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Advanced Deep Learning and Transformer-Based Approaches for Apple Leaf Disease Detection and Smart Agriculture Applications: A Comprehensive Review

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ABSTRACT

Apple leaf diseases greatly impact agricultural yield, crop quality, and the economic stability of current farming systems. Getting the disease spotted early, and accurately, is crucial for reducing crop losses and also for improving precision agriculture routines. Usual identification approaches still depend heavily on manual checking by specialists, and that is pretty slow, costly, and sometimes misread by humans , even when the effort is careful. In the last few years AI, ML, Deep Learning, plus computer vision tools, have shifted plant disease monitoring toward automated and more intelligent recognition pipelines. This review paper tries to cover advanced deep learning and Transformer centered methods for apple leaf disease detection, while paying special attention to YOLO families, Convolutional Neural Networks, ResNet based models, Swin Transformers, and hybrid deep learning frameworks. The discussion examines new progress related to YOLOv8 YOLOv10 YOLOv11, attention mechanisms, multi scale feature extraction, Bayesian optimization , and lightweight detectors that are made for real time field use. Also the review touches image preprocessing approaches, feature extraction techniques, data enlargement strategies, and hyperparameter tuning methods that collectively raise classification precision and detection quality. When models are compared, hybrid CNN Transformer designs tend to deliver better disease localization, stronger feature encoding , and higher classification accuracy in difficult weather and background conditions. The paper additionally points to smart farming integration, like IoT setups, UAV monitoring, and edge computing, to enable more automated agricultural surveillance. Toward the end, the current research gaps, practical limits, ongoing obstacles, and future work paths are laid out, with the goal of supporting efficient scalable, and intelligent plant disease detection systems, aimed at sustainable agriculture and precision farming.

Keywords: Apple Leaf Disease Detection, YOLOv8, Swin Transformer, Deep Learning, Computer Vision, Smart Agriculture.

I. INTRODUCTION

Agriculture plays a vital role in keeping food security, economic development, and sustainable living steady across the whole world. Among different fruit crops, apples are seen as one of the most economically valuable horticultural products, mainly because of their high nutritional value, strong commercial demand, and wide spread cultivation. Still, apple production gets disturbed by several leaf diseases like Apple Scab, Cedar Apple Rust, Powdery Mildew, Black Rot, and Alternaria Leaf Spot. These problems damage leaf tissues, interfere with photosynthesis, make plant growth weaker, and then the crop yield and fruit quality drop. Because of this, early detection that is also accurate for apple leaf diseases has become a must, so agricultural productivity improves and the orchard can stay sustainable. [1] In the past, disease detection in apple plants was usually done by hand, through visual checking by agricultural experts or even farmers. Even if the traditional diagnosis methods can spot obvious symptoms, they tend to be quite time-consuming, labor heavy, costly, and strongly tied to specialized experience. Also, when orchards get big and the environment keeps shifting, manual inspection becomes hard to keep steady. People looking at the plants can miss details too, because fatigue builds up, judgment is not always consistent, the lighting changes, and several diseases show symptoms that look very similar. Because of these weak points, treatment often starts later than it should, and infections spread more easily, leading to serious economic harm for both farmers and the wider agriculture sector [2]. The rapid growth of Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), and Computer Vision technologies has changed the usual agriculture monitoring routines into intelligent and automatically driven disease detection frameworks. AI based farming systems can process big volumes of image data with speed and precision, which supports real time crop watch and disease recognition. Better deep learning methods have proven a strong ability to pull out useful visual cues from leaf images, without the need for manual feature engineering. Therefore, these intelligent plant ailment detection systems are getting more and more important for today’s precision agriculture and smart farming applications.

