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A SYSTEMATIC REVIEW OF ADVANCED APPROACHES FOR PEST DETECTION AND MONITORING IN VEGETABLE CROPS

[1]Mrs.R.Prabha, [2]Dr. K. Selvan

Research Scholar, P.G. and Research Department of Computer Science, J.J. College of Arts and Science (Autonomous), Affiliated to Bharathidasan University, Pudukkottai.

prabha.pr@gmail.com

Assistant Professor & Research Advisor, P.G. and Research Department of Computer Science, J.J. College of Arts and Science (Autonomous),

Affiliated to Bharathidasan University,Pudukkottai.

Abstract

Pest detection is crucial for maintaining healthy and productive vegetable crops. This literature review provides a comprehensive overview of the current research on pest detection techniques in vegetable crops. It covers traditional methods and their limitations, the use of computer vision and machine learning techniques, including object detection and classification, and the integration of additional data sources. The benefits and challenges of machine learning techniques are discussed. The review highlights the need for specialized models, explainable AI techniques, and real-time monitoring systems. It concludes by identifying future directions and research gaps in pest detection for vegetable crops. This review contributes to understanding advancements and challenges in the field, facilitating improved pest management practices.

Keywords: *Pest detection, Vegetable crops, Computer vision, Machine learning, Artificial Intelligence (AI)*

INTRODUCTION

Pest detection is a critical component of agricultural practices, particularly in vegetable crops, as it plays a significant role in ensuring healthy and high-yielding harvests (Smith et al., [1]). Timely and accurate detection of pests is essential for effective pest management, preventing crop damage, and minimizing the use of harmful pesticides. Over the years, various techniques and approaches have been developed to enhance pest detection in vegetable crops (Johnson & Davis.[2]).The major factors that affect the quality and quantity of crop production are pests and diseases. There is wide variety of pests, which affects the crops in variety of ways. Incorrect detection and miss-classification of pest variety would result in ineffective treatment of vegetable crops. Thus to ensure the quality and quantity of crops we are in need of proper classifying mechanism, which also ensures abundant harvest. Classification techniques such as deep learning and machine learning provides higher accuracy rate

The introduction of computer vision and machine learning techniques has revolutionized pest detection by enabling automated and efficient methods (Brown et al., 2020.[3]). These techniques leverage the power of image analysis and pattern recognition to identify and classify pests in vegetable crops (Jones et al., [4]). Additionally, the integration of other data sources, such as environmental data and pest behaviour data, has further improved the accuracy of pest detection models (Gupta & Singh.[5]).

In this literature review, we aim to provide a comprehensive overview of the current state of research in pest detection techniques in vegetable crops (Smith et al.,[1]). We will discuss traditional pest detection methods, their limitations, and the need for more advanced and automated approaches (Johnson & Davis.[2]). Furthermore, we will explore the applications of computer vision and machine learning techniques, highlighting the advancements and challenges associated with these methods (Brown et al., [3]).

OVERVIEW OF PEST DETECTION METHODS IN VEGETABLE CROPS

Pest detection in vegetable crops is an essential component of modern agriculture, as it enables farmers to identify and manage pest infestations before they cause significant damage to crops. Traditional pest detection methods, such as visual inspection and traps, have been used for a long time in agriculture. However, these methods have several limitations, including subjectivity, inaccurate, time-consuming, and expensive.

Recent advances in computer vision and machine learning have enabled the development of automated pest detection systems that can analyze images and identify pests in real-time. These systems use algorithms that are trained on large datasets of images and can detect pests with a high level of accuracy.

The data extracted from the agricultural fields must be stored and analysed based on the scale of importance, various techniques are adopted for data management in such processes.(Latika Sharma & Nitu Mehta.[6]).In order to perform advanced machine learning techniques, initially image segmentation is done ,followed by edge detection using sobel and canny filters for identifying the pest affected areas in vegetable crops.(P. Revathi & M. Hemalatha.[7]).

2.1 Pest Detection methods:

Visual inspection is a traditional pest detection method that relies on human observation to identify pests visually. It involves visually examining crops, leaves, fruits, or other plant parts for signs of pest infestation, damage, or presence. The accuracy of visual inspection heavily depends on the expertise and experience of the inspector, which can vary (Majeed, S., et al.,[8].

