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Leveraging Computer Vision for Crop Health Monitoring, Automated Yield Estimation, and Enhanced Disease Detection in Precision Agriculture

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Abstract: Precision agriculture is revolutionizing classical farming through the use of technologies such as computer vision (CV) and artificial intelligence (AI) to meet the increasing global food demand, which is likely to rise along with a predicted global population of 9.7 billion by 2050 (UN, 2019). Herein, we present a review of nine landmark studies (2020-2024) that identify the critical impact of computer vision (CV) in the future of three high-impact verticals: crop health monitoring, automated yield estimation, and higher disease detection rates. Among the significant advancements, there is the Smart Weed Detection and Removal Bot (SWDRB) that achieved a weed detection accuracy of 96% (Praveenraj et al., 2024) and Random Forest (RF) model that can reliably predict the Indian crop yields with an accuracy of 98.96% (Sharma et al., 2023) along with deep learning (DL) frameworks that can classify the plant diseases with an accuracy of 99.35% (Li et al., 2021). Additional developments include: autonomous agricultural vehicles (AAVs) for safety (Avila et al., 2023); generative AI for visual yield prediction (Majumder et al., 2024); robotics for real-time diseases detection (ElSayed et al., 2024); automation for fruit quality checking (Lin & Qi, 2023); microclimate monitoring (Kempelis et al., 2022); and bibliographical analysis for smart farming trends (Unal, 2020). These studies demonstrate how CV can conserve re-¨ sources, reduce environmental impact, and increase productivity. However, there are still challenges in aspects, such as, scalability, dataset diversity, and real-time deployment. Here we consolidate these developments and assess their policy relevance, and outline future research needs to fill gaps, providing a roadmap towards sustainable precision agriculture.

I. INTRODUCTION

A. Background

This poses a major challenge for agriculture; how to ensure an increasing global population can be fed, as well as dealing with climate change, soil erosion and resource scarcity. According to the Food and Agriculture Organization (FAO, 2017), 40% of crops in developing regions are lost to pests and diseases, exacerbated by poor management practices, necessitating innovative solutions. The integration of computer vision (CV), machine learning (ML), deep learning (DL), robotics, and the Internet of Things (IoT) technologies for efficiency and sustainability is known as precision agriculture. This review provides an overview of nine studies published between 2020-2024 that exemplify the diverse applications of CV, as summarized below:

1. Avila et al. (2023) provide an assessment of CNNs including YOLOv4 and SSD Mobilenet V2 in AAV (autonomous agricultural vehicle) security in sugarcane harvesting [1].
2. Majumder et al. (2024) model a system leveraging generative AI (pix2pix) for yield forecasting in controlled environment agriculture (CEA) [2].
3. Praveenraj et al. The Smart Weed Detection and Removal Bot (SWDRB) for weed management in vegetable fields[3].
4. In Jilin Province, China, Lin and Qi (2023) introduce an automatic apple quality grading approach [4].
5. Li et al. (2021) focused DL review on plant disease recognition addressing CNNs and hyperspectral imaging (HSI) [5].
6. Sharma et al. Kumar et al. (2023) use ML, and DL methods to forecast crop yields in India based on the past data [6].
7. Kempelis et al. (2022), CV and ML to monitor plants in IoT networks [7].
8. Unal (2020) examines DL trends in nine domains of smart¨ farming [8].
9. ElSayed et al. (2024) uses a combination of robotics and CV for tomato disease detection [9].

Importantly, other global efforts underway to modernize agriculture are evidenced through research from Latvia (Kempelis et al., 2022), India (Sharma et al., 2023), and Egypt (ElSayed et al., 2024) .

B. Research Problem

Traditional agricultural methods — manual monitoring of crop health and checkups, centralized and uniform spraying of pesticides, statistical analysis of output in previous seasons for yield predictions — are labor-intensive, slow, error-prone, and environmentally unviable. The later detection of disease leads to much larger losses of the crop (Li et al., 2021), while weed competition also results in lower yields (Praveenraj et al., 2024). While CV-based solutions provide automation and precision, they experience critical challenges as follows:

1. Variability in Environment: None of the models can detect an object with the best accuracy under variable light condition, occlusion (large bodies covering separate entities), nor complex terrains (Kempelis et al., 2022; Avila et al., 2023) [7].
2. Lack of Diversity in Datasets: High-quality agricultural datasets are crucial but often scarce and lack diversity (Majumder et al., 2024; Li et al., 2021) [2].
3. Computational Constraints: Challenges exist in deploying models in the edge (Unal, 2020; ElSayed et al., 2024) [8]¨

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4. Scalability: Field conditions may differ greatly from the controlled environments in which innovations (Majumder et al., 2024) have been validated [2].

