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A REVIEW OF MACHINE LEARNING AND OLFACTORY TECHNOLOGIES FOR RAPID VEGETABLE DISEASE DETECTION

Abstract. *Plant disease detection is crucial to modern-day agriculture because timely diagnosis can reduce the loss of crops to an appreciable level and improve productivity. This review presents advanced disease detection systems based on machine learning techniques and multimodal data analysis. A comprehensive comparison of different machine learning algorithms, including convolutional neural networks (CNNs), transfer learning models, and object detection methods like YOLO, has been done. This study demonstrates that combining visual data with the analysis of volatile organic compounds (VOC) enhances the accuracy and reliability of the diagnosis. This provides opportunities for the actual development of satellite and cheap systems for monitoring operable in the field. Theoretically, this work contributes to developing strategies for integrating heterogeneous data and optimizing deep neural network models to make them lightweight and effective. The review emphasizes developing scalable and adaptive technologies for plant disease detection within precision agriculture.*

Keywords: *plant disease detection, machine learning, convolutional neural networks, MobileNet, multimodal data, real-time detection, agricultural technology, VOC sensors.*

Introduction.

The rapid detection of plant diseases, particularly in vegetables, plays a crucial role in ensuring both food security and agricultural sustainability. Traditional diagnostic methods, such as visual inspection, microscopy, and biochemical analysis, are widely used but have significant drawbacks. These methods tend to be slow, labor-intensive, and susceptible to human error, especially when differentiating between diseases with similar symptoms or when infections are in their latent stages. Moreover, these approaches often result in delayed interventions, which can exacerbate the spread of diseases and lead to substantial crop losses. With the increasing demand for quicker and more reliable plant disease detection, advances in computer science, particularly machine learning (ML) and computer vision (CV), have emerged as transformative solutions.

Recent research has pointed out that deep learning techniques, such as CNN, can effectively automate the process of plant disease detection through plant leaves images. This method has identified diseases using their symptoms, which were visible; hence, these techniques became effective and less time-consuming than the traditional methods. The process usually starts by acquiring high-resolution images of both healthy and infected plants, mostly using Internet of Things-enabled sensors deployed in agricultural fields. High-quality images are quite essential for the perfection of disease detection; hence, different pre-processing steps like noise reduction, distortion correction, and color space conversion are performed to optimize the images for further analysis [1]. These systems save a lot of money, reduce laborious work, and offer quicker and more accurate results, hence improving the overall management of crop health by automating disease diagnosis [2]. For example, deep learning in plant disease detection is feasible with an incredible accuracy of 99.35% [3]. Another interesting aspect reviewed was the integration of IoT-based sensors and imaging technologies for real-time data collection in the field and monitoring of diseases [4].

Purpose and objectives:

The study aims to analyze and compare existing machine learning and olfactory technologies for vegetable disease detection in terms of their strengths, weaknesses, and applications for real-world agricultural purposes. The main objectives are as follows:

- To assess the feasibility of CNNs and other deep learning techniques for plant disease recognition.
- To assess the role of VOC sensors in the early detection of diseases and their combinations with ML models.
- To identify computational challenges and propose optimizations for any application in real time.

Methodology.

The review provided an overview of studies related to the application of ML models in plant disease detection, advances in imaging techniques in agriculture, and signal processing frameworks applied in the analysis of VOCs, important in the identification of stress and disease symptoms in plants.

Reviews were filtered to prioritize studies highly relevant to computer science, namely those that introduced algorithmic novelties, brought improvement in computational efficiency, or demonstrated real-world deployment scenarios. Special emphasis was given to deep learning models, such as convolutional neural networks (CNNs), which have shown very high accuracy in plant disease classification using image-based data.

The review further considered how machine learning models are coupled with advanced signal processing techniques for VOC analysis, which plays a role in the early detection of plant diseases prior to the appearance of visible symptoms. This approach promises to enhance speed and reliability in disease diagnosis in agricultural environments. Such diverse methodologies will be analyzed in the review to identify gaps and further propose areas where computational innovations may be developed to enable efficiency and scalability in the detection of plant diseases for improved agricultural practices.

Literature review.