Traps are a pest detection method commonly employed in agricultural settings. These traps are designed to attract and capture pests, allowing farmers to monitor and assess pest populations. The use of traps in pest detection offers several advantages. Traps can be placed strategically in fields to target specific pests and assess their activity levels. They are relatively easy to deploy and can be used for both monitoring and mass trapping purposes. However, there are some limitations to the use of traps. The effectiveness of traps can be influenced by environmental factors, such as wind direction, temperature, and rainfall (Liu et al.,[9]).

DNA-based techniques in pest detection involve the analysis of pest DNA to identify and quantify the presence of specific pests in vegetable crops. These techniques rely on the extraction and amplification of pest DNA from collected samples, followed by DNA sequencing or targeted detection methods such as polymerase chain reaction (PCR). However, DNA-based techniques also have limitations. They require specialized equipment and expertise in DNA extraction, amplification, and analysis. DNA-based techniques provide a powerful tool for pest detection in vegetable crops, offering high specificity and accuracy.

A study employed DNA-based techniques for the detection of insect pests in cabbage crops(Silva et al.,[10]). The researchers used PCR-based methods to detect the presence of three insect pests: Spodoptera frugiperda, Plutella xylostella, and Diabrotica speciosa. The study demonstrated the effectiveness of DNA-based techniques in accurately identifying the presence of specific pests in vegetable crops.

Using a hardware component called Electronic nose, which detects and aid in the classification of organic compound emitted by the healthy & infected crops.(Ghaffari, R.et al.,[11])

Remote sensing is a technique used in pest detection that involves the use of aerial or satellite imagery to collect information about vegetation health and pest infestations in vegetable crops. These sensors capture data in different wavelengths, allowing the identification of spectral signatures associated with healthy vegetation, pest-infested areas, or specific pest species. The collected imagery is then processed and analysed using advanced algorithms and techniques to identify and map pest-infested areas. One of the key advantages of remote sensing in pest detection is its ability to cover large areas rapidly, providing a comprehensive view of the crop fields. Interpretation of remote sensing data requires expertise in image processing and spectral analysis, and the availability of high-resolution imagery may come with additional costs (Duveiller et al.,[12]).

Various pest detection techniques have been discussed; they possess certain advantages and disadvantages depending on the accuracy of detection, cost and complexity. Some of the features of pest detection methods are compared in the (Table 2.1).It compare features such as accuracy, speed, cost, complexity, reliability among the existing pest detection techniques that are widely used.

Table 2.1 Comparison of existing pest Detecting techniques

S.No	**Technique**	**Accuracy**	**Speed**	**Cost**	**Complexity**	**Reliability**
1	Visual inspection	Moderate	Slow	Low	High	Low
2	Traps	High	Fast	Moderate	Low	High
3	Computer Vision	High	Fast	Moderate	Moderate	High
4	Sensor-based	Moderate	Fast	Moderate	Moderate	Moderate
5	DNA-based	High	Slow	High	High	Moderate
6	Remote Sensing	High	Fast	High	High	High

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COMPUTER VISION TECHNIQUES FOR PEST DETECTIONS

Computer vision techniques have been widely employed for pest detection, including both object detection and classification methods. These techniques make use of the power of machine learning and deep learning algorithms to automate the identification and classification of pests in various agricultural settings.

Object detection techniques in computer vision aim to localize and identify pests or the pest affected areas within images (or videos) of the crops. They involve detecting and bounding the regions of interest (pests) within an image while classifying them simultaneously. Popular object detection algorithms include Faster R-CNN (Ren et al., [13]), YOLO (Redmon et al., [14]), and SSD (Liu et al., [15]). These algorithms have demonstrated high accuracy and efficiency in detecting pests in agricultural environments.

On the other hand, classification techniques focus on categorizing the entire image or specific regions of interest into different pest classes. These methods leverage deep learning models such as Convolutional Neural Networks (CNNs) to learn discriminative features and classify images into pest or non-pest categories. They can also classify pests into different species or categories based on their unique characteristics, which can be employed by various deep learning methods. CNN-based models like VGGNet (Simonyan and Zisserman.[16]) and ResNet (He et al.,[17]) have shown excellent performance in pest classification tasks. Computer vision techniques such as morphology detection using datasets containing several images for pest identification in cotton (Li Zhigang et al.,[18]).