Machine learning methods like Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Decision Tree, and Random Forest were first brought up for helping with plant disease classification . Mostly, these approaches rely on crafted feature extraction steps, using color, texture, shape, and edge cues taken from sick leaf images. Even if classic machine learning models reached a decent accuracy at times, their results were often not stable, because they generalize poorly, they depend heavily on feature engineering, and they struggle when real outdoor conditions get complicated. Because of that, many researchers moved their attention toward deep learning approaches, where the system can learn layered visual features by itself, from huge agricultural datasets. Deep learning models, especially Convolutional Neural Networks (CNNs), have really helped a lot with the accuracy and efficiency of plant disease recognition systems. CNN designs like AlexNet, VGGNet, ResNet, EfficientNet, DenseNet, and MobileNet have been used widely for image classification and for disease detection duties. These models can automatically pick up low level, and later high level, visual patterns from plant leaf images so they can identify healthy leaves versus diseased ones with good precision. In practice, deep learning methods remove the need for manual feature extraction, and they also strengthen how well disease recognition systems work when the environment is tricky, for instance with changing light or background noise [3]. Lately, object detection frameworks that follow the YOLO (You Only Look Once) architecture, they have been getting a lot of attention in agricultural image analysis. In practice, YOLO models can do object detection and localization in real time using just one neural network pass. Compared with usual region based detection schemes, YOLO looks at the entire image at once so detection tends to be quicker, and the computational use feels more efficient. There are many YOLO versions, like YOLOv5 YOLOv7 YOLOv8 , YOLOv10 and YOLOv11, and they have been used for things such as diagnosing apple leaf illness, recognizing pests, keeping track of fruits, and for smart agricultural surveillance too. Between those models, YOLOv8 seems to have shown up as one of the most advanced object detection setups because it uses an anchor free detection mechanism, plus better feature extraction, and stronger localization performance. With YOLOv8 , disease identification can be done quickly while keeping high precision and also lower computational complexity, so it fits real time smart farming systems. The design brings together a capable backbone, feature pyramid style structures, and tuned detection heads, which helps recognition when orchard conditions change. A lot of researchers have also put attention mechanisms into YOLO models, along with feature fusion modules , and lighter convolution structures to push the disease detection capability even further.

Figure 1 depicts a plant health monitoring system that uses imaging and analytical techniques to continuously assess crop condition and detect early signs of stress or disease.

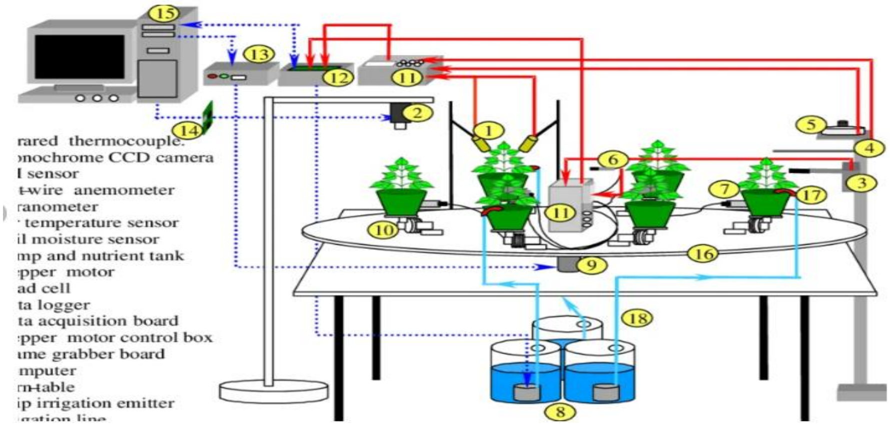

Figure 1: Plant health monitoring system [7]