Some common methods applied to image classification tasks in plant pathology include supervised learning, mainly through the use of Convolutional Neural Networks. The ResNet and InceptionNet are great at extracting complex visual features from plant images that could signal disease symptoms in crops. The basic CNN model relies on the convolution operation, which is for hierarchical feature extraction from the input image, from simple edges and textures to more complex ones. The deeper the network is, the more abstract features it can capture. ResNet uses residual connections to enable the network to train deeper architectures by preventing common issues such as vanishing gradients. InceptionNet has used multiple filter sizes in each layer to take simultaneous feature scales. Regarding the VOC analysis, Support Vector Machines have been adapted to classify the VOC patterns emitted from plants under stress due to infection or pest infestation. The SVMs work to seek a hyperplane in the high-dimensional space that will optimally separate different data classes. Applied to VOC data, SVMs can identify if a plant is healthy or diseased based on their chemical signatures, thus providing added diagnostic power to the techniques already applied [5].

Advanced models in deep learning, such as Transformers and Graph Neural Networks, have just started showing promise for the fusion of multimodal data, where both images and VOC signals are integrated toward better comprehension of plant health. Transformers, originally developed for natural language processing, make use of attention mechanisms in focusing on important features in sequences of data, such as time-series VOC signals. This makes them suitable for combining sequential data with other types of features, such as visual data. On the other hand, GNNs are appropriate for tasks where data points are interrelated, especially because they can model this relationship through nodes and edges in a graph. For example, GNNs can be used to capture dependencies between different plant features, such as the spatial distribution of disease symptoms, or the correlation between different VOC signals emitted over time. According to Domingues et al. (2022), these architectures can process sequential or graph-based data, which is crucial when combining time-series data (such as VOC emissions) with image-based features [6]. Mohanty et al. (2016) noted, these models have performed well, especially in early disease detection across different crops, with some studies reporting accuracy above 92% [3].

Computer vision techniques have enlightened plant disease detection, offering sophisticated methodologies for identifying and segmenting diseased regions in plant images. One of the major roadblocks in this area is lack of labeled data, and that has consequences on how efficient the machine learning models can really get. Data augmentation techniques like rotation, scaling, and image synthesis through Generative Adversarial Networks are proved to be effective in battling this ill. Lightweight models such as MobileNet can be optimized for such environments where a trade-off between computing efficiency and detection is paramount. In fact, recent examples have demonstrated the successful deployment of deep learning models on such edge devices for real-time disease detection and low latency [7]. In fact, DeepLab and U-Net show promising performances in segmenting damaged tissue of diseased leaves from the healthy ones of the plants. These models are of utmost importance in precision agriculture as they provide very much detailed and accurate disease mapping. Research has indicated that the performance of detection accuracy in various plant diseases could be boosted by combining CNNs with semantic segmentation. According to Alomar et al. (2023), the use of a U-net facilitates further segmenting the diseased portion from the healthy part of the infected plant, allowing integrated management practices, thus reducing pesticide application for targeted treatment [8].

In particular, the electronic nostrils or olfactory technologies depend greatly on signal processing and machine learning methodologies that enhance recognition and classification of specific odors like VOCs associated with diseases. These systems rely on efficient content extraction, enabling accurate counting of willing odors. Usually, e-noses noise preprocessing involves methods like Fast Fourier Transform (FFT) and wavelet decomposition, which improve the quality of signals by filtering out irrelevant noise and focusing on the relevant features that represent the odors. It makes a time-domain sensor response into a frequency domain and can thus be used to identify periodic patterns of some odors. On the other hand, wavelet decomposition disentangles signal components with the ability to capture both frequency and time aspects, and thus is excellent for describing the complicated signal behavior commonly found in VOC detection [9].

Another critical stage is dimensionality reduction in the processing pipeline. Principal Component Analysis (PCA) is typically used for reducing the complexity of the VOC data, transforming it into a lower-dimensional subspace for a better explanation of the most relevant features of the data. This simplification improves the performances of different classification models by reducing their overfitting and computational burden. t-SNE (t-distributed Stochastic Neighbor Embedding) is another helpful method that allows visualizing high-dimensional data in two or three dimensions to understand how different VOCs cluster together [10].