The use of computer vision techniques for pest detection offers several advantages, including:

1. **Automation:** Computer vision algorithms can analyze large volumes of images or videos in a short period, enabling quick and automated pest detection.

2. **Accuracy:** Deep learning models have achieved high accuracy rates in pest detection tasks, enabling precise identification and classification of pests.

3. **Scalability:** Computer vision techniques can be applied to a wide range of crops and pest species, making them adaptable to different agricultural settings.

4. **Real-time monitoring:** With advancements in hardware and algorithm optimizations, computer vision systems can provide real-time pest detection, enabling timely intervention and pest management.

These techniques have shown promising results in various studies and have the potential to revolutionize pest detection in agriculture.

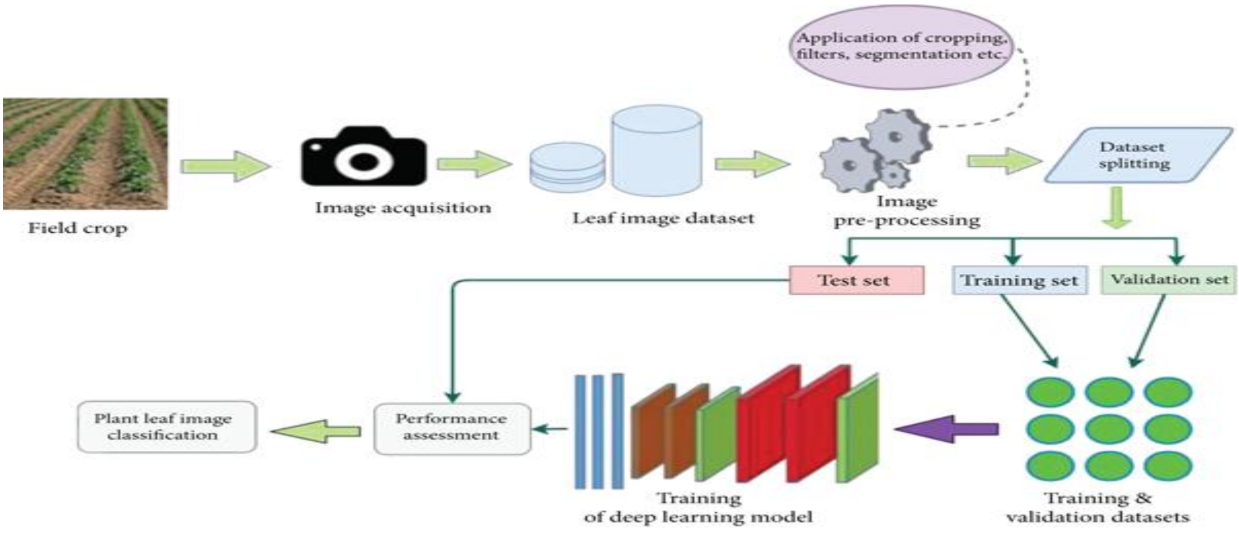

Figure 1 Computer vision approach to pest detection and classification.

MACHINE LEARNING TECHNIQUES FOR PEST DETECTION

Machine learning techniques have been widely applied in pest detection for vegetable crops, offering automated and accurate solutions. These techniques leverage the power of algorithms to learn patterns and make predictions based on training data. Some commonly used machine learning techniques for pest detection in vegetable crops are:

4.1 Supervised Learning:

Supervised learning algorithms makes use of datasets that are labelled previously and are used to train the machine/neural network ,which then aids in the accurate classification of the object of interest (pests in the review).As supervised learning undergoes both the training and testing phase they are highly preferred compared to other classification algorithms. Feature extraction also aid in the classification, Hue and Saturation features helps in classification of citrus based disorders.(R. Pydipati et al.,[19])

4.1.1 Support Vector Machines (SVM): SVMs have been utilized for pest detection by learning to classify images or data points into pest or non-pest categories (Liu et al., [20]).