Alongside the CNN based approaches, Transformer architectures have been showing pretty remarkable results in computer vision lately. Vision Transformers ViTs, and Swin Transformers can grasp long-range or global contextual links between different parts of an image better than the usual CNN models. While CNNs mostly lean on local feature extraction, Transformer models look at distant dependencies as well as spatial interactions inside agricultural images. Because of this, they tend to improve disease pinpointing and classification performance, especially when the orchard scene has tricky backgrounds, and when parts of the plants are blocked or partially hidden [5]. Hybrid deep learning setups that mix CNNs with Transformers are turning out to be a really promising path for intelligent plant disease detection, even if the whole workflow is a bit complex. In these designs, CNN backbones like ResNet50 are used mainly to pull out local spatial clues from leaf images, while Transformer parts, for instance Swin Transformer, gather wider global context across the same inputs. To make the model behave more stead fast, researchers often add attention mechanisms plus Bayesian optimization, and then rely on feature fusion strategies that merge information more effectively. As a result, these hybrid systems have shown higher accuracy, precision, recall, and F1-score than many conventional deep learning approaches [6].Image preprocessing together with data augmentation seems to matter a lot in boosting disease detection performance. Methods like image resizing and normalization, random cropping, rotation, flipping, affine transformation, grayscale conversion, color jittering , and random erasing are used to increase dataset diversity. In turn, this helps the model generalization capability, it also makes deep learning systems more robust against variations in illumination, background complexity, image orientation , and those environmental conditions we often see in agricultural fields [7]. The emergence of smart agriculture and precision farming tech has further sped up the uptake of AI based plant disease monitoring systems, I mean it is moving fast. In today's smart farming, there is an integration of AI, IoT devices, drones, UAV imaging systems, edge computing, and cloud analytics, which together help with automated crop health monitoring and more informed farming choices. With drone surveillance, high resolution cameras paired with deep learning models can keep watch over big orchards fairly efficiently, and this also cuts down labor expenses while limiting direct human involvement. In a similar way, IoT enabled agricultural setups allow continuous visibility into crop status, weather related parameters, and early disease outbreaks, this improves the way farms are managed and supports better productivity. Even with major advancements, there are still a handful of obstacles in apple leaf disease detection systems. A lot of deep learning models need huge labeled datasets, lots of computational capacity, and a long training period. In real orchards the detection accuracy can drop a bit when things get complicated, like overlapping leaves, different lighting conditions, occlusions, and background noise, which all together make the inputs messier than ideal lab images. Also, lightweight models that can be deployed at the edge, for phones or on device use in real time, they are still not fully solved and remain a busy research topic. Because of that, building efficient scalable and computation friendly hybrid deep learning frameworks keeps looking like a key research goal in precision agriculture [8].

Overall intelligent apple leaf disease detection systems, built on deep learning, YOLO architecture , and transformer models have shown big potential for boosting agricultural productivity, disease management , and sustainable farming practices. Putting AI-driven monitoring together with smart agriculture technology can help with early disease diagnosis, cut down crop losses, reduce pesticide usage, and even improve food quality. And as the research keeps moving forward, more advanced hybrid frameworks are expected to give better accuracy, more dependable performance, and real-time capabilities for automated plant disease recognition, plus smarter agricultural management.