Currently, the methods used for detecting diseases based on VOCs face several challenges. The primary challenge is the sensitivity of these methods to environmental factors since the emission of VOCs can vary due to humidity, temperature, and plant physiology, resulting in inconsistent detection values. Next is the data complexity, which requires good preprocessing methods like the Fast Fourier Transform (FFT) and wavelet decomposition to treat noises and bring out meaningful patterns. Limited classification accuracy is another killer, since VOC sensors do great with early detection but lack specificity as compared with image-based methods in the classification of diseases. Moreover, the factors regarding price and maintenance are sort of a financial constraint, since the VOC sensors require periodic calibration and upkeep that easily outprice them for applications in widespread agriculture. Yet another limit in the applicability of VOC sensors is that most of the models are trained for very specific plant species, which makes it difficult to generalize results across different crops and environmental conditions.

In addressing such limitations several solutions can be implemented: From calibration, which can enhance and standardize VOC detection protocols, thereby minimizing any environmental vagaries affecting sensor readings. Multimodal fusion of VOC data with image-based analyses has the potential to enhance classification through a coupling of both data sources. Optimizing signal processing for VOC-based models using dimensionality reduction techniques, including Principal Component Analysis PCA) and t-SNE, can improve their performance by extracting more relevant features. The development of low-cost VOC sensors is crucial for broadening the reach of this technology to farmers by relieving them of the burden of using an expensive high-end sensor. Transfer learning for cross-crop model training will also improve the generalizability of VOC sensor models by allowing models trained on one plant species to more readily adapt to varied agricultural environments.

The assimilation of advanced signal processing with machine learning technologies is the hallmark that will put e-noses at a whole new level in the prompt, non-invasive, and real-time monitoring of various diseases and gases-impressive achievements in the diagnostic technology field.

Table 1 – Comparative analysis of machine learning methods for plant disease detection

Study	*Machine Learning Method*	*Object of research*	*Effectiveness (%)*	*Limitations*	*Reference*
Review of the State of the Art of Deep Learning for Plant Diseases: A Broad Analysis and discussion (2020)	DBN (unsupervised DL model)	Plant leaves	96-97.5	• Small datasets and limited image diversity hinder model effectiveness. • Early symptoms and irregular lesion shapes complicate detection. • Environmental factors affect accuracy. • Automated labeling and hyperspectral imaging are underdeveloped. • Similar diseases require specialized datasets and robust validation.	[11]
Real-time plant health assessment via implementing cloud-based scalable transfer learning on AWS DeepLens (2020)	DCDM	Plant leaf disease	98.78	• Model accuracy may be affected by inconsistent real-world backgrounds. • Limited to specific plant species (25 classes). • Future scalability may require more species and multi-spectral testing.	[12]
Tomato diseases and pest's detection based on improved Yolo V3 Convolutional neural network	YOLOv3	Tomato diseases and insect pest's detection	92.39	• May require fine-tuning for other types of crops or pests. • Performance may vary with non-standard resolutions or highly complex environments.	[13]

(2020)				• Sensitive to very small object sizes, though improvements are made in this area.	
Classification of citrus plant diseases using deep transfer Learning (2021)	MobileNetv2 and DenseNet201 (transfer learning + feature fusion)	Classification of citrus plant diseases	95.7	• Specific to citrus, may not apply to other crops. • Relies on MobileNetv2 and DenseNet201, which may not generalize well. • Feature fusion increases processing time.	[14]
Cucumber disease recognition using machine learning and transfer learning (2021)	Traditional ML (Random Forest) & Transfer Learning (MobileNetV2)	Cucumber disease detection	93.23	• Limited data available for model training, affecting performance and recognition accuracy. • High dependency on specific hardware, which may not be universally accessible. • Computationally expensive methods, requiring significant processing power. • High costs associated with implementing advanced techniques, such as deep learning and hyperspectral imaging. • Narrow scope, as most studies focus on a limited number of diseases in cucumber crops.	[15]
Image-based Onion Disease (Purple Blotch) Detection using Deep Convolutional Neural Network (2021)	Deep Convolutional Neural Networks (CNN)	Onion crop disease classification (Alternaria porri)	85.47	• The small dataset may reduce the model's ability to generalize and affect robustness. • Performance varies, with better results observed when using a batch size of 16. • The training process is resource-intensive and requires significant computational power. • Without a sufficiently large dataset, overfitting is a concern. • Image preprocessing and augmentation play a crucial role in determining accuracy.	[16]
Deep learning-based segmentation and classification of leaf images for detection of tomato plant disease (2022)	Deep CNN	Plant leaves diseases and pests	99-99.2	• Relies on a benchmark dataset. • Needs more validation in diverse environments. • Requires significant computational resources. • Real-time application not fully evaluated. • User experience needs further assessment.	[3]
An improved YOLOv5-based vegetable disease	YOLOv5s (object detection model)	Tomato virus disease	93.1	• Long training time due to inadequate optimization. • Needs reduction in model	[17]