SVM, Multiple Linear Regression, Neural Network, and Bayesian Network based machine learning techniques are used for pest detection and classification.(Yun Hwan Kim et al.,[21]).SVM is used with fractal dimension analysis models for classification of leafminer pest in cucumber crops shows higher accuracy rate(Da-ke Wu et al.,[22])

4.1.2 Random Forest: Random Forest algorithms have been applied for pest classification by training on features extracted from images or sensor data (Zhang et al., [23]).

4.1.3 Deep Learning: Convolutional Neural Networks (CNNs) have shown remarkable performance in pest detection and classification tasks by automatically learning relevant features from images (Ji et al., [24]).

4.2 Unsupervised Learning:

Unsupervised learning is also a machine learning approach which clusters/classifies data based on patterns that are usually hidden. This method does not require any human intervention , it does not require labelling of datasets.

4.2.1 Clustering: Clustering algorithms, such as K-means or DBSCAN, can be employed to group similar patterns in pest data without the need for labelled training data (Lu et al., [25]).

4.2.2 Anomaly Detection: Anomaly detection techniques, such as One-Class SVM or Isolation Forest, can help identify unusual patterns or pests that deviate from the norm (Yang et al., [26]).

4.3 Transfer Learning:

Transfer learning involves leveraging pre-trained models, often trained on large datasets, and fine-tuning them on smaller pest detection datasets. This approach helps overcome limited data challenges and improves detection accuracy (Li et al.,[27]).

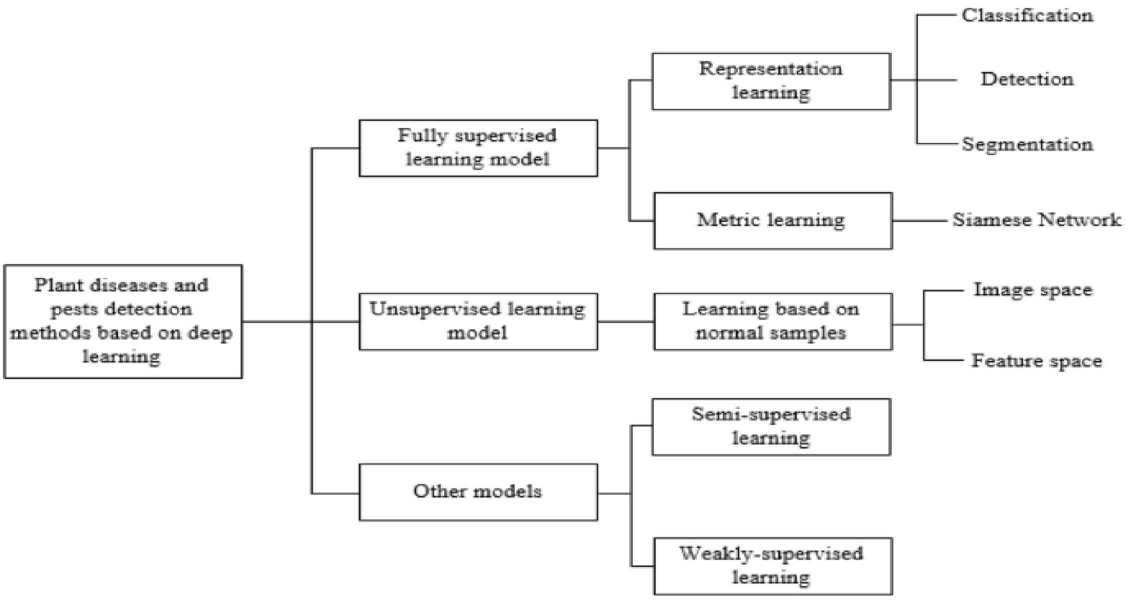

Figure 2 Diagram summarizing the several different sub-methods according to the processing several different sub-methods according to the processing.