II. ARTIFICIAL INTELLIGENCE AND DEEP LEARNING IN PLANT DISEASE RECOGNITION

Artificial Intelligence (AI) has become one of those really transformative technologies in modern agriculture, especially in the plant disease recognition side and for smart crop monitoring. In the beginning, traditional farming approaches mostly depended on manual inspection of crops, plus a kind of visual check by experts or farmers, who look for disease signs. Even if those methods were common for many years, they are still often slow, hard on labor, costly, and really tied to human know-how. In bigger farming setups, keeping track of diseases by hand becomes more and more tricky, because the weather and environment change, the diseases themselves are complex, and observation needs to happen continuously. Because of that, putting Artificial Intelligence to work in agriculture has become an efficient way to enable automated, accurate, and real time plant disease recognition systems [9]. AI-based systems for agriculture use advanced computational methods to process field data, spot disease trends, and help with smarter choices during the season. The main goal of AI for plant disease recognition is to catch infected plants in an early stage, before the trouble spreads across the whole crop field. When diagnosis happens early, farmers can decrease crop losses, use less pesticide, boost crop quality, and raise overall agricultural productivity. These AI tools also aid sustainable farming habits, because they support precision agriculture and better use of resources, which is really the point in the end. Machine Learning (ML), a big part of Artificial Intelligence , was first presented for automated plant disease detection jobs. In general ML models learn patterns from training data sets and then use statistical ways to tell apart healthy from diseased plant samples. In agricultural disease finding, you often see techniques like Support Vector Machine (SVM), Decision Tree, Random Forest, K-Nearest Neighbor (KNN), Naïve Bayes, and Artificial Neural Networks (ANN). These methods mostly lean on feature engineering, meaning someone designs and extracts the traits ahead of time, from leaf photographs. Things like the visual tone, surface texture, overall form, plus edge related information, get manually pulled out and then handed to the classifier. In traditional machine learning pipelines , image preprocessing along with segmentation are key stages before classification. At first, diseased leaf images are taken in by cameras, or other sensors, then a set of preprocessing steps comes next , including noise reduction, image enhancement, contrast tuning, and normalization. After that, feature extraction is used to pick up disease-linked cues from infected parts of the leaf [10]. Then, classification algorithms decide what disease it is using the extracted features. Even though standard machine learning approaches can reach moderate accuracy for plant disease recognition, their results often rely a lot on dataset quality and on handcrafted feature engineering. Also, these traditional ML models typically have trouble when conditions get more complicated in the field, for example illumination shifts, background clutter, occlusion, and overlapping leaves.

Researchers have been trying to work around the limits of conventional machine learning methods, so lately there has been a noticeable shift towards Deep Learning DL, for agricultural image analysis and also disease detection. In practice DL is a branch within machine learning that makes use of multilayer neural nets, so it can automatically learn layered image representations from huge datasets. When you compare it with older ML approaches, deep learning models remove the need for manual feature extraction and they can just take raw image data in and continue from there. Because of this, the outcomes tend to be better for disease classification accuracy, and the overall system robustness feels stronger too. Convolutional Neural Networks , CNNs have become one of the most used deep learning models for recognizing plant diseases. In practice CNN architectures can automatically pick up both low-level and more semantic image features, using convolutional operations, pooling layers , and activation functions. Because of that they can spot recognizable visual patterns like lesions, spots, uneven discoloration, plus changes in surface texture that often show up when a plant is sick [11]. A bunch of CNN designs, such as AlexNet, VGGNet, ResNet, DenseNet, EfficientNet, MobileNet, and InceptionNet, have shown strong results in agricultural disease classification tasks. Between these models, ResNet brought in residual learning ideas, which helps with feature extraction more effectively, and also lessens the vanishing gradient problem when you train really deep networks. In a similar vein, EfficientNet plus MobileNet use lightweight design patterns, and they fit well for mobile and edge computing tasks in smart farming settings. Overall, these deep learning approaches can still reach strong classification accuracy even when the agriculture scene is hard to read, like when lighting keeps changing, leaves show up at different angles, and backgrounds are messy or complicated. Plant disease recognition has also seen a big rise in the use of object detection models. When compared with image classification models that just assign an entire picture to a disease group, object detection frameworks do more than that, they can spot and locate the infected parts directly on the leaf. In the range of object detection methods, the YOLO (You Only Look Once) architecture has become really well liked in agricultural monitoring because of its fast detection speed and its real time processing [12]. YOLO based deep learning models go through the whole image in one go, in a single stage , so they tend to be pretty computationally efficient compared with the old region proposals approaches like R-CNN and Faster R-CNN. In practice, different YOLO generations, for example YOLOv5, YOLOv7, YOLOv8, YOLOv10, and YOLOv11, get used a lot for apple leaf disease detection, fruit recognition, pest monitoring, and crop surveillance tasks. From those, YOLOv8 feels especially useful because it brings improved anchor free detection, stronger feature extraction, and better localization results. With those perks, YOLO systems are well matched for real time smart agriculture , and even precision farming scenarios. Recently, Transformer based deep learning models have been bringing a new path into computer vision and agricultural image analysis, especially. Vision Transformers, or ViTs, and Swin Transformers look at connections across different image regions using self attention. Compared to CNNs that usually lean on local spatial cues [13], Transformers tend to grasp wider contextual dependencies over the full image, so they feel more panoramic. With that, disease recognition in tricky orchard scenes becomes more reliable even when backgrounds change a lot, and when occlusions show up.