C. Proposed Solutions

The reviewed studies provide diverse CV-based methods:

- Monitoring Crop Health: contaminants and barriers are identified using autonomous bots (Praveenraj et al., 2024) and AAVs (Avila et al., 2023) employing CNN, in concert, IoT-integrated CV tracks microclimates (Kempelis et al., 2022). [1] [3] [7].
- Yield Prediction: The prediction accuracy was improved using machine learning (ML) and deep learning (DL) models (Sharma et al., 2023), generative artificial intelligence (AI) (Majumder et al., 2024), and automatic grading systems (Lin and Qi, 2023). [2] [4] [6].
- Diagnosing Diseases: DL frameworks (Li et al., 2021), robotic systems (ElSayed et al., 2024), and trend analyses (Unal, 2020) improve classification and early interven-¨ tion. [5] [8] [9].

These solutions employ advanced algorithms (e.g., CNNs, YOLO, GANs), data augmentation, and hardware innovations, such as Jetson AGX Orin and Tesla GPUs, to overcome agricultural challenges.

D. Significance and Impact

For farmers, these technologies minimize labor, maximize inputs – e.g., a 15-25% reduction in pesticide use (ElSayed et al., 2024)—and improve yield, especially for distressed areas (Sharma et al., 2023). On an academic scale, they reiterate the importance of the CV, offering benchmarks for future research. And in the industry context, they facilitate scalable automation that improves competitiveness in the market (Lin and Qi, 2023) and contributes to sustainability goals, such as SDG 2: Zero Hunger [4] [6] [9].

II. LITERATURE REVIEW

A. Agricultural Challenges and Technological Needs

It is increasingly projected that the world will not be able to feed itself: by 2050, the global population will reach 9.7 billion people (UN, 2019) and food production will have to be increased almost twofold to meet the demand, while arable land, climate variability, and resource depletion will do everything they can to make sure this is impossible to achieve (Kok et al., 2019). These issues are exacerbated by unique threats: weeds outgrow crops and consume their nutrients, decreasing yields by as much as 30% in vegetable fields (Praveenraj et al., 2024); plant diseases account for 20-40% of crop losses, with even higher rates in developing regions (FAO, 2017; Li et al., 2021); and a lack of efficiency in monitoring systems leads to resource waste, making traditional sensors costly and non-scalable (Kempelis et al., 2022) [3] [5] [7].

B. Advances in Computer Vision and AI

The intersection of CV and AI has paved the way for revolutionary progress throughout precision agriculture, as illustrated through the nine reviewed studies between 20202024. Collectively, these studies demonstrate the ability of CV to tackle three critical areas of agriculture: crop health monitoring, automated yield estimation, and improved disease detection, employing a variety of approaches ranging from convolutional neural networks (CNNs) to generative adversarial networks (GANs) to robotics.

1) Crop Health Monitoring: Crop health monitoring encompasses weed management, obstacle detection for autonomous vehicles, and microclimate analysis, each benefiting from CV’s ability to process visual data in real time.

- **Weed Detection and Removal:** Praveenraj et al. (2024) present the Smart Weed Detection and Removal Bot (SWDRB), an autonomous plant with 96% weed detection accuracy in vegetable fields. This system takes high-resolution images of crops using various crops, weeds (Horseweed, Velvetleaf) to identify crops using shape, color, and texture through CNN segmentation and feature extraction. The bot employs two removal methods—mechanical arms or targeted herbicide sprayers—reducing chemical usage by 20-30%. (Praveenraj et al., 2024), making it a production method compatible with sustainable farming. The system is trained on datasets from Kaggle and PlantVillage (400-500 images per weed type), the system demonstrates declining loss trends, underscoring its robustness [3].
- **Autonomous Agricultural Vehicles (AAVs) and obstacle detection:** Avila et al. (2023) assess CNN architectures such as YOLO (v3, v4, v5, v8) and SSD Mobilenet (v1, v2, Inception v2) to guarantee AAV safety as sugar cane is harvested across Brazil. Processing 82M (5 FPS) of video data on Nvidia Jetson AGX Orin and RTX 3060 Ti, this shows that SSD Mobilenet V2 has performance oriented for rapid obstacle avoidance (48.41 frames per second [FPS]), while YOLOv4 with

OpenCV shows the best accuracy, with an example for cars at a confidence of 0.84, on an FPGA embedded system. It increases operational safety and minimizes the chances of collision during field operations by balancing speed and precision[1].

- **Microclimate Analysis:** Kempelis et al. (2022) perform a systematic review of 32 studies (2015-2022) from IEEE, Scopus, and other databases emphasizing the role of CV-ML in monitoring microclimatic parameters such as humidity, soil moisture, and temperature. With CNNs and YOLO algorithms being prevalent, they extract features of visual information so that for physical sensors, which are expensive and energy-intensive, it decreases their dependence on these sensors (Tzounis, 2017). By researchers from Riga Technical University, Latvia, the study highlights uses in both disease detection and soil analysis and suggests energy-efficient protocols, including energygenerating solar-powered sensors, to even further reduce costs [7].

2) Automated Yield Estimation: Automated yield estimation leverages CV and AI to predict crop output and assess quality, supporting farmers in planning and resource allocation.

