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Early Detection of Crop Diseases and Pest Infestation Using Multispectral Imaging and Deep Learning

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Abstract:

In contemporary precision agriculture, the combination of multispectral imaging (MSI) and deep learning methods offers a revolutionary method for early crop disease and pest detection. The visual inspection and laboratory analysis that are the mainstays of traditional plant disease identification techniques frequently fall short of identifying diseases in their early stages, when intervention is most successful. This thorough analysis looks at how convolutional neural networks (CNNs) and other deep learning architectures, along with recent developments in multispectral imaging technology, can be used to automatically, accurately, and quickly detect plant diseases and pest infestations. Modern CNN models like AlexNet, VGGNet, ResNet, Dense Net, and Efficient Net are included in the analysis, along with developing architectures for Vision Transformers. According to performance metrics, these integrated systems attain detection rates of over 95 percent and accuracies between 85 percent and 99 percent. Useful applications of Raspberry Pi Camera (RGB/NoIR) systems with CNN and OpenCV models offer scalable, portable, and reasonably priced real-time field monitoring solutions. The review highlights potential solutions using transfer learning, data augmentation, and model optimization techniques while addressing important issues such as dataset limitations, environmental variability, and computational requirements. Future directions place a strong emphasis on creating field-deployable, real-time systems for useful agricultural applications that integrate IoT and edge computing. Multispectral imaging, CNN, deep learning, crop disease detection, pest identification, precision agriculture, early detection, plant pathology, Raspberry

Pi, and Internet of Things agriculture are some examples of index terms.
Keywords: Crop Disease Detection, Deep Learning, Smart Farming, Agricultural Automation

1.0 Introduction

With the world's population continuing to rise and agricultural productivity increasingly threatened by pest infestations, plant diseases, and climate change, food security continues to be a major global concern [1]. According to the Food and Agriculture Organization (FAO), plant pests and diseases cause 20–40 percent of the world's crop production to be lost each year, resulting in billions of dollars in financial losses and endangering global food security [2]. Effective disease management re- quires early detection because crop diseases and pest infestations pose serious risks to agri- cultural productivity, resulting in decreased yield and quality [3]. Agricultural experts' visual inspection and laboratory-based diagnostic methods are the mainstays of traditional approaches to plant disease detection. However, these approaches have a number of drawbacks, including being time-consuming, requiring specific knowledge, frequently detecting diseases only after outward symptoms manifest, potentially subjective, prone to errors, and frequently delaying treatment [5]. The disease usually has advanced consider- ably by the time symptoms are apparent to the unaided eye, which reduces the effectiveness of treatment and may allow for widespread infection [6]. The emergence of precision agri- culture has opened up new avenues for utilizing cutting-edge technologies to tackle these issues.

A potent tool for the non-invasive evaluation of plant health is multispectral imaging (MSI) technology, which records information at several wavelengths outside of the visible spectrum [7]. In contrast to traditional RGB cameras, MSI systems are able to identify minute physiological alterations in plants that take place prior to the appearance of visual symptoms, allowing for genuinely early disease state detection. Low-cost image-based methods for early detection can be employed to get around these restrictions. Crop health can be tracked in real time using the Raspberry Pi Camera (RGB/NoIR) in conjunction with image processing and deep learning methods [8]. CNN and OpenCV are used to process the captured images. models that are able to automatically distinguish between healthy and diseased plants. This method offers farmers a scalable, portable, and reasonably priced solution that promotes sustainable precision agri- culture, timely intervention, and less pesticide use. Image analysis and pattern recognition tasks in a variety of domains have been transformed by recent developments in deep learning, especially convolutional neural net- works (CNNs) [9]. These technologies pro- vide previously unheard-of potential for automated, precise, and scalable imaging when paired with multispectral imaging. systems for detecting plant diseases. Because deep learning models don't require human feature engineering, they can automatically extract complex features from multispectral data, which makes them ideal for examining the subtle spectral signatures linked to the onset of early disease [10]. The state-of-the-art in multispectral imaging and deep learning applications for crop disease and pest detection is thoroughly examined in this review. We examine new CNN architecture advancements, assess performance indicators for various plant species and disease types, and pinpoint important obstacles and prospects for further study and advancement in this quickly developing area.