III. IMAGE PROCESSING AND COMPUTER VISION TECHNIQUES FOR LEAF DISEASE ANALYSIS

Image processing , and computer vision technologies have become essential bits in modern farming setups, for automated plant disease recognition and crop health monitoring. These tools help with smart analysis of plant images, for spotting disease signals, finding affected regions, and also backing precision agriculture tasks. Earlier disease diagnosis methods mostly depended on visual checking by agricultural experts, which often took too much time, cost a lot, and was inaccurate when large fields were involved. When image processing and computer vision are put together, the speed, reliability, and overall efficiency of plant disease analysis systems improved a lot. Image processing is basically the use of computational techniques to enhance, inspect, and understand digital images, at least that is the idea. In agriculture, people use image processing quite a lot to spot disease symptoms from plant leaves, fruits , stems, and even whole crops. Then computer vision comes in, which helps machines grasp the visual information in images and videos, in a way that feels close to how humans see things. When these two work together, they make up the base, of intelligent agricultural monitoring systems that can do real-time disease detection and run automated crop analysis. The whole process of leaf disease analysis usually starts with image capturing, and not that "clean" beginning like people expect. In this step, images of healthy leaves as well as diseased ones are taken using digital cameras, smartphones, drones, UAVs, and also imaging sensors. Getting decent image capture is important, because the accuracy of disease detection systems mostly hangs on how clear the picture is, the resolution level, and how consistent the captured images remain. In practice, agricultural datasets often hold images collected under different environmental conditions like changing light, shadows that move around, messy backgrounds, and various leaf orientations [14]. So, the image acquisition setup really needs to be able to grab enough detailed visual information, for reliable disease analysis.

Once the image acquisition is done, preprocessing techniques get applied so the image quality is improved and those unwanted distortions can be removed. Preprocessing is one of the most important stages in image processing, because the raw agricultural images often end up with noise, weak contrast, uneven illumination, and irrelevant background information that can confuse later steps. In practice, people usually do resizing of the image, normalization, contrast enhancement, noise filtering, smoothing, histogram equalization, and color correction. With these steps the images look better, but also they are prepared for faster feature extraction and for classification later on. Image resizing is usually used to make image dimensions consistent before pushing them into deep learning models. Normalization is applied to the pixel intensity values so computations stay steadier while training [15]. For noise reduction, people often use Gaussian filtering, and also median filtering, to clear out annoying image disturbances that happen because of environmental effects or camera limitations. Contrast enhancement methods are another step, they make the infected areas more visible, so disease symptoms become easier to spot. Taken together, these preprocessing steps help strengthen the robustness and the accuracy of computer vision disease detection systems. Image segmentation is another key part of leaf disease analysis, because it helps break the picture into meaningful regions without too much trouble. In general these techniques separate the diseased sections from the healthy leaf parts, so the later steps can pay attention to the infected area only, not the whole image each time. For example segmentation methods often use thresholding, edge detection, clustering methods, region based segmentation, watershed algorithms, and deep learning based segmentation models. When the separation works well the analysis becomes more direct, and less distracted.

