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An Innovative Method: Identifying Pests Through Artificial Neural Networks and Image Processing

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Abstract: Effective and precise pest detection technologies are of the utmost importance on a global scale in order to reduce the negative effects of pests on crop yields. "This research presents a new method for detecting pests using ANNs and image processing tools. By combining machine learning with image analysis", our suggested approach offers a powerful tool for pest identification in a variety of agricultural contexts. Artificial neural networks (ANNs) make it possible to train specialised models that can visually distinguish between different kinds of pests in digital photos. Research using large real-world datasets has shown that preprocessing techniques improve model performance and feature extraction, making them more efficient and accurate than traditional pest detection methods. This research contributes to the field of precision agriculture by providing a trustworthy and automated method for early pest detection, which allows for prompt action and reduces crop loss. Our method takes use of ANNs—which can learn complex patterns from picture data—by combining the most recent developments in deep learning with image processing. Morphological operations and histogram equalisation are two preprocessing methods that help minimise noise and improve the discriminative power of retrieved features. Our technique has been rigorously tested across multiple datasets with different pest species and habitats. It has proven to be quite accurate and scalable in agricultural settings. "The automation and efficiency benefits of our technology are further highlighted when compared with traditional pest identification methods, such as chemical-based procedures and human inspection". This research highlights the significant impact that AI and image processing may have on pest control tactics. It paves the door for agricultural systems that are more robust and sustainable, and can better handle new threats as they arise.

Keywords: *ANN Pests Recognition, Artificial Neural Network Based Pests Recognition, Image Processing.*

1. Introduction

To ensure food security and protect crop yields, modern agricultural operations rely heavily on the accurate detection and control of pests. Hand inspections are a common component of traditional pest detection methods, but they are labor-intensive, error-prone, and time-consuming. In light of these difficulties, new technology has arisen that shows promise as a tool for automated pest identification: ANNs and image processing approaches. By combining artificial neural networks with image processing approaches, this research presents a new way to improve pest detection. This approach aims to provide farmers with dependable and effective ways of early pest identification and mitigation by utilising the power of computer vision and machine learning. Its goal is to revolutionise pest control techniques. The next parts will explore the methods used in this new approach, focusing on how it could improve agricultural sustainability and production. The goal of our extensive testing and validation is to prove that this technology can effectively identify and control pests, which will help precision agriculture move forward.

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1.1. Motivation

Evaluating the present situation of agricultural commodities is the bedrock of smart farm research. These goods have been thoroughly examined using a range of imaging and extraction techniques, including those developed specifically for insect study. The importance of investigating issues linked to the analysis and results of images related to diseases is highlighted by our image database. Instead of actively analysing formal data to anticipate and avoid pest occurrences, previous methods for pest data analysis could only examine photos after the fact. Food security is under risk in many parts of the world where resources are limited and it is difficult to identify crop diseases and pests in their early stages. That is why it is critical to tackle this problem by using Artificial Neural Networks (ANNs).

1.2. Objective of Work:

This study aims to provide a novel method for developing plant pest detection models by utilizing artificial neural networks that have been trained for the categorization of leaf images. A more rapid rollout of the system is possible because to the novel training strategy and methodology. Using neural networks trained on massive publically available datasets, this allows for the large-scale detection and severity evaluation of plant pests. Along with increasing production, decreasing costs, and increasing profits, the project's principal goal is to decrease use of pesticides. In addition, by isolating the pest-affected regions of the plant, the process helps reduce fertilizer usage.

1.3. Objective of Work:

Classification, pest categorization, infected area proportion estimation, dispersion area, and pest grading are all covered extensively in this study. We accomplish these goals by utilising a wide variety of approaches, such as morphology, binarization, and artificial neural networks (ANNs) for training classification data, which allows us to compare and cluster the original image with pests. When calculating the pest rating, Neural-Fuzzy logic is also helpful.