detection method (2022)				size and complexity. • Further development needed for mobile device deployment. • Dataset may lack real-world diversity.	
Detection and classification of tomato crop disease using convolutional neural network (2022)	CNN	Tomato plant diseases	88.17	• Limited to tomato crops. • Testing accuracy could be improved. • Needs adjustments for real-world conditions.	[18]
Tomato fruit disease detection based on improved single shot detection algorithm (2023)	CNN with SDD	Tomato Disease Detection	98.8	• Limited to controlled environments, making real-world application challenging. • Small datasets restrict the model's ability to generalize to new data. • Pre-trained models may not be optimized for specific datasets, affecting accuracy. • Additional processing may be needed to improve accuracy, adding complexity.	[19]
A Framework for Agriculture Plant Disease Prediction using Deep Learning Classifier (2023)	Enhanced GoogleNet, MobileNetV2, SGD, Adam Optimizer	Detection of tomato fruit diseases	99.5(GoogleNet with Adam)	• High-quality image data is necessary for accurate detection. • The method may not generalize well to all types of plants. • Performance can decrease when using certain optimizers like RMSProp and Adamax.	[20]
Brinjal leaf diseases detection based on discrete Shearlet transform and Deep Convolutional Neural Network (2023)	Deep CNN	Leaf disease detection in brinjal	93.30 (with fusion)	• Data imbalance could affect the performance of the model, especially with unequal class representation. • The results of the study were not compared or benchmarked against previous research in the field. • Image size variation across classes could potentially introduce inconsistencies in the model's performance.	[21]
Sustainable smart system for vegetables plant disease detection: Four vegetable case studies (2024)	MobileNet (convolutional neural network)	Tomato disease	84.49	• Requires large, diverse datasets for accurate model performance. • Struggles with generalizing across different environments or new diseases. • High com putational power needed, limiting real-time application on low-resource devices. • Challenges in detecting early or subtle disease symptoms effectively.	[22]
	MobileNet (convolutional neural network)	Cucumber disease	97.65		
	CNN	Lettuce disease	100		

Machine vision algorithm for detection and maturity prediction of Brinjal (2024)	K-means clustering	Brinjals disease	95.9	• Small dataset, which may limit generalizability. • High computational cost and complexity. • Challenges in accurately labeling brinjals due to environmental factors. • Inconsistent lighting and device variability affecting detection. • Difficulty in detecting partially occluded brinjals.	[23]
Apple varieties classification using deep features and machine learning (2024)	Deep features, PCA and ML	Apple disease	99.77	• Small dataset of only 10 apple varieties. • Misclassification due to class variability. • Real-world applicability requires more varied lighting and image acquisition setups. • Ripening stage affects classification accuracy.	[24]
Vegetable disease detection using an improved YOLOv8 algorithm in the greenhouse plant environment (2024)	YOLOv8n-vegetable model	Vegetable disease	82	• Model tested on a self-built dataset, limiting generalization to other environments. • Focus on greenhouse settings may not fully account for outdoor variations. • Need for streamlining the model for embedded hardware platforms. • Further development needed for real-time video capture and disease alerts.	[25]
Enhanced rendering-based approach for improved quality of instance segmentation in detecting green gram (Vigna Rediata) pods (2024)	PointRend	Green gram pod disease	68.5	• Custom dataset used, limiting generalization to other datasets. • Challenges in field environments due to similarity between pods and background (leaves). • Need for more diverse dataset (including diseased pods) to improve robustness.	[26]
ViT-SmartAgri: Vision Transformer and Smartphone-Based Plant Disease Detection for Smart Agriculture (2024)	Vision transformer (ViT)	Tomato diseases	95.7	• Accuracy depends on dataset and setup. • ViT has slightly lower accuracy than some other models. • Model complexity may affect deployment in low-resource settings. • Performance evaluation should consider more than just accuracy.	[27]