- **Historical Yield Prediction:** Sharma et al. (2023) use ML and DL to predict the yields of ten major crops of India (rice, wheat, etc.) with historical data (1997-2020) collected from government portals (https://data.gov.in). Among ML models (DT, RF, XGBoost), RF provides the best prediction accuracy (98.96%) with RMSE of 2.45 and MAE of 1.97, whereas deep learning(DL) models (e.g. CNN) exhibit the lowest test loss (0.00060). Evaluated with 4-fold cross-validation, this method captures nonlinear interactions between rainfall, crop type, and area, providing actionable insights into India's 297,319 thousand hectares of arable land [6].
- **Visual Yield Forecasting:** Majumder et al. (2024) pioneer generative AI in Controlled Environment Agriculture (CEA), employing GANs (DCGAN, pix2pix) and stable diffusion (instruct-pix2pix) to visually predict yields from 8,479 fruit images. Pix2pix outperforms DCGAN, achieving SSIM scores of 0.7-0.9 compared to DCGAN's 0.5-0.7, generating high-quality synthetic images for forecasting. Integrated with CV-based fruit detection, this method enhances monitoring in controlled settings, though instruct-pix2pix's randomness highlights a need for refinement [2].
- **Apple Quality Grading:** Lin and Qi (2023) automate the apple grading in China's Jilin Province using CV with CCD cameras (8 mm and 16 mm lenses). The system operates with less than 11.8% error for graded apples and zero errors for out-of-grade fruits, based on 280 video frames obtained in natural and ring light settings to calculate equivalent diameter and projected area. This precision, alongside environmental monitoring (e.g., stable air temperature within 2%), can minimize labor costs and enhance market consistency in cold-climate context[4].

3) Enhanced Disease Detection: Disease detection benefits from CV and DL's ability to identify subtle symptoms early, mitigating losses and reducing pesticide overuse.

- Li et al. (2021) reviews 117 studies (2012-2020), documenting the superiority of DL in plant disease classification, with CNNs reaching over 99.35% accuracy on 54,309 images from PlantVillage (Mohanty et al., 2016). Integrated techniques such as transfer learning (i.e. ResNet, GoogLeNet), few-shot learning (FSL) for small dataset (90% with only 60 images, Medela et al. 2019), and hyperspectral imaging (HSI) for pre-symptomatic detection (96.25%, Wang et al. 2019) showcase the versatility of DL in crop types like tomatoes or wheat[5].
- Robotics Integration: ElSayed et al. (2024), of the Arab
 Academy for Science, Technology & Maritime Transport (AASTMT), Egypt, propose a lightweight convolutional neural network (CNN) for the detection of tomato disease, obtaining an accuracy of 95.91% on 32,535 images of the Tomato Disease dataset. It saves 57.9083% training time (28.45 seconds) and 31.609% inference time (43.623 milliseconds) with respect to transfer learning models (e.g. InceptionNetV3 at 98.97%), which makes it relevant for robotic deployment [9].
- Bibliographical Trends: Unal (2020): 120 papers of¨ SCI (2016-2019): disease detection (19 papers) and plant classification and weed detection are considered as a leading DL domain. In showcasing the rapid growth of DL—with a peak of 76 papers in 2019—the study, conducted by NIS¸TA Company, Turkey, found that CNNs are key to the DL phenomenon, also made possible by the use of Internet of Things (IoT) and unmanned aerial vehicles (UAVs) to gather data that is then processed to support smart farming from a large perspective [8].

C. Research Gaps

Even with these innovations, substantial gaps still exist that hinder the comprehensive adoption of CV and AI in precision agriculture:

- **Environmental Robustness:** Variations in lighting, occlusion, and weather conditions reduce detection precision. Avila et al. (2023) also find SSD Mobilenet V2's speed suffers on complex backgrounds, whereas Kempelis et al. (2022) identify noisy image data as a recurring challenge in microclimate monitoring that requires either adaptive algorithms or better preprocessing [7].
- **High-Dimensionality with Limited Data:** Majumder et al. (2024) observe the reliance of generative AI on vast datasets of fruit images, with instruct-pix2pix's randomness indicating low diversity. Similarly, Li et al. 2023) in PlantVillage challenge lab-based bias and limit applicability; Unal (2020) raises small dataset hurdles for¨ DL scalability [8] .
- **Real-Time Constraints:** Field deployment is limited due to computational complexity. ElSayed et al. (2024) achieved optimized inference time, nevertheless more guides like InceptionNetV3 are inappropriate for resource constrained robotic. According to Unal (2020), high¨ demands on processing power indicates a significant limiting factor for real time smart farming applications, especially on embedded systems such as the Jetson AGX Orin (Avila et al., 2023) [1].
- **Crop and Regional Diversity:** A number of studies only emphasize specific crops or geographical areas (e.g., tomatoes (ElSayed et al., 2024), apples (Lin and Qi, 2023) or Indian staples (Sharma et al., 2023)) reducing generalizability. Li et al.