2. LITERATURE REVIEW

Shilpa Itnal et al. (2019): Timely crop evaluation is crucial for maintaining crop health in the face of agricultural diseases and pests, which pose considerable hazards to crop production. To avoid significant reductions in crop yield, it is crucial to identify and eradicate pests as soon as they show signs on leaves. Reducing pesticide usage and increasing insecticide efficacy are both achieved by early disease detection.

J. Mahalakshmi et al. (2017): Research on field-based automated irrigation control and environmental monitoring systems has highlighted the need for constant vigilance and quick responses to changes in plant growth. Just as important as measuring pH and other environmental variables is keeping an eye on moisture content.

Abhishek Dey et al. (2016): A number of crops are at risk from white fly infestations, therefore it's important to find a way to automatically tell healthy leaves apart from those that are sick. Support vector machine (SVM) is the most computationally efficient classifier with remarkable accuracy rates, according to a thorough comparison of well-established classification techniques. An automated system that can quickly and accurately identify white flies in leaf images is proposed as a solution.

Madhuri Devi Chodey et al. (2020): Through the use of visual aids such as photos and films, farmers can learn to recognise and identify pests that pose a threat to their crops. To aid in pest identification using feature retrieval and support vector machines (SVMs) for training, this study presents k-means and EM clustering techniques for recognising twelve different pest species. It also makes it possible to find sick spots on crops using this technology.

Muhammad Benny Chaniago et al. (2021): In order to help field workers identify citrus fruit pests and illnesses, data management system approaches are being implemented. These methods will provide web-based tools for identification. The system classifies pests and diseases by using images of pest-affected citrus leaves and techniques from Neural Networks and Support Vector Machines.

Dan Jeric et al. (2005): To improve upon the capabilities of wireless cameras alone, an automated system for pest insect monitoring incorporates software and hardware for image and environmental sensor network integration. This technology streamlines greenhouse management and Integrated Pest Management (IPM) by collecting data on environmental variables and insect pest numbers in real-time.

Telmo De et al. (2020): While there are obstacles, such as the need for tailored convolutional neural networks (CNNs) for precise detection, deep learning and image processing methods allow for the detection of insects and sick plants. Considerations like as image quality, object density, available hardware, and dataset size impact techniques. Combining convolutional neural networks (CNNs) with image processing techniques has the ability to efficiently manage overlapping objects, according to the study.

K. Dimililer et al. (2017): Eight separate insect species that feed on crops have been identified by an intelligent pest bug classification system that uses backpropagation neural networks. In order to classify insects using retrieved characteristics, the framework employs a pattern averaging technique to picture segmentation and morphological feature extraction.

Adao Nunes Alvesa et al. (2020): In order to test classification models for cotton pest identification, a photo dataset collected in the field is presented. The study shows that the ResNet34 model is better at categorising cotton pests, and it has the ability to expand to other crops and ecosystems.

Johnny L. Miranda et al. (2014): We provide an automated method that uses a number of image processing techniques to identify and remove bugs from photos. Pests in photos can be more easily identified and extracted with the use of background modelling and median filtering. Though encouraging, there is still a long way to go before we have a completely automated system for detecting and identifying pests, perhaps with the help of neural network techniques for better precision.

3. Methodology

3.1. Introduction

This research presents a novel strategy for detecting agricultural pest insects using image processing techniques. Included in the technique are the following steps: Initial image preparation employs a variety of techniques, including binarization and k-means clustering, to eliminate noise, define object borders, and discover count values. A "low" or "high" level of insect infestation is labeled on the photograph after the count values are known. The process of insect segmentation from the original photo is made easier by providing an input image. The MATLAB platform is utilized for the purpose of identifying plant pests and analyzing photographs of diseased crops. Image processing techniques are utilized by this platform. For the purpose of disease detection and diagnosis, the image undergoes multiple processing steps.