Thresholding techniques split diseased regions using pixel intensity gaps, even though it feels a little more straightforward. Edge detection methods on the other hand, try to catch the disease boundaries by looking at gradient cues, rather than intensity alone. Clustering approaches like

K-means cluster pixels that have similar traits and then they are used to isolate infected areas. More advanced deep learning based segmentation models such as U-Net, Mask R-CNN, and YOLO segmentation architectures have shown strong results when dealing with tangled, real agricultural patterns. Overall these strategies tend to boost the localization quality, and also enable more effective analysis of how severe the disease is. Feature extraction plays a pretty critical role in image based plant disease recognition systems. In other words, it involves pulling out the most relevant visual cues from leaf images, so the system can tell healthy leaves apart from diseased ones. In the traditional setup, many machine learning models leaned a lot on handcrafted feature extraction, and those features were usually built from color, texture , shape, plus some statistical details [16]. For example, color features look at how leaf pigmentation changes when disease shows up, like yellowing, browning, or dark lesions. Texture features then focus on messy surface patterns, and on roughness that tends to appear in infected areas. Shape based features, meanwhile, aim to capture structural deformities, or the abnormal edges you might see as the disease progresses.

Computer vision systems use a variety of deep learning architectures for disease identification and localization problems, in practice. CNN models like AlexNet VGGNet ResNet DenseNet EfficientNet, and MobileNet get used a lot for agricultural image classification. They look at leaf images and then assign them into healthy or diseased groups with strong accuracy. Between these architectures, ResNet made residual connections popular, which helps the models learn better features and also makes training in very deep networks less difficult. Object detection frameworks have, further enhanced computer vision applications in agriculture, in a way that traditional classification models cannot. Instead of only labeling what is present, object detection systems can detect the location and also the category of diseased regions inside images. YOLO (You Only Look Once) has become one of the more commonly used object detection architectures for plant disease analysis, mainly because it runs quickly in real time and still keeps strong localization accuracy. In addition, YOLO models handle the whole image in one stage, so they can spot multiple disease regions at the same time without needing to scan step by step [17]. Different versions of YOLO, like YOLOv5, YOLOv7, YOLOv8, YOLOv10, and YOLOv11, have been applied successfully for apple leaf disease detection plus smart farming tasks. YOLOv8 especially delivers better feature extraction, anchor free detection, and more efficient computation . On top of that researchers went ahead and improved the YOLO networks by adding attention modules, feature fusion units, and lighter convolution layers, so the models can cope with changing light, messy backgrounds, and occlusions in orchards, even when conditions change often.

Transformer based computer vision models are showing up as real strong tools for agricultural image analysis , especially when dealing with leaf imagery. Vision Transformers, or ViTs, and Swin Transformers can grab long-range dependencies and a more global sort of contextual view from leaf images, mostly thanks to self-attention mechanisms. In contrast, CNNs tend to lean on local patterns too much, Transformers instead examine how separated parts of an image relate to each other, and that helps improve disease recognition even when the conditions are tricky or noisy. There are also hybrid frameworks that mix CNNs with Transformers , and they have repeatedly shown better classification accuracy plus stronger feature representation for leaf disease analysis.

In computer vision systems data augmentation techniques get used a lot to improve model generalization and also to stop overfitting, sometimes. Approaches like rotation, flipping, scaling, cropping random erasing, affine transformation, and color jittering all add more variety to the dataset, so the model becomes more resilient against real world environmental changes. With these methods disease detection systems can end up performing well in actual agricultural environments, not just in the lab [18]. Overall, image processing plus computer vision technologies have helped shift leaf disease analysis, making automated, accurate, and almost real time plant disease recognition possible. People keep refining preprocessing techniques, segmentation procedures, and deep learning based feature extraction, plus they use YOLO frameworks and Transformer models that keep raising how well agricultural disease monitoring works. When these tools get pulled into smart agriculture platforms, it supports precision farming, more sustainable crop management, and wiser decision making, for the modern way agriculture is done.

