



USING IMAGE PROCESSING AND COMPUTATIONAL INTELLIGENCE TO DETECT PEST AT EARLY STAGES OF CROP

Mrs. Padmini Chattu¹, K. Sathwik², Ch. Sravani³, A. Sai Teja⁴, B. Samhitha⁵

¹Assistant Professor, Department of CSE (Data Science), ACE Engineering College, Hyderabad, Telangana, India

^{2,3,4,5}IV B. Tech Students, Department of CSE (Data Science), ACE Engineering College, Hyderabad, India

ABSTRACT:

Early Pest Detection is a major challenge in the agriculture field. The easiest way, to control pest infection is the use of pesticides. But the excessive use of pesticides is harmful to plants, animals as well as human beings. Integrated pest management combines biological and physical methods to prevent pest infection. The techniques of machine vision and digital image processing are extensively applied to agricultural science and it have great perspective, especially in the plant protection field, which ultimately leads to crop management. This paper deals with a new type of early detection of pests system. Images of the leaves affected by pests are acquired by using a digital camera. The leaves with pest images are processed for getting a grey coloured image and then using feature extraction, image classification techniques to detect pests on leaves. The images are acquired by using a digital camera. The images are then transferred to a PC and represented in python software. The RGB image is then converted into grey scale image and the feature extraction techniques are applied on that image.

Keywords: *Pest Detection, Image Processing, Feature Extraction, Grey Scaling*

I. INTRODUCTION

India is a nation that relies heavily on agriculture. Agriculture is the primary source of income for 70% of the population. Increasing agricultural yield is thus a crucial issue at the moment. The majority of scientists are working in this sector. This is relatively simple to accomplish utilizing their new methodologies and real-world applications. In the agricultural industry, pest infestation is a major problem that threatens food security and reduces crop output. Historically, the main strategy for managing pest infections has been the use of pesticides; however, abuse of these chemicals has resulted in negative consequences for animals, the environment, and human health.

In response to these worries, integrated pest management, or IPM, has been known as a comprehensive strategy that successfully reduces pest populations by combining biological and physical measures. But in order to use IPM, early pest identification is necessary, and this is a duty that has been transformed by the incorporation of digital image processing and machine vision technology into agricultural research.

With the use of machine vision and digital image processing, early pest identification has become more feasible, providing researchers and farmers with effective tools to track crop health and spot any risks. With the use of these technologies, it is possible to collect and examine photos showing leaves contaminated by pests, which offers important information about the existence and extent of pest infestations. These systems can precisely identify and categorize pests on leaves by using sophisticated algorithms for feature extraction and picture classification. This allows for timely intervention and focused pest control techniques.

The first step in the procedure is taking high-resolution pictures of the pest-affected leaves using digital cameras. These photos provide the raw data required for processing, which forms the basis of the pest detection system. After being obtained, the pictures go through preprocessing in order to improve their quality and fit for analysis. This may include methods like picture normalization, contrast enhancement, and noise reduction to guarantee accuracy and consistency in later processing stages.

The transformation of color pictures into gray scale, which streamlines analysis and lowers computer cost, is an essential preprocessing step. Images in grayscale preserve structural details while removing color fluctuations that might make it more difficult to locate pests. After converting grayscale data, feature extraction methods are used to pinpoint distinctive patterns linked to insect infestations. To gather pertinent data on the presence and distribution of pests on leaves, these methods may include, among others, texture analysis, shape recognition, and pixel intensity profiling.

After the extraction of features, picture classification algorithms are used to classify pests according to their traits and actions. For this, Support Vector Machine (SVM) classifiers are often used. SVMs are well-known for their capacity to manage high-dimensional data and nonlinear decision limits. Farmers are able to detect the many kinds of pests present and

determine the extent of infestation by using SVM classifiers, which evaluate extracted features and apply labels to photos according to preset pest categories.