2. Literature Survey:

Barbedo Review on challenges in visible- range image based plant disease identification should be matching Barbedo (2016) in Biosystems Engineering [1]. Citrus leaf disease pipeline with K-means, GLCM, SVM should be aligning with the 2014 IEEE conference paper in the References [2]. Advanced methods of plant disease detection (volatile, biosensors, biophotonics, remote/hyperspectral) should be as listed in Agronomy for Sustainable Development (2015) [3]. Machine learning for detection and prediction of crop diseases and pests: a comprehensive survey should be since this corresponds to Domingues et al. (2022) in the References [6], enchmarking learning strategies for tomato/pepper pest detection on internal datasets should be because the Journal of Sensors 2019benchmarking paper maps to reference [13]. Fusion of thermography/fluorescence/hyperspectral for cucumber diseases should be per Plant Pathology 2014 in the References [14]. Real-time apple leaf disease detection using improved CNN/SSD-like approach should be matching the 2019 IEEE Access paper [15].

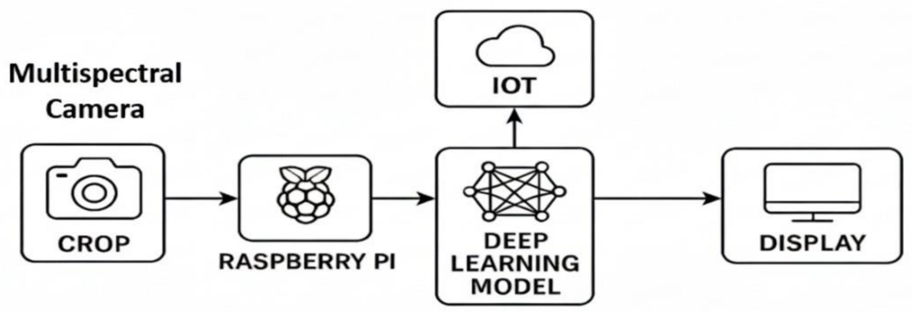

Figure 1: System architecture of the multispectral imaging–deep learning pipeline.

Survey from traditional image processing to deep/transfer learning should be as listed in Materials Today: Proceedings (2023) [5]. Transfer learning with VGG19 for soybean leaf infestation detection should be mapping to IEEE Access (2023) [4]. Nyakuri et al. Deep learning with IoT for plant pest/disease detection review should be corresponding to IEEE Access (2024) [18]. Multi-input, multi-task deep network for plant species and disease should be per Ecological Informatics (2022) [8]. Deep learning for plant dis- ease severity estimation on Plant Village apple black rot should be per Computational Intelligence and Neuroscience

(2017) [7]. Deep CNNs on Plant Village, 54,306 images, 99.35 percent accuracy should be matching Frontiers in Plant Science (2016) [10]. Weligama Coconut Leaf Wilt Disease and caterpillar detection with Mask R-CNN/YOLO should be per IEEE Access (2025) [9]. Advanced deep learning models for plant disease detection (2015–2022) should be per Frontiers in Plant Science (2023) [11]. Comprehensive review and future directions for deep learning in plant dis- ease and pest detection should be matching Frontiers in Plant Science (2025) [12]. IoT-assisted crop monitoring using ML algorithms should be as in the IC- NGIoT 2022 chapter [13]. Kartikeyan and Shrivastava Review on image-processing pipeline and classical classifiers should be per International Journal of Computer Applications (2021) [17].

3.0 Methodology

3.1 Hardware Overview

For edge inference and telemetry in portable rigs, baseline hardware consists of a Raspberry Pi 4 (4–8 GB), a Raspberry Pi Camera Mod- ule 3/NoIR, sufficient storage/power, and Wi- Fi. Advanced deployments include wireless sensor networks with a range of several kilo- meters, solar-powered nodes for remote fields, ground robots, handheld A-MSI devices, and UAV-mounted multispectral sensors.