(2021) and Kempelis et al. (2022), and this limitation should be addressed by broader datasets and validation in different agroecosystems [8].

- **Integration with New Technologies:** Although Unal¨ (2020) and Kempelis et al. Although Sharma et al. (2023) and (2022) promote integrating IoT and UAVs, there are limited studies that exploit (big) remote sensing analytics. This gap constraints predictive models from being able to incorporate dynamic environmental inputs, which are vital for real-time inference [7].

D. Synthesis and Future Directions

We found that the studies reviewed, when taken together, highlight the transformative potential of CV and AI, being able to achieve high accuracy (e.g. 99.35%, Li et al, 2021), speed (e.g. 48.41 FPS, Avila et al, 2023), and environmental sustainability effects (e.g. lower herbicide usage, Praveenraj et al, 2024). In contrast, environmental robustness must be handled through either advanced preprocessing or multi-modal data fusion (e.g., HSI with RGB, Li & al., 2021). Data scarcity can be addressed through extensive generative AI (Majumder et al., 2024) or crowd-sourced field datasets. Realtime deployment requires lightweight models (ElSayed et al., 2024) and integration with edge computing, and a wider range of crop and region adaptability needs collaborative, openaccess datasets (Unal, 2020). To fully deliver on precision agriculture's promise future research should focus in these areas, together with validation in uncontrolled field environments.

III. RESEARCH METHODOLOGY

A. Research Design

In this overview, we use an approach with complex methods that synthesize nine studies, quantitative experimental data, and qualitative systematic analyses to assess the uses of computer vision (CV) and artificial intelligence (AI) in precision agriculture. The framework was introduced by Sharma et al. and Li et al. (2021) Trends and roadblocks in DL applications. The integration enables both technical assessments on an overall CV methodology effectiveness (e.g., on-the-go weeds by Praveenraj et al., 2024), and practical implications targeting agricultural relevant issues like harvesting (specific crop or parts of the plants), harvest prediction and automation reliability. The study employed a three-area focus to frame their analysis concerning: disease harvesting, yield estimation, and recognition and tested whether different experimental designs were validated using metrics like RMSE, SSIM, and inference period.

B. Data Collection

The data collection across the nine studies differs by methodology, Study of diverse agricultural contexts and technological applications:

1. Avila et al. (2023): Recorded 82 mins of 5 FPS video with a FLIR Blackfly camera fit on the Arocs truck during the sugarcane harvest operation in Iracemapolis-SP, in Brazil.´ It comprises 24,600 frames (82 × 60 × 5), representing urban and rural scenes to assess AAV safe navigation by evaluating object detection performance, mainly for obstacles like human beings, an automobile, and a truck[1].
2. Majumder et al. [2024] — Collected 8,479 images of fruit from Kaggle along with 200 apple-only images for generative AI training in Controlled Environment Agriculture (CEA). Data: Images include different growth stages (S1, S2, S3, S4) at various locations, normalized to [-1,1] using resize to 256x256 pixels [2].
3. Praveenraj et al. (2024): Used 400-500 images for each weed type (e.g., Horseweed, Velvetleaf, Pigweed) obtained from Kaggle and PlantVillage (1,600-2,000 in total) The images are collected from various vegetable fields, providing training data for identifying the weedcrop for the Smart Weed Detection and Removal Bot (SWDRB) [3].
4. Lin and Qi, 2023: Collected 280 video frames of apple orchards in Jilin province, China, under natural light and posted ring light conditions with CCD cameras equipped with 8mm and 16mm lenses. Visual data for quality grading is augmented by environmental data (e.g., air temperature, and soil humidity) from the warehouses [4].
5. Li et al. Plant Pathology Challenge (3,651 apple disease images)] (2021): Screened 117 trials (2012-2020), pooling datasets including PlantVillage (54,309 images for 14 crops and 26 diseases). These datasets underwrite a qualitative synthesis of DL's role in the detection of disease [5].
6. Sharma et al. (2023): Extracted time series data (19972020) from the open data platform, Government of India (https://data.gov.in, https://aps.dac.gov.in) for ten major crops (rice, wheat, etc.) for an area of 297,319 thousand hectares. Features include rainfall, area, production, and yield utilized to construct a multi-decadal data set for ML(DL) Prediction [6].
7. Kempelis et al. (2022): Reviewed 32 papers (2015-2022) indexed in IEEE (11), ScienceDirect (7), Scopus (6), and Springer Link (8), 5,408 filtered results extracted from 17,906 entries. CV-ML for microclimatic elements (humidity, soil moisture) [7].
8. Unal (2020); Analyzed 120 SCI-indexed (2016-2019)¨ papers in 39 journals, using the keywords "deep learning" and "agriculture or farming" There are many applications ranging from disease detection to weed identification supported by the data collected using IoT and UAV [8].
9. ElSayed et al. (2024): Utilized the "Tomato Disease Multiple Sources" dataset from Kaggle (PlantVillage) consisting of 32,535 images divided into 11 classes (e.g., Bacterial Spot, Early Blight). It is divided into training (20,680), validation (6,684), and testing (5,171) sets and helps in robotic disease detection [9].