II. RELATED WORK

There has been some earlier work in the field of automated pest detection in crops. A Relative Difference in pixel Intensities (RDI) algorithm has been used to detect the pest [1]. This algorithm works well for both greenhouse and agricultural crops. It uses 100 images for evaluation and provides 97% accuracy. It works well when dealing with overlapping pests, but does not detect the complete shape of the pests. This can lead to false detections.

It also includes the method to differentiate between affected and unaffected leaves. This algorithm uses a support vector machine and extracts different image features to give as input to classify them. The 'Watershed method' takes highest time but performs best for occluded objects and Otsu's method takes least time for object detection [6]. This method is over sensitive to noise and gives false positive in presence of very little noise.

Image Segmentation: It can isolate specific regions of interest within the image, such as separating a leaf from its background or distinguishing a healthy leaf from a pest-infested one [5].

Image Enhancement: It can improve the quality of the image by adjusting brightness, contrast, or noise levels, ensuring the extracted features are clear and reliable for analysis [7].

Machine Learning: Algorithms are trained on massive datasets containing images of healthy crops and crops infested with various pests. The algorithms learn to identify patterns and relationships between the features extracted from the images and the presence of pests [8].

Deep Learning: A specific type of machine learning inspired by the structure and function of the human brain expand more Deep learning models can automatically learn complex features directly from large datasets of images, achieving high accuracy in pest classification without the need for manual feature engineering [8].

In one of the approaches studied, the authors performed detection of pests by using classification as a learning approach. It evaluates different classifiers like k-nearest neighbour, radial basis function, artificial neural networks and support vector machine. Support vector machine provides better results as compared to other classifiers by taking input parameters as colour, shape and texture features. It uses many irrelevant features of the image which resulted in erroneous results.

Feature Extraction: It can identify and quantify specific characteristics within the image, such as colour variations, texture patterns (smooth, rough, bumpy), and shapes of leaves or pest bodies [4].

Another proposed method for white fly detection is measuring white fly size and counting the white flies by using background subtraction of images with white flies [3]. Then Sobel edge detection operator is applied to detect edges of whiteflies in the image so that they can be differentiated easily. This algorithm detects three times faster and covers three times more leaf surface. Edge detection algorithms perform poorly in presence of noise, as the noise is also considered as edges.

III. EXISTING SYSTEM

The current system primarily concentrates on identifying pests within agricultural crops through image analysis. It begins by receiving images of agricultural fields captured by digital cameras or similar devices. These images serve as the input for subsequent processing. Upon receipt, the system employs various image processing techniques such as filtering, segmentation, and feature extraction to enhance and isolate relevant information from the agricultural scenes. Following this preprocessing stage, the system proceeds to analyze the extracted data to detect the presence of pests.

This analysis entails comparing the extracted features with predefined patterns or models associated with known pests. Detection algorithms are then utilized to classify whether the crops are infested by pests or not. By leveraging computational methods and advanced algorithms, the system aims to provide accurate and timely identification of pest infestations, enabling farmers to take appropriate measures to mitigate crop damage and ensure agricultural productivity.[2]

IV. PROPOSED SYSTEM

The system suggested approach for early insect identification in crops, marks a substantial improvement in agricultural pest control techniques. By incorporating essential elements like automated insect pest detection, disease detection, pest forecasting, and the decrease of human error via computational intelligence, the model provides a thorough resolution to the difficulties farmers encounter in minimizing pest-related hazards and guaranteeing crop well-being.

Fundamentally, the program uses advanced image processing methods to automatically identify insect pests in crops. The system is capable of precisely identifying and evaluating the degree of pest infestation in crops via the use of sophisticated image processing algorithms. In addition to streamlining the detection process, this automation increases the efficacy and efficiency of pest control initiatives, empowering farmers to reduce crop loss and react quickly to new threats.