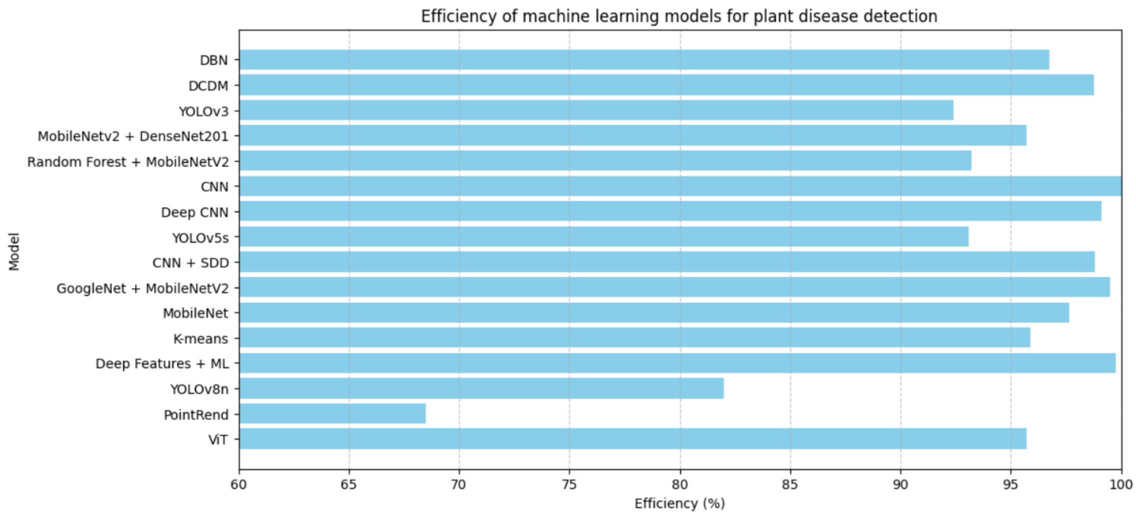

Figure 1 – Efficiency comparison of machine learning models for plant disease detection according to the table

Results and Discussion.

The review of research papers is shown in Table 1 and Figure 1, which have been addressed to bring out trends and gaps in machine learning (ML) and olfactory technologies that can be harnessed for vegetable disease detection while emphasizing some factors such as type of technology, dataset limitations, resource efficiency, and multimodal data integration. They include:

Type of technology employed. Often integrated with VOC detectors into CNNs for plant disease detection from images, in which CNNs showed up high accuracies' prediction capability. The drawback is, VOC sensors developed only for early detection and not for classification accuracy. But, may be integrated for effective detection especially in early detection cases.

Dataset characteristics. Most published literature employ relatively small, narrow datasets, i.e. studies intended for few plant species or limited incidence-type plant diseases, which affect the generalization of results. A massive, diverse dataset has definite improvement in screens applicability and accuracy of diagnosis technology, yet it is very expensive or complex to establish.

Computational efficiency. There is high accuracy from deep learning, most especially CNN; however, it needs high computational resources which would ultimately prevent being run in real-time applications. Lightweight such as MobileNet and EfficientNet would maintain that equation with good accuracy but less resources. Model pruning and quantization are also termed optimization methods as applied to CNN for real-time use.

Multimodal data integration. Recognition capability is usually enhanced through the use of image data and combined VOC signals; however, very few studies have explored successful fusion of both data types within one model. Such further enriching would likely enhance disease detection systems by using much increased strength from the integration of vision and chemical data.

Proposed Solutions:

Augmented Datasets. Examples include data augmentation and synthetic data generation using GANs for increasing dataset diversity, such as rare diseases or under-represented plant species.

Lightweight and Optimized Models. With efficient CNN architectures like MobileNet or EfficientNet, coupled with pruning and quantization, it becomes possible to obtain real-time detection without compromising accuracy.

Cross-Modal Fusion. Building very complex architectures that can take in both image and VOC data together might improve detection performance by combining the strengths of both data types.

