accepted by agricultural experts [44-46], and more compact models are also being created to enable them to be implemented on edge devices in real-time [59]. These are trends pointing towards more complex and scalable and application sensitive solutions in precision agriculture.

4. Limitations

Although the current studies on machine learning and deep learning-based plant disease detection have reported great progress, a number of limitations are still common in the current studies. Heavy dependence on controlled or laboratory-curated datasets is one of the key constraints as it may not always be able to reflect the complexity of real-field agricultural situations. The difference in illumination, background disturbance, leaf coverages, and the presence of disease still lacks a proper representation, which restricts the generalization ability of the developed models when used in a real environment. Another weakness that is worth noting will be the unavailability of crop and region-specific information that is especially the okra crops and the agro climatic regions like South Gujarat.

The number of researches grounded in publicly available, crop-agnostic data not representative of local disease presentation, seasonal variability, and local pathogen dynamics is numerous. The literature aggregated performance of the models may thus not be a real sign of the performance within the real field. Even though the hybrid machine learning methods proved more precise and resolute, regardless of the complexity of the model, the cost of the calculation can be a major problem. The hybrid and ensemble models might be harder to implement to the

resource-limited agricultural scenarios as they are generally more time-consuming to train and more resource-demanding, and the parameters need to be optimized. Besides, most of the studies focus on classification accuracy and have not focused much on inference speed, energy use and scalability to make in real-time. Comparative analysis is further complicated by the fact that there is no standard evaluation protocol used in all studies.

The difference in dataset, distribution of each classes, image resolution and performance measures do not allow objective benchmarking to be done among various approaches. Also, numerous studies provide high accuracy rates that are not backed by adequate statistical validation and cross-dataset testing, which is a cause of concern regarding the reproducibility of the results. Lastly, little focus has been directed towards model interpretability and explainability that play a key role in developing trust between farmers and agricultural practitioners. Most of the existing models are black-box models and they provide little information about the decision-making processes. This constraint is especially of paramount importance in situations of early-stage disease identification, and integrated decision-support systems, where transparency and practical suggestions are paramount.

Although machine learning and deep learning methods have managed to achieve major milestones in the detection of plant diseases, it still has a number of constraints. Numerous available existing studies use publically accessible or laboratory-controlled data, a fact that restricts the external validity of models to a real-field setting with different illumination, multifaceted backgrounds, and occlusions. Class imbalance and the lack of labeled data on rare diseases also have an impact on model robustness and reliability. Even though deep learning and transformer models can be highly accurate, they can easily consume significant computational resources, and it is difficult to implement them in real-time on edge or mobile devices.

Moreover, majority of the models concentrate more on the classification of the disease compared to estimating its severity and at an earlier stage, which is important in the timely agricultural intervention. Little has also been done on the interpretation of models, which doubt the issue of trust and acceptance by farmers and agricultural professionals. These difficulties indicate that more varied datasets, lightweight architectures, explainable models, and field-level validation should be used in future studies.

5. Direction for Future Research

Future studies of hybrid machine learning systems to detect okra plant diseases ought to focus on enhancing generalization of the models, calculation efficiency, and scalability to the field. It would be essential to develop large scale, region-based data, with real field effects, including variations in illumination, background complexity and varied disease stage development, to improve robustness and lower domain shift. More focus ought to be on the early disease detection and multi-label classification to cater to realistic situations of co-occurring diseases.

Implementation wise, future research should aim at designing lightweight hybrid architectures based on model compression strategies such as pruning, quantization, and knowledge distillation, and be able to implement them on resource-constrained edge devices such as smartphones and IoT-based agricultural systems. The explainable artificial intelligence methods, including attention visualization and gradient-based attribution-based methods, need to be implemented to enhance the interpretability of the models and aid in agronomic decision-making. Besides, cross-dataset validation, inference latency and cost measures of standardised assessments should be part of the practice to guarantee reproducibility and feasibility.

One of the key directions towards scalable and intelligent crop disease management systems are precision agriculture, disease detection models, and decision-support systems with the regional adaptive transfer learning strategies. Further research must aim at creating strong and

lean deep learning frameworks that can work well in the real field settings where the lighting and backgrounds are different and the type of crops are varied. It is also important to focus on the development of various and well-labeled datasets to enhance the generalization and stability of models. Also, by combining explainable artificial intelligence and hybrid CNN-transformer models, it is possible to improve model transparency and accuracy, which makes the model practical in precision agriculture applications.

6. Conclusion

The systematic review included hybrid machine learning methods used in plant disease detection, and focused on okra crops and agricultural climatic conditions closely related to South Gujarat. While these techniques are usually considered traditional, both machine learning and image processing methods present shortcomings in the representation of features, as well as having a limited generalisability when used in complex environments in the field. Deep - learning models particularly convolutional neural networks have been shown to outperform conventional approaches in plant disease classification under conditions of varying illumination, background noise and inter- class similarity.

The hybrid system, which opposes CNNs along with vision transformers, classical ML classifiers, ensemble techniques and fusion of features, is more resistant, reaches a greater degree of generalization, and the high degree of performance within the heterogeneous environment. However, significant gaps still exist that include the lack of region-specific okra data, insufficient early-stage and multi-disease detection, low model interpretability, and the lack of focus on the possibility of deployment.

The future research improvement areas comprise of region adaptive datasets, lightweight hybrid architecture, standard evaluation protocols, and even explainable integration of AI. This is a viable move towards scalable and field-deployable disease management through combination of hybrid models with precision agriculture and decision systems that will bring about sustainable okra in South Gujarat and other agro-climatic regions.

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