Apart from identifying insect pests, the model is designed to discern the particular crop disease kind using picture analysis. Farmers may get vital insights into the health state of their crops by using the system's ability to categorize and distinguish between various illnesses, which is made possible by the integration of computational intelligence methods like machine learning algorithms. This skill makes it possible to implement customized treatment plans and prompt interventions, which reduces yield losses and stops the spread of illness.

In addition, the model includes forecasting features to identify the most probable pest causing the sickness that has been seen. Proactive pest control methods may be put into place since the system can predict the presence of certain pest species by evaluating patterns and attributes gleaned from the photos. With less dependence on reactive methods and more efficiency in pest control operations, this predictive capacity eventually results in more sustainable crop management techniques.

The suggested model's capacity to reduce human error in pest identification by using computational intelligence approaches is one of its main advantages. The model improves the precision and dependability of pest identification by automating the detection process and depending on data-driven analysis, guaranteeing that farmers get accurate and timely information about pest risks. This decrease in human error improves crop health and yield overall and increases the efficacy of pest control techniques.

All things considered, the suggested model addresses the shortcomings of current methods and advances the area of agricultural pest control by providing a comprehensive method for early insect identification in crops. Combining image processing, illness detection, pest prediction, and artificial intelligence to minimize human error, the model gives farmers effective tools to protect their crops from pest-related hazards and maximize production potential. Innovative solutions, such as the suggested model, will be essential to maintaining the resilience and sustainability of food production systems worldwide as agriculture continues to confront changing challenges.

V. METHODOLOGY

5.1. Image Capturing:

Selecting Imaging Devices: Opt for appropriate imaging devices like digital cameras capturing images with impressive clarity and detail. taking precise pictures of foliage on plants in farming areas.

Improving Imaging Parameters: Enhance imaging parameters like Adjusting exposure, focus, and white balance is essential for capturing clear and high-quality images. Minimum amount of distortion or interference.

Consideration of field conditions: Take into account environmental factors like lighting. factors like weather conditions, growth stage of crops, and overall conditions when taking photos of crops. Reduce fluctuation and guarantee samples are truly representative.

5.2. Image Pre-processing:

The process of preparing images for pest detection starts with capturing the image, then reducing noise, adjusting contrast, and correcting colors. Pictures are logged, trimmed, and adjusted in size to highlight important areas of the crop. Segmentation breaks images into significant parts, making it easier to extract features. Normalization decreases variation, while eliminating artifacts removes defects. Increasing diversity is achieved through data augmentation, while effectiveness is ensured by quality control. This methodical approach enhances the quality of images to ensure precise pest identification in farming.

5.3. Feature Extraction:

Feature extraction involves recognizing and collecting important information from data in order to accurately portray its fundamental attributes. In the context of identifying pests in agricultural crops using images, feature extraction involves recognizing unique characteristics like color, texture, shape, and spatial arrangement of objects in the image. Color histograms can represent color distribution, Haralick features can describe surface texture, and contour properties can outline the shape of pests or affected crop areas. These features that are obtained are used as inputs for machine learning algorithms, helping to accurately classify and detect pests in agricultural images.

5.4. Detection, Classification, and Prediction:

Identifying, categorizing, and forecasting are fundamental steps in controlling pests that affect agricultural produce. Identification recognizes pests or indications of their presence. Classification groups pests or diseases into different categories. Anticipation is when future events are foreseen by analyzing past data and environmental conditions. These procedures allow for proactive and focused pest control tactics, improving crop protection.

5.5. Evaluation and Validation:

Assessment includes measuring the performance of a system by using metrics such as precision and recall. Validation ensures reliability by conducting tests on separate datasets. Comprehensive assessment and confirmation guarantee the precision, expandability, and usefulness of pest detection systems, cultivating confidence and acceptance in agricultural societies.

5.6. Integration and Testing:

The development of pest detection systems for agricultural uses relies heavily on integration and testing and integration.

Integration: Bringing together different parts of the system, like image processing algorithms, machine learning models, and user interfaces, to create a unified and operational entity. This stage verifies that all parts work together smoothly and communicate efficiently to achieve the desired functions.