These datasets collectively span field-collected imagery, historical records, and literature reviews, ensuring a broad evidence base for evaluating CV and AI's agricultural impact[5].

C. Sampling Techniques

Sampling strategies reflect the objectives of each study, offering a balance between specificity and representativeness:

- **Systematic Literature Review:** The criteria for articles included those that used purposive sampling to sample datasets for specific tasks in agriculture. Avila et al. Praveenraj et al. (2023) selected sugarcane harvest footage for AAV contexts (2024) focused on weed images consisting of the vegetable fields while ElSayed et al. (2024), stratified sampling can be implemented so that tomato disease classes were balanced. Majumder et al. (2024) and Lin and Qi (2023) purposefully sample fruit images and apple frames that meet CEA and grading needs, respectively. Sharma et al. (2023) focus on ten staple crops of India, that were validated using a 70:30 train-test split and 4-fold cross-validation for robustness [2] [3] [4] [6].

- **Review Studies:** Systematic sampling consolidates relevant literature as per inclusionary principles. Kempelis et al. (2022) screened post-2015 English-language literature on CV-ML, from 17,906 to 32 papers. Unal (2020), uses¨ similar criteria (2016-2019 DL focused) to winnow down 133 SCI papers to 120. Li et al. (2021) purposively extracted 117 studies to focus on that emphasize CNNs, FSL, and HSI, indicating congruence with disease detection trends [7] [8] .

This ensures both contextual depth for experimental outcomes and comprehensive coverage for review insights, although the biases of their dataset (for example, lab-based PlantVillage images) are acknowledged as limitations.

D. Data Analysis

Data analysis combines quantitative metrics and qualitative trends to evaluate CV and AI performance:

- **Quantitative Metrics:**
  - Accuracy: Praveenraj et al. Sharma et al. (2024) report 96% weed detection accuracy (2023) report 98.96% with Random Forest (RF), and Li et al. PlantVillage (2018) and Chen et al. (2021) cite accuracies of up to 99.35% for CNNs on PlantVillage. ElSayed et al. (2024) 95.91% record for their lightweight CNN, accrued to their 98.97% for InceptionNetV3 [3] [4] [6] [9].
  - Speed: Avila et al. (2023) run SSD Mobilenet V2 on Jetson AGX Orin at 48.41 FPS, with YOLOv4 running only 11.10 FPS with higher confidence (for example, 0.84 for cars). ElSayed et al. (2024) then have 31.609% less inference time than InceptionNetV3 [1] [9] .
  - Quality/Error: Majumder et al. (2024) analyze GANs with SSIM (pix2pix: 0.7-0.9, DCGAN: 0.5-0.7), but Lin and Qi (2023) find an 11.8% grading error rate and no errors of out-of-grade apples. Sharma et al. for RF (2.45 RMSE, 1.97 MAE) (2023) [2] [6] .
  - Efficiency: ElSayed et al. (2024) reduced the training time to 57.9083% which better suited robotic feasibility [9].
- **Qualitative Trends:**
  - 2019 Quchy et al (2019) has increased from 135 in 1987 to 8179 in 2019 with the top three keywords disease detection, machine learning, and classification. Kempelis et al. (2022) show CNN superiority in microclimate monitoring in 32 studies [7].
  - Baseline Algorithm (Tradition): CNN and YOLO are popular in experimental (Avila et al., 2023; Praveenraj et al., 2024) and review (Li et al., 2021; Unal, 2020)¨ studies [1] [3] [8].

The analysis culminates in the integration of these metrics summarising performance for CV's application in real-time (e.g. AAV safety, weed removal) and predictive (e.g. yield forecasting, disease classification) tasks identifying limitations such as environmental noise and computational overhead [9].

E. Tools and Techniques

The studies adopted diverse hardware, software, and methods used in precision agriculture:

- **Hardware:**
  - Avila et al. Embedded Systems. (2023) Conduct AAV tests using Nvidia Jetson AGX Orin (30W mode) alongside an RTX 3060 Ti desktop for highperformance benchmarks [1] .
  - GPUs: ElSayed et al. (2024) utilize dual Tesla T4 GPUs (with Kaggle) to train CNNs, whereas Sharma et al. (2023) suggest the use of GPUs for DL models (i.e., CNN, LSTM) [6] [9].
  - Cameras: Praveenraj et al. (2024) utilize highresolution cameras on the SWDRB, Lin and Qi (2023) utilize CCD cameras (8mm/16mm lenses), and Avila et al. (2023) employ a FLIR Blackfly camera [1] [3].
  - Robotics: ElSayed et al. (2024) and Praveenraj et al. Integrated CV with RAs/RSs for in-field applications (2024) [1] [3][9] .
- **Software:**
  - Frameworks: OpenCV (Avila et al., 2023; Majumder et al., 2024), PyTorch (Avila et al., 2023), TensorFlow (ElSayed et al., 2024), and Hugging Face Transformers (Majumder et al., 2024) — frameworks used for model development and image processing [1] [2] [9] .
  - Libraries: Jetson Inference (Avila et al., 2023) enhances embedded performance; Python-based instrumentation (Sharma et al., 2023) enables ML/DL [1] [6] .
- **Techniques:**
  - Neural Networks: CNNs in charge (Praveenraj et al.,2024; ElSayed et al., 2024), uses of CNN variants (YOLO (see Avila et al., 2023; Kempelis et al., 2022), GANs (DCGAN, pix2pix in Majumder et al., 2024) [2] [3] [7].
  - New Solutions: Transfer learning (Li et al., 2021; ElSayed et al., 2024), few-shot learning (FSL, Li et al., 2021), and hyperspectral imaging (HSI, Li et al., 2021) improve detection performance. Data augmentation (e.g., gamma correction, blurring in ElSayed et al., 2024) provide robustness [5] [9].
  - Preprocessing: Input data is refined through segmentation and feature extraction (Praveenraj et al., 2024), contour extraction (Lin and Qi, 2023), and normalization (Majumder et al., 2024) [2] [3].
  - Optimization: Adam/Adamax optimizers (ElSayed et al., 2024; Sharma et al., 2023), categorical crossentropy/MSE loss (ElSayed et al., 2024; Sharma et al., 2023) and ReLU functions (Unal, 2020) [6] [9] .¨

These tools and techniques together allow for high-precision analysis, from real-time obstacle detection (Avila et al., 2023) to generative yield forecasting (Majumder et al., 2024), but computational complexity as well as dataset integrity remain challenges for field implementation.

F. Validation and Limitations

Validation is study type dependent:

- **Experimental:** Avila et al. Sharma et al. ran ten trials for reliability (2023). (2023) applied 4-fold crossvalidation, while ElSayed et al. (2024) divided data into training/validation/testing sets with 30 epochs of training. Praveenraj et al. In line with previous methodologies, the search approach directly selects road networks using accuracy and error rates concerning field data (Lin and Qi, 2023) while for further verification compares the structured nodes to reconstruction speculations (2024) [3] [6] [9] .
- **Reviews:** Kempelis et al. Data Researcher (2022) and Unal (2020) apply systematic criteria to ensure represen-¨ tativeness, while Li et al. (2021) use benchmark datasets (e.g., PlantVillage) to cross-reference findings [7].

Limitation: The inclusion of datasets with modality sensitivity bias (example: Li et al., 2021 use lab-captured images), low adaptability in time with environmental conditions (Avila et al., 2023), and limitations in crop extensiveness (example: ElSayed et al., 2024 use exclusively tomatoes) hint at methodological improvement opportunities [5].

IV. EXPECTED OUTCOMES AND IMPACT

A. Expected Outcomes

All nine studies utilizing computer vision (CV) and artificial intelligence (AI) is a leading indicators of a profound change in precision agriculture, which can contribute to crop health monitoring, automated yield estimation, and improved disease detection. These results reflect evidence-based impacts and methods that yield concrete advancements in agricultural productivity and sustainability.

1) Crop Health Monitoring: Crop health monitoring is crucial to minimizing losses and efficient resource utilization. The studies show remarkable advances in this field:

- **Integrated Weed Management on Natural Dyeing Practices:** Praveenraj et al. report that the Smart Weed Detection and Removal Bot (SWDRB) can identify weeds (Horseweed, Velvetleaf) from vegetable crops with 96% accuracy using CNNs trained on 400-500 images per weed type. This accuracy diminishes competition for nutrients in the environment and leads to water and sunlight with a decreasing trend of loss (e.g., box _loss and cls loss), where loss was able to confirm proper convergence of the model after a few thousand iterations during training. Mechanisms for autonomous removal—the SWDRB employs robotic arms or targeted sprayers—also improve efficiency in the field and reduce crop damage relative to traditional herbicide applications [3].
- **Safety in Automation:** Avila et al. (2023) demonstrate YOLOv4's impressive performance with an average confidence score of 0.84 at 11.10 FPS from Nvidia Jetson AGX Orin in terms of AAV safety for obstacle detection (e.g., cars). While maintaining reliability in sugarcane real-time detection, this is a higher speed (48.41 FPS) but lower confidence than the previous SSD Mobilenet V2. Based on its ten-trial validation, this study affirms consistency which helps minimize collision risks as well as bolster operational reliability specifically in dynamic field environments [1].
- **Microclimate Optimization:** Kempelis et al. Data up to October 2023: The focus on microclimate attributes underlines the potential for CV-ML as a monitoring tool; studies are covered here: (2022): CV-ML for microclimate (humidity, soil moisture, temperature)— selon 32 studies, CNNs particularly suitable in the context of tasks such as soil analysis and disease symptom detection. This methodology enables the extraction of these features from visual data, thereby minimizing the dependence on costly physical sensors and subsequently reducing monitoring costs through the utilization of existing camera infrastructure. This scalability is crucial in resourcelimited settings, although precise accuracy metrics vary by context across the papers reviewed [7].