IV. YOLO-BASED ARCHITECTURES FOR REAL-TIME APPLE LEAF DISEASE DETECTION

YOLO (You Only Look Once) style architectures have become one of the more effective and widely adopted deep learning options for real-time apple leaf disease detection in smart agriculture systems, honestly. With the increasing need for automated crop monitoring, precision agriculture, and intelligent disease management, people have pushed forward the development of advanced YOLO based object detection models that can spot plant diseases with good accuracy and computational efficiency. Before, disease detection was mainly based on manual inspection by agricultural experts, which is time consuming, labor heavy, and sometimes not consistent when orchards scale up. Also, environmental problems like changing illumination, leaf occlusion, overlapping foliage, background clutter and the messy orchard layouts reduce how well conventional image processing techniques perform, in practice. In general, YOLO is a single stage object detection framework that handles the entire image at once, unlike older region based methods like R-CNN and Faster R-CNN which do object proposal then classification separately. This single stage idea boosts inference speed a lot, which helps with fast disease localization and classification [19]. Typical YOLO architectures split an image into grid regions, then predict bounding boxes, object confidence scores and class probabilities at the same time. That makes them especially useful for agricultural setups where rapid detection matters. Early versions such as YOLOv3 and YOLOv5 already looked promising for plant disease detection because they run fast and still keep solid localization accuracy. But newer improvements including YOLOv7, YOLOv8, YOLOv10, and YOLOv11 raise the detection ceiling by bringing in stronger backbones, feature fusion schemes, attention blocks, and tuned detection heads. Among them, YOLOv8 has become one of the most advanced and efficient architectures for apple leaf disease detection, mainly because it uses an anchor free detection strategy, a lightweight layout, better feature extraction, and strong object localization accuracy. YOLOv8 improves the handling of small and overlapping disease patches while cutting down computational complexity and training time. Researchers used YOLOv8 to identify multiple apple leaf diseases such as Apple Scab, Cedar Apple Rust, Black Rot and Powdery Mildew even when conditions get tough, like uneven lighting or cluttered scenes. Several papers report that YOLOv8 can reach high precision, recall, mAP, and F1-score, while still keeping real-time inference speed that fits smart farming workflows.

Beyond plain YOLOv8, there are also modified YOLO architectures aimed at pushing detection performance higher. For instance, HEFM-YOLO plugs Hybrid Enhanced Feature Modules into YOLO so disease features and localization improve under real world orchard conditions. In a similar direction, MGDS-YOLO applies multi scale feature extraction plus deep supervision to strengthen recognition under varying illumination and messy background scenarios. ALD-YOLO uses lightweight convolution structures and attention mechanisms to improve localization accuracy while lowering computational overhead, which is useful for edge computing devices. TGL-YOLO uses local global feature enhancement to catch diseases across multiple scales when the environment is difficult. There is also YOLO-SPDNet, which brings sequence modeling and attention ideas into the YOLO pipeline to improve detection accuracy and generalization ability. Overall, these changes improve feature representation, disease localization, and robustness to environmental variations.

Attention mechanisms also became a major add on for YOLO based disease recognition systems [20]. With attention blocks, the network can emphasize the most informative disease areas while suppressing irrelevant background content. Methods such as Coordinate Attention, Channel Attention, Spatial Attention, and Self-Attention have been added into YOLO variants to boost feature extraction and disease discrimination. Multi scale feature fusion techniques further support detecting diseases of different sizes and severity. Approaches like Feature Pyramid Networks (FPN), Path Aggregation Networks (PANet), and cross layer feature integration help preserve both fine texture details and higher level semantic cues from leaf images.