Testing: Testing also confirms that the system meets defines, requirements and user anticipations. Through thorough integration and testing procedures, developers can guarantee the reliable and efficient performance of the pest detection system in agricultural settings, ultimately enhancing crop protection and management strategies.

5.7. User Interface Design and Deployment:

Designing and implementing User Interface (UI) is vital in creating user-friendly and easily accessible pest detection systems for agricultural purposes.

Design: The focus of UI design is on developing user-friendly interfaces that allow efficient interaction with the system for users like farmers or agricultural workers. Factors to consider in design are layout, navigation, data visualization, and accessibility options. The user interface should be attractive, simple to comprehend, and adaptable on various devices.

Developers can improve the usability and adoption of pest detection systems among farmers by focusing on efficient UI design and smooth deployment, which will lead to better crop management and productivity in agriculture.

5.8. User Training and Support:

User training educates farmers on system usage, data interpretation, and troubleshooting. Ongoing technical support assists users with system-related issues promptly. Comprehensive training and support services empower farmers to effectively utilize pest detection systems, enhancing crop management practices and productivity in agriculture.

5.9. Continuous Improvement and Updates:

Continuous improvement involves analyzing user feedback and enhancing system performance. Regular updates deliver new features and bug fixes to maintain system relevance and reliability. By prioritizing both, developers ensure pest detection systems remain effective tools for farmers, supporting sustainable crop management practices in agriculture.

VI. MODEL DEVELOPMENT

In order to ensure that the model can generalize beyond the training set, a strong assessment framework for machine learning is provided throughout the model construction phase of the startup success prediction. The basis for transferring information to the machine algorithms was the training set.

The VGG16 Algorithm:

With 16 layers (13 convolutional and 3 fully connected) VGG16 is a convolutional neural network design. It was first presented in 2014 by Oxford's Visual Geometry Group and has 2x2 max-pooling windows and basic 3x3 convolutional filters. Despite being parameter-intensive, its deep architecture and pre-trained models on datasets like ImageNet, which enable effective feature extraction and identification, make it popular for image classification, object detection, and transfer learning applications.