2) Automated Yield Estimation: Accurate yield estimation helps with harvest planning, resource allocation, and market readiness, and the studies provide advanced predictive capabilities:

- **Prediction Accuracy:** Sharma et al. (2023) show that Random Forest (RF) has performed exceptionally with 98.96% accuracy in predicting the yields of ten major Indian crops (rice, wheat, etc.) with historical data (19972020). Indeed, RF achieves 2.45 RMSE, and 1.97 MAE, beating Decision Tree (89.78%) and XGBoost (86.46%) by four-fold cross-validation. Such high accuracy with real-time verification of data helps farmers to make better decisions about which crops to plant, and also helps with hedge against financial loss, especially in climate-prone regions of countries like India [6].
- **Generative AI for Visual Insights:** Majumder et al. (2024) use pix2pix GANs to create high-fidelity fruit imagery (SSIM 0.7-0.9) from 8479 Kaggle fruit images and 200 apple-specific data, better than DCGAN (SSIM 0.5-0.7). The instruct-pix2pix diffusion model offers visual yield forecasts in controlled environment agriculture (CEA) but needs optimization considering its randomness in the output. These visual predictions aid in the decisionmaking processes through modeling of growth stages, offering fresh perspective-based collaboration with traditional number-based forecasts [2].
- **Grading Precision:** Using 280 frames of CV with CCD cameras (8mm/16mm lenses) on orchard images from Jilin Province, Lin and Qi (2023) achieved 11.8% error in apple quality grading. Importantly, no errors for out-ofgrade apples guarantee valid classification (small: 255.2 pixels, large: 276.6 pixels average diameter), confirmed by MAE value 0.012 and IoU 0.85. This accuracy minimizes the time-consuming, manual work of grading by hand, creating more uniformly consistent products that can compete on the market, even in different light conditions [4].

3) Improved Disease Detection: Timely and accurate disease detection is vital to prevent crop losses, and the studies highlight leading-edge solutions:

- This is the most accurate classification by Li et al. DL performance is reviewed in [4], with CNNs reaching an accuracy of 99.35% in the PlantVillage dataset across 26 diseases (54,309 images). The tasks are solved by traditional methods (Dubey & Jalal, 2012; 93%), transfer learning (Huang et al., 2020; 99.01%) and hyperspectral imaging (HSI; 96.25%; Wang et al., 2019) when it comes to pre-symptom disease detection across 14 crops. This leads to very high accuracy and facilitates timely interventions while minimizing economic losses [5].
- Robotic Efficiency: ElSayed and coworkers (2024) present a relatively light CNN with 95.91% accuracy on the Tomato Disease dataset (32,535 Images) with 57.9083% training time and a 31.609% inference time reduction compared to InceptionNetV3 (98.97%) Augmented by data augmentation (e.g., gamma correction, noise), this system's efficiency is appropriate for robotic deployments, allowing for real-time monitoring of 11 tomato disease classes (e.g., Bacterial Spot) with minimal computational overhead [9].
- Least Popular: The convergence of many methods from these separate fields is only new (source here, correct as of Oct 23, 2023); Disease Detection is a popular DL application (19 out of 120 papers, 2016-2019), with a peak in 2019 (76 papers) indicating interest. CNNS and optimization techniques (e.g. ReLU, Adam) remain dominant given the scalability of automation over manual processes but also live constraints need to be imposed which still haven't been overcome via even IoT and UAV data [8].

B. Impact

The anticipated impacts extend through academia, industry, and society, illustrating the efficacy of precision agriculture, which aims for cost-effective, sustainable approaches to reduce resource inputs while maintaining food security [8].

1) Academic Contributions: The studies as a suite build a scientific understanding of CV and AI in agriculture, delivering strong benchmarks and mapping out research frontiers:

- Performance benchmarks: ElSayed et al. (2024) established a benchmark for lightweight CNNs (95.91% accuracy, 57.9083% time faster training), and Avila et al. 2017 (48.41 FPS) for YOLOv4 (0.84 confidence) and SSD Mobilenet V2 accuracy on embedded systems. Sharma et al. (2023), prove RF achieved excellent prediction (98.96%) in yield prediction, make measurable and reproducible for further studies [9] .
- Research Gaps and Directions: Li et al. (2021) call out issues with dataset bias (e.g., lab-based PlantVillage images) and robustness, calling for validation in real-world datasets. Kempelis et al. (2022) ask for advancements in sensor fusion and Unal (2020) cites computational¨ bottlenecks that hinder real-time DL. The gaps provided incentives to innovate in the directions of data diversity, optimization of models, and integration with those new emerging technologies i.e. UAVs and Big Data [7] .
- Method Innovation: Majumder et al. generative AI in CEA pioneer (SSIM 0.7-0.9, (2024) and Praveenraj et al. (2024) that integrated CV with robotics (96% accuracy), developing interdisciplinary research that combined agronomy, AI and machine engineering (96.09% accuracy) [2] .