Transfer Learning. This approach is where models that have been trained on huge, diverse datasets can be transferred to specific crops for better generalization.

Conclusion. The integration of computer vision techniques and multimodal data analysis offers a viable solution to the challenges currently faced in vegetable disease detection. By optimizing computational efficiency, improving data diversity, and integrating sensor technologies more effectively, it is possible to develop a robust, real-time disease detection system. While the use of olfactory signals in conjunction with image data is still in its infancy, the potential for these combined systems to transform plant disease diagnostics is significant, offering a path forward for more accurate, scalable, and cost-effective solutions in agriculture.

Conflict of interest. The author(s) declare that there is no conflict of interest.

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КӨКӨНІС АУРУЛАРЫН ЖЫЛДАМ АНЫҚТАУҒА АРНАЛҒАН МАШИНАЛЫҚ ОҚЫТУ ЖӘНЕ ИІС СЕЗУ ТЕХНОЛОГИЯЛАРЫНА ШОЛУ

Аңдатпа. *Өсімдік ауруларын анықтау қазіргі ауыл шаруашылығы үшін өте маңызды, өйткені уақтылы диагноз қою егін шығынын айтарлықтай азайтады және өнімділікті арттырады. Бұл шолу Машиналық оқыту әдістеріне және мультимодальды деректерді талдауға негізделген озық ауруларды анықтау жүйелерін ұсынады. Машиналық оқытудың әртүрлі алгоритмдерін, соның ішінде конволюциялық нейрондық желілерді (CNN), трансферлік оқыту модельдерін және YOLO сияқты объектілерді анықтау әдістерін жан-жақты салыстыру жүргізілді. Бұл зерттеу визуалды деректерді ұшпа органикалық қосылыстарды (VOC) талдаумен біріктіру диагностиканың дәлдігі мен сенімділігін арттыратынын көрсетеді. Бұл далада қолдануға болатын спутниктік және арзан бақылау жүйелерін нақты дамытуға мүмкіндіктер ашады. Теориялық тұрғыдан, бұл жұмыс гетерогенді деректерді біріктіру стратегияларын әзірлеуге және оларды жеңілдету және тиімдірек ету үшін терең нейрондық желілерге негізделген модельдерді оңтайландыруға ықпал етеді. Шолуда дәл егіншілікте өсімдік ауруларын анықтауға арналған масштабталатын және бейімделетін технологияларды әзірлеуге баса назар аударылады.*

Түйін сөздер: *өсімдіктер ауруларын анықтау, машиналық оқыту, конволюциялық нейрондық желілер, MobileNet, мультимодальды деректер, нақты уақыттағы анықтау, ауыл шаруашылығы технологиялары, VOC датчиктері.*

ОБЗОР МАШИННОГО ОБУЧЕНИЯ И ОБОНЯТЕЛЬНЫХ ТЕХНОЛОГИЙ ДЛЯ БЫСТРОГО ВЫЯВЛЕНИЯ БОЛЕЗНЕЙ ОВОЩЕЙ

Аннотация. *Обнаружение болезней растений имеет решающее значение для современного сельского хозяйства, поскольку своевременная диагностика может значительно снизить потери урожая и повысить производительность. В этом обзоре представлены передовые системы обнаружения болезней, основанные на методах машинного обучения и мультимодального анализа данных. Было проведено всестороннее сравнение различных алгоритмов машинного обучения, включая сверточные нейронные сети (CNN), модели трансферного обучения и методы обнаружения объектов, такие как YOLO. Это исследование демонстрирует, что сочетание визуальных данных с анализом летучих органических соединений (ЛОС) повышает точность и надежность диагностики. Это открывает возможности для реальной разработки спутниковых и недорогих систем мониторинга, которые можно использовать в полевых условиях. Теоретически, эта работа способствует разработке стратегий интеграции разнородных данных и оптимизации моделей на основе глубоких нейронных сетей, чтобы сделать их более легкими и эффективными. В обзоре особое внимание уделяется разработке масштабируемых и адаптивных технологий для обнаружения болезней растений в точном земледелии.*

Ключевые слова: *обнаружение болезней растений, машинное обучение, сверточные нейронные сети, MobileNet, мультимодальные данные, определение в реальном времени, сельскохозяйственные технологии, VOC датчики.*

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