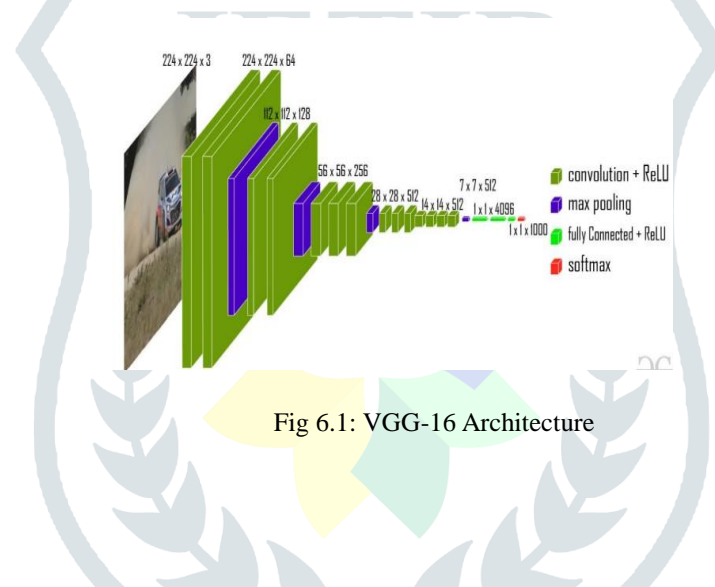


Fig 6.1: VGG-16 Architecture

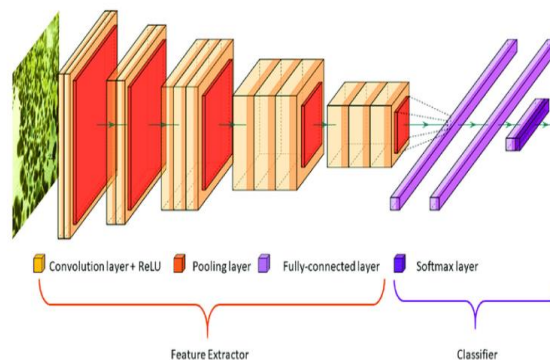


Fig 6.2: VGG-16 Detailed Information

Architecture of the System

System Architecture, which defines the general structure and organization of the system, is an essential component of the System Design process. The major steps involved in this are the parts' placement, their connections, and the design's guiding principles.

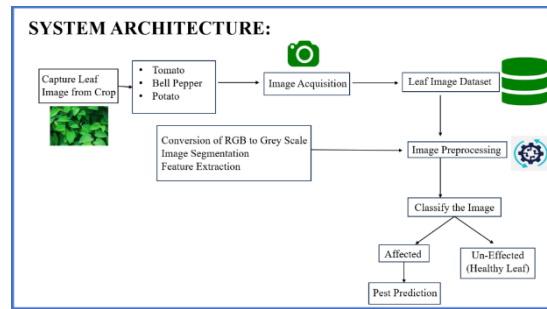


Fig 5.1: System Architecture

The system architecture is being outlined in order to provide a clear conceptual foundation for the early pest detection system's design and execution. To give an organized approach to development, this entails specifying the essential elements, relationships, and data flow inside the system.

The system's design seeks to break down its functions into more manageable, smaller parts. Developers are better able to comprehend and handle the entire system's complexity when it is divided into smaller components, which makes development and maintenance more effective.

By pointing out the bounds and restrictions of its functions, it helps to make the system's scope more clear. since a result, there will be alignment with project goals and objectives since all stakeholders, including developers and end users, will know what the system can and cannot accomplish.

By dividing components into distinct modules with well defined interfaces, the system design prioritizes modularity and reusability. Because individual modules may be changed or replaced without affecting the system as a whole, this modular approach facilitates simpler maintenance, upgrades, and future improvements.

In order to guarantee that the system can support future development and expansion, scalability issues are taken into account. Scalability allows developers to prepare for future needs, including growing data volumes or user demand, and foresee possible obstacles while developing the system architecture.

Performance optimization is the main emphasis of the system design, which makes sure the system satisfies performance requirements and runs effectively. To reduce processing time and resource consumption while increasing throughput and responsiveness, this entails optimizing algorithms, data structures, and system settings.

To guard against possible threats and weaknesses, security measures are included into the system design. To protect sensitive data and stop unwanted access or harmful assaults, this entails putting authentication, authorization, encryption, and other security measures in place.

It places a strong emphasis on fault tolerance and dependability to make sure the system can keep working properly even in the face of interruptions or failures. To reduce downtime and preserve system availability under challenging circumstances, redundancy, error management, and recovery measures must be included.

Finally, by anticipating technology breakthroughs and shifting needs, the system design seeks to make the system flexible and future-proof. In order to do this, the system must be built with extensibility and flexibility in mind. This will enable it to change and adapt over time to new possibilities and problems

VII. ALGORITHM TRAINING RESULTS

| Algorithm Used | Accuracy (%) |
|----------------|--------------|
| SVM | 67 |
| VGG16 | 79.5 |