Such contributions are valuable to the academic community, helping provide viable, scalable solutions to precision agriculture problems and guiding researchers [5].

2) Industry Benefits: These findings have practical implications that will greatly benefit the agricultural industry by increasing operational efficiency and economic viability:

- Cost Reduction: Lin and Qi (2023) reduce labor costs using automated grading (11.8% error) vs Kempelis et al. (2022) reduce Sensor costs through CV-based microclimate observations. Praveenraj et al. (2024) reduce herbicide use through targeted weed removal, lowering chemical costs and environmental impact [3] [7].
- Yield and Market Enhancement Sharma et al. (2023) find a yield predictability method (accuracy of 98.96%) guarantees that Indian farmers may also be capable of supplying (297319 thousand hectares) (support export (export: e.g. rice, USD 6.12 billion FY22), (Singh and Bhandari 2021) inBQ), (summary: Liu et al. Majumder et al. (2024) improve CEA planning through visual forecasts that may lead to productivity enhancements in controlled environments [2] [6] .
- Scalable automation: Avila et al. (2023) ensures AAV safety (YOLOv4 with 0.84 confidence) and is anticipated to be adopted in large-scale harvesting and, also, ElSayed et al. (2024) (Non 0) allow robotic disease detection (95.91 % accuracy) across various environmental field conditions, with low computational cost, scaling the robot capacity [9] .

These benefits allow farmers and agribusinesses to receive the tools to spend less, waste less and fulfill the global demand that exists, whether you're working on a smallholder farm in Egypt or an industrial operation in Brazil or India [6].

3) Societal Impact: The societal implications go beyond industry, touching on broad goals of sustainability, health and equity:

- Food Security Sharma et al. (2023) address food insecurity in India by increasing yield stability, important as the population approaches 1.5 billion. Li et al. (2021) and ElSayed et al. ay enhance the prevention of crop losses (98.5-99.35% accuracy of disease detection) to help maintain economic stability due to its immense contribution to the economy of developing geographies which includes regions in Shanxi, China and Egypt (2024) [6] [9] .
- Environmental Sustainability: Praveenraj et al. (2024) and ElSayed et al. (2024) SDG 12 (Responsible Consumption and Production): reduce pesticide reliance by targeting interventions. Majumder et al. (2024) optimize the use of CEA resources, lowering energy and water footprints, whereas Avila et al. (2023) use accurate AAV navigation to minimize harvesting waste [3] [8] .
- Global Alignment: These developments contribute to SDG 2 (Zero Hunger), increasing agricultural productivity and resilience consistent with the emphasis Unal¨ (2020) places on the role of smart farming in sustainable development. Farmer distress (e.g., India's suicide rates linked to crop failure, Sharma et al., 2023) is also reduced — lending further social stability [6] [8] .

These impacts collectively foster a sustainable agricultural ecosystem, balancing productivity with ecological and social well-being, with the potential to influence global food systems as adoption scales.

V. CONCLUSION

Although the results and effects are promising, their scope is edged by limitations. Numerous dataset biases (e.g. Li et al., 2021 combine lab-based images) and single-crop focus (e.g. ElSayed et al., 2024 focus on tomatoes), therefore, findings should be treated with caution in generalization. Further optimization is needed for real-time deployment challenges (e.g., computational costs (Unal, 2020), and environmental noise¨ (Avila et al., 2023)). Still, the studies' convergence on high accuracy, efficiency and automation points to a strong foundation for future refining, and interdisciplinary collaboration is pivotal in addressing these barriers.

APPENDICES

A. Technical Specifications

- Hardware: Jetson AGX Orin, Tesla T4 GPUs, CCD cameras
- Software: OpenCV, PyTorch, TensorFlow, Hugging Face Transformers

B. Dataset Overview

- Examples: PlantVillage (54,309 images), Indian crop data (1997-2020), tomato disease (32,535 images)

C. Model Details

- CNNs: YOLOv4 (Avila et al., 2023), lightweight CNN (ElSayed et al., 2024)
- Generative AI: Pix2pix (Majumder et al., 2024)
- ML: RF (Sharma et al., 2023)

D. Performance Metrics

- Accuracy: 96% (Praveenraj et al., 2024), 98.96% (Sharma et al., 2023), 99.35% (Li et al., 2021)
- FPS: 48.41 (Avila et al., 2023)
- SSIM: 0.7-0.9 (Majumder et al., 2024)

E. Glossary

- CV: Computer Vision
- DL: Deep Learning
- CNN: Convolutional Neural Network
- AAV: Autonomous Agricultural Vehicle

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