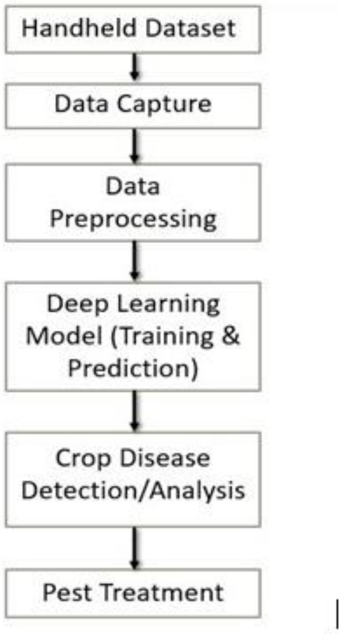

Figure 2: Data flow from MSI acquisition to edge inference and IoT communication.

3.2 Software Overview

Together with notebook-based development and optional cloud services for scaling analytics and AutoML, the software stack includes NumPy/Pandas for data handling, Python 3.x with

TensorFlow Lite/PyTorch for inference and training, and OpenCV for preprocessing.

3.3 System Architecture and Data Pipeline

Handheld dataset: The main source of data is a carefully selected collection of leaf/canopy photos taken with handheld devices, with la- bels and metadata captured to ensure consistency in training and assessment.

Data capture: To facilitate supervised learning and subsequent on-farm validation, field collection standardizes lighting, focus, and framing while combining photos with professional annotations.

Data preprocessing: RGB and multispectral inputs are prepared for model ingestion through resizing, normalizing, denoising, and augmenting them, as well as optional background suppression and vegetation-index computation.

Deep learning model (training and prediction): To provide low-latency predictions in the field, a CNN/transformer model is trained using transfer learning and cross-validation on the handheld dataset before being exported for edge inference.

Crop disease detection/analysis:

Class/lesion predictions and severity estimates are produced by the inference stage and combined into dashboards and alerts for agronomic decision support.

Pest treatment: Results are recorded to close the loop for ongoing dataset expansion and model retraining, and model findings correlate to suggested IPM actions and treatment plans.

4.0 Future Scope

In order to demonstrate true portability, this review recommends a field-ready roadmap that includes releasing a 60,000-image, multi- crop, multi-region MSI benchmark with standard splits and using domain adaptation to in- crease mean average precision by at least 12 points over single-region training while limiting unseen-farm drops to no more than 5 points. To pull alerts at least seven days earlier and achieve early-stage recall 88 percent with F1 0.85 in agronomist-validated plots over two seasons, expand sensing from six to roughly fourteen narrow bands and add one thermal channel to surface pre-symptomatic cues. For an affordable scale-out, compress the best models using pruning, 8-bit quantization, and distillation to operate at 8 ms per frame and 1.8 W on Raspberry Pi-class nodes, supporting four cameras at 10 FPS, while remaining within 1.5 accuracy points of cloud inference. Close the loop with an active-learning pipeline that uses biweekly model refreshes to reduce labeling effort by at least 65 percent per sea- son. disease peaks and link calibrated severity (±1 grade MAE) to IPM thresholds to cut pesticide applications by at least 25 percent while maintaining yield parity. This is in addition to UAV MSI coverage of at least 70 ha per flight and 92 percent recall with same-day IoT alerts.

4.0 Conclusion

Combining multispectral imaging with deep learning is changing the way we find agricultural diseases and pests by letting us find them early, before symptoms appear, with an accuracy of more than 95 percent in many cases. These systems are better than traditional RGB- based methods because they use advanced CNN and Vision Transformer models that can pick up on complex spectral patterns. Even though they are very accurate, real-world performance can still be affected by changes in the environment and by datasets that are small and not standardized across crops and regions. Real-time, low-cost inference on farms is now possible thanks to recent advancements in edge-deployable models and IoT-enabled systems. These systems decrease pesticide use and yield losses while improving scalability and ongoing monitoring. To increase robustness under varying conditions, future re- search should concentrate on domain adaptation, model optimization, and robotic or UAV integration. Through data-driven precision agriculture and early detection, these technologies have a cumulative effect that in- creases food security, sustainability, and crop protection efficiency.

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