Table 7.1: Algorithm Training Results

7.1 Model Performance

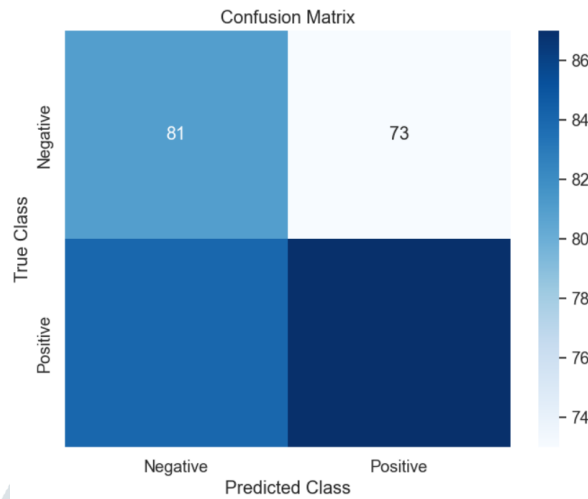


Fig 7.1: Confusion Matrix

VIII. RESULTS

Predicted disease:
Pepper bell Bacterial_spot (alt)

Treatment

- Remove and destroy infected plant parts.
- Apply copper-based fungicides or bactericides following label instructions.
- Rotate crops and practice good sanitation.

Confidence: 77.29%

Fig 8.1 Pepper_BellBacterial_Spot

Predicted disease:
No disease detected (Healthy Leaf)

Treatment

Confidence: 99.99%

Fig 8.2: Bell_Pepper Healthy Leaf

Predicted disease:
Potato Early blight

Treatment

- Remove and destroy infected leaves and plant debris.
- Apply fungicides containing chlorothalonil or copper-based fungicides following label instructions.
- Practice crop rotation, provide good airflow, and avoid overhead watering.

Confidence: 86.52%

Fig 8.3: Potato Early Blight

Predicted disease:

Potato Late blight

Treatment

- Remove and destroy infected plants and fruit.
- Apply fungicides containing chlorothalonil or copper-based fungicides following label instructions.
- Practice crop rotation, provide good airflow, and avoid overhead watering.



Confidence: 64.42%

Fig 8.4: Potato Late Blight

5.

Predicted disease:

No disease detected (Healthy Leaf)

Treatment



Confidence: 99.97%

Fig 8.5: Potato Healthy Leaf

Predicted disease:

Tomato Bacterial Spot

Treatment

- Remove and destroy infected plants and fruit.
- Apply fungicides containing chlorothalonil or copper-based fungicides following label instructions.
- Practice crop rotation, provide good airflow, and avoid overhead watering.



Confidence: 68.75%

Fig 8.6: Tomato Bacterial Spot

Predicted disease:

Tomato mosaic virus

Treatment

- Plant resistant varieties if available.
- Control whiteflies, which spread the virus, using sticky traps or insecticides.
- Remove and destroy infected plants.



Confidence: 77.99%

Fig 8.7: Tomato Mosaic Virus

Predicted disease:

Tomato YellowLeaf Curl Virus

Treatment

- Plant resistant varieties if available.
- Control whiteflies, which spread the virus, using sticky traps or insecticides.
- Remove and destroy infected plants.



Confidence: 85.40%

Fig 8.8: Tomato Yellow Leaf Curl Virus

IX. CONCLUSION

In conclusion, early pest detection through image processing and computational intelligence presents a promising avenue for effective crop management. By swiftly and accurately identifying pests, farmers can proactively mitigate infestations, thus improving crop yields and reducing chemical usage for sustainable agriculture. However, challenges such as cost and complexity require careful consideration and ongoing evaluation. Through strategic planning and implementation, coupled with continuous monitoring and adjustment, the integration of image processing and computational intelligence can offer substantial benefits in crop protection and management, paving the way for more efficient and environmentally-friendly agricultural practices.

X. FUTURE SCOPE

The future of predicting plant leaf diseases using machine learning appears promising. As machine learning techniques evolve, we anticipate more precise and efficient disease prediction models. Integration of IoT technologies, like sensors and data connectivity, will provide real-time environmental and plant health data, enhancing predictive capabilities. Advancements in image recognition algorithms and deep learning will further refine disease identification accuracy. Coupled with precision agriculture methods, these technologies will revolutionize crop management, enabling targeted interventions and resource optimization. Ultimately, machine learning's application in disease prediction holds significant promise for sustainable and efficient agricultural practices in the future.

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