Moreover, lightweight YOLO models have been developed for deployment on mobile devices, UAV platforms, drones, and IoT enabled smart farming systems. These compact models reduce memory usage and compute demands while staying accurate, so disease monitoring can happen in real time directly in the field. During YOLO training, data augmentation is also commonly used, including image rotation, flipping, scaling, color jittering, random cropping, and affine transformations, to improve generalization across diverse orchard conditions. On top of that, hyperparameter optimization such as Bayesian Optimization, Random Search, and One-Factor-at-a-Time (OFAT) tuning have been used to optimize learning rate, batch size, momentum, and weight decay for better overall performance. Finally, combining YOLO based architectures with drones, UAV imaging, IoT hardware, and cloud computing has improved automated agricultural surveillance and precision farming [21]. Drone based YOLO systems can collect high resolution orchard imagery and detect diseases over large cultivation regions with minimal human effort. In summary, YOLO based methods have reshaped real-time apple leaf disease detection by delivering accurate, fast, scalable intelligent agricultural solutions. Future progress in YOLO frameworks, feature fusion strategies, attention modules, and lightweight model development is expected to push disease recognition even further and support sustainable smart agriculture systems later on. Table 1 presents a comparative analysis of existing deep learning approaches for plant disease detection, highlighting their methodologies, performance improvements, and major research challenges in smart agriculture applications [22].

Table 1: Comparative Analysis of Existing Deep Learning Approaches and Research Challenges

Ref	Technique / Model	Key Contribution	Major Findings	Limitation
[1]	YOLOv8 with Hyperparameter Optimization	Optimized YOLOv8 for apple leaf disease recognition using OFAT and Random Search	Achieved high precision, recall, F1-score, and mAP with improved computational efficiency	Requires extensive tuning and training data
[2]	YOLO-ALD	Lightweight and robust apple leaf disease detection model	Improved detection accuracy and fast inference in complex orchard environments	Performance may reduce in severe occlusion conditions
[3]	YOLO11 Deep Learning Model	Real-time apple scab identification and quantification	High precision disease localization under preharvest and postharvest conditions	Sensitive to extreme illumination variations
[4]	HEFM-YOLO	Hybrid Enhanced Feature Module integrated with YOLO	Enhanced disease feature extraction and localization accuracy	Performance affected in cluttered backgrounds
[5]	Improved YOLOv11s	Enhanced apple surface disease detection framework	Better detection of multiple defects and small disease spots	Increased model complexity
[6]	YOLO-Based Apple Detection Framework	Efficient apple detection in complex orchard environments	High-speed real-time fruit detection and localization	Difficulty under overlapping fruit conditions
[7]	TGL-YOLO	Multi-scale feature enhancement with YOLO11	Improved precision, sensitivity, and mAP	Higher computational requirements

			for plant disease detection	
[8]	YOLO with Fuzzy Logic Severity Grading	Integrated disease identification with severity analysis	Accurate disease severity grading and classification	Requires complex fuzzy rule design
[9]	WFS-YOLO	Weighted feature selection for tomato leaf disease detection	Improved feature representation and detection stability	Computational overhead due to feature fusion
[10]	GCE-YOLO	Global contrast enhancement for foggy agricultural environments	Enhanced cherry ripeness detection under foggy conditions	Limited validation on diverse crop datasets

V. CONCLUSION AND FUTURE WORK

In this review, a bunch of Artificial Intelligence, Deep Learning, image processing, and YOLO based architectures were really analyzed for apple leaf disease detection and smart agriculture. The study kind of emphasized how automated plant disease recognition systems can help with agricultural productivity, reduce crop losses, and also back precision farming practices. Older or traditional disease identification methods were described as somewhat limited because they really rely on manual inspection and expert knowledge. Meanwhile, newer deep learning frameworks like CNNs, YOLOv8, YOLOv10, YOLOv11, Swin Transformers, and several hybrid architectures showed better accuracy, stronger robustness, and real time detection ability when tested in busy orchard environments, with all that lighting variation and clutter. The review also went over preprocessing techniques, feature extraction methods, attention mechanisms, multi scale feature fusion, plus lightweight models. These parts are said to improve disease localization and classification, quite a lot. For future directions, researchers may want to build lightweight, energy efficient models that fit mobile and edge devices, make detection more reliable under extreme environmental conditions, expand the multi crop disease datasets, and combine Transformer based architectures with real time IoT enabled agricultural systems, so the whole plant disease management approach becomes scalable, sustainable, and highly accurate.

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