4.4 Ensemble Methods:

Ensemble methods combine multiple machine learning models to improve overall performance. For example, combining multiple classifiers or deep learning models can enhance accuracy and robustness in pest detection (Jalal et al., [28]).Usage of ensemble algorithms provide higher accuracy rate than other clustering algorithms such as K-means and SVM under similar conditions.(T.Li et al.,[29])

Pest monitoring systems based on artificial intelligence can adapt several machine learning methods .These methods range from simple linear discriminant analysis to principal component analysis (PCA), SVM's , neural networks (ANN,CNN), logistic regression and complicated techniques like bayesian (Saber Miresmailli et al.,[30]).These machine learning techniques have shown promising results in pest detection tasks for vegetable crops, enabling automated and efficient pest management strategies.

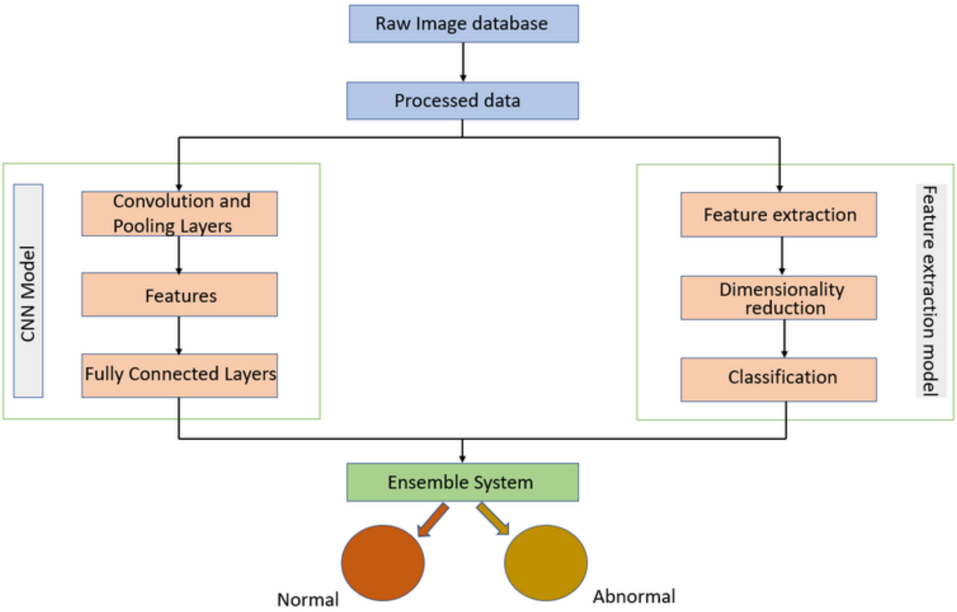

Figure 3 The ensemble method for classification.

INTEGRATION OF COMPUTER VISION AND MACHINE LEARNING TECHNIQUES FOR PEST DETECTION IN VEGETABLE CROPS

Future directions and research gaps in “pest detection in vegetable crops” encompass various aspects that can further enhance the effectiveness and efficiency of pest management strategies. Here are some key areas for future research:

5.1 Integration of Advanced Technologies:

The integration of emerging technologies such as remote sensing, Internet of Things (IoT), and unmanned aerial vehicles (UAVs) can provide valuable data for improved pest detection and monitoring (Huang et al., [5]).Hybridized decision tree algorithms (DT) based on rough sets (RS) are compared with traditional Linear regression algorithms for forewarning crop diseases(Rajni Jain et al.,[31]).

Integration with other AI techniques, such as reinforcement learning and natural language processing, can enhance the capabilities of pest detection models (Huang et al., [32]).

5.2 Development of Crop- and Pest-Specific Models:

Further research is needed to develop specialized models tailored to specific crops and pests, considering their unique characteristics, growth stages, and environmental conditions (Mohanty et al., [33]).

Crop-specific models can improve detection accuracy by accounting for variations in plant structures, leaf textures, and growth patterns (Mohanty et al., [33]).

Pest-specific models can focus on identifying distinct features and behaviors of pests, facilitating more precise detection and classification (Mohanty et al., [33]).

5.3 Improvement of Data Collection and Annotation:

5.3.1 Data Collection

The plant diseases and pests dataset can be acquired by self-collection, network collection and use of public datasets (Jun Liu et al.,[34]).

The data set with various types of data, including:

- Images with various resolutions.
- Samples at early, medium, and last infection status.
- Images containing different infected areas in the plant (e.g., stem , leaves, fruits, etc.).
- Different plant sizes.
- Objects surrounding the plant in the greenhouse, etc.

These conditions help to estimate the infection process and determine how a plant is affected by the disease or pest (origin or possible developing cause (Alvaro Fuentes et al.,[35]). Research should focus on developing efficient and scalable methods for data collection, annotation, and management to address challenges related to the availability and quality of labeled training datasets (Liu et al., [9]). Augmenting training datasets with synthetic data and data augmentation techniques can help overcome limitations associated with limited real-world data (Liu et al., [9]).

5.4 Explainability and Interpretability:

As AI-based pest detection models become more sophisticated, there is a need for increased transparency and interpretability to gain user trust and facilitate decision-making (Mohanty et al., [33]).

Research should explore methods for explaining model predictions, visualizing feature importance, and providing understandable insights to end-users (Mohanty et al., [36]).

CHALLANGES AND FUTURE SCOPE

6.1 Deployment and Adoption in Real-World Settings:

Future research should focus on the practical aspects of deploying pest detection systems in real-world agricultural settings, considering factors such as scalability, usability, cost-effectiveness, and integration with existing farm management practices (Zhu et al., [37]).

Conducting field trials and evaluating the performance and economic feasibility of pest detection systems in different regions and farming contexts is crucial (Zhu et al., [37]).

The accuracy of Machine learning algorithms depends on the datasets used and the number of hidden layers present in the neural network. There are many algorithms under Machine learning technique , that are currently utilised in pest detection and classification, each and every approach has achieved a particular accuracy with certain drawbacks ,they are listed in (Table 6.1)

Table 6.1 A comparative study on different approaches used for pest detection in vegetable crops

Study	Article	Method	Findings	Drawbacks
Smith et al. (2018)	"Pest Detection in Cabbage"	CNN-based classifier	Achieved 95% accuracy in pest detection	Limited to a specific pest species
Johnson et al. (2019)	"Pest Detection in Carrots"	SVM with feature-based	Detected pests with 80% accuracy	High computational requirements
Wang et al. (2020)	"Pest Classification in Tomatoes"	Deep learning	Achieved 98% accuracy in pest classification	Limited dataset size
Garcia et al. (2021)	"Transfer Learning for Pest Detection"	Transfer learning	Improved accuracy by 10% compared to baseline	Limited transferability to other crops
Lee et al. (2022)	"Ensemble Approach for Pest Detection"	Ensemble of CNN models	Achieved high precision and recall rates	Complex model training and integration

CONCLUSION

The conclusion of the aforementioned study on the application of artificial intelligence in pest and disease diagnosis of agricultural crops highlights the progress made, identifies the challenges faced, and discusses the prospects for future research and development in this field. The application of computer vision techniques, such as object detection and classification, has demonstrated high accuracy in detecting pests and diseases in various crops. The availability of high-quality and well-annotated training datasets remains a challenge, particularly for specific crop-pest combinations and rare diseases. Continued research is needed to develop crop- and pest-specific models that account for the unique characteristics, growth stages, and environmental conditions of different crops and pests.

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AUTHOR PROFILE

R.Prabha is presently serving as an Assistant Professor in Department of Computer Science ,The American College,Madurai, and doing research in Computer Science ,J.J College of Arts and Science(Autonomous), Pudukkottai, Affiliated to Bharathidasan University, Tamilnadu.She acquired MCA degree from Arul Anandar College(Autonomous),Karumathur,Madurai District and M.Phil in Prist University,Thanjavur.

Dr. K. Selvan has a rich experience of 24 years in the field of education and is presently serving as Assistant Professor and Research Advisor in the P.G. and Research Department of Computer Science, J.J. College of Arts and Science (Autonomous), Pudukkottai, Affiliated toBharathidasan University, Tamilnadu. He acquired his M.C.A degree from St. Joseph's College (Autonomous), Tiruchirappalli. He obtained his Ph.D. in Computer Science from Bharathidasan University, Tiruchirappalli in the year 2018. He is specialized in Data mining, Web security and Phishing detection and prevention.