3.2. Basic System model for pest detection:

Below are the steps for pest classification:

To initiate the pest detection process, the first step involves capturing images of the pests and saving them in various formats like .jpg, .png, etc. Subsequently, image preprocessing is conducted to enhance the quality of the captured images. This preprocessing phase consists of two primary methods. Firstly, images captured in the RGB format, which are composed of red, green, and blue colors, are converted to grayscale. This conversion is favored for its efficiency in both time and storage utilization. Secondly, the dimensions of the images are adjusted through resizing to meet the system's requirements. Following preprocessing, feature extraction is performed. This crucial step involves extracting features such as standard deviation, mean, entropy, etc., from the captured images. These extracted properties serve as vital data points for training the classification dataset. Finally, the process concludes with identification and classification. Both affected and unaffected portions of images are compared against the provided training dataset to accurately identify and classify the pests present, thereby facilitating effective pest management strategies.

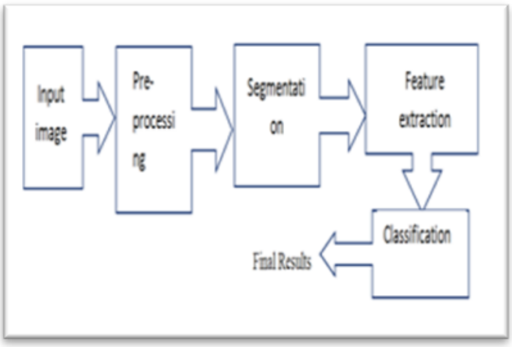

Fig: 3.2 System Model

3.2.1 Preprocessing:

A number of issues can make the processed photos unfit for direct detection and classification, including noise, lighting patterns, weather, low resolutions, superfluous backdrops, etc.

3.3 Segmentation: K-means clustering

A number A basic and unsupervised learning process, K-means clustering is among the many clustering algorithms available. Clusters are found by comparing the similarity of objects within each group. Unsupervised algorithms rely entirely on dataset input to generate assumptions, without any prior knowledge of outcomes.

In K-means clustering:

In the realm of data clustering, several key terms play significant roles. First and foremost, "K" represents the number of centroids, which are pivotal points within a dataset. These centroids serve as representatives for clusters, groups of data points that share similarities. Moreover, "mean" refers to the statistical concept of averaging data, often used in determining centroids' positions. The process of clustering involves organizing data into these groups, with each cluster representing a distinct set of characteristics or patterns. This clustering process encompasses two primary functions. Initially, it endeavors to find the optimal value for "K" by iteratively testing various values to achieve the most suitable clustering outcome. Subsequently, the algorithm assigns each data point to the nearest centroid, thereby forming clusters based on their proximity to these central points. Through this iterative approach, data clustering facilitates the identification of meaningful patterns and relationships within datasets, aiding in insightful analysis and decision-making processes across various domains.

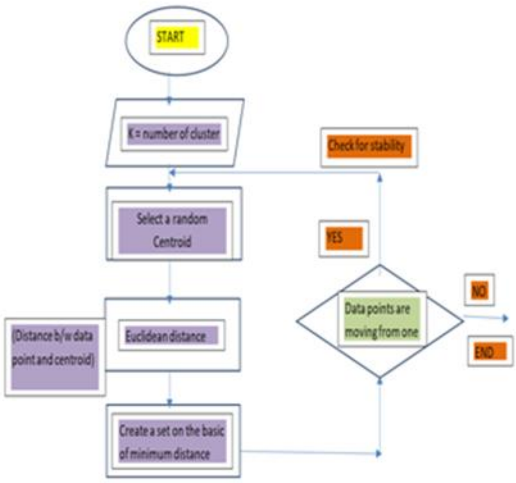

Figure: 3.3 K-Mean Clustering

It uses colour segmentation to show five groups, and then it finds the one that looks most different from the greenish part of the leaf. Clusters of diseases will thereafter be forecasted.

Classifier: ANN in Pest Detection

The goal of this research project is to mimic brain activities in a lab environment by employing Neural Networks (NN) to accomplish data grouping and classification. The main way that neural networks learn is by comparing different examples. With sufficient training data, NN should be able to detect trends and patterns in data and classify it accordingly. The input, output, and hidden layers make up a conventional NN. Compared to the input layer, the hidden layer could have more nodes. Interconnections between output layer nodes and hidden layer nodes reflect the weights of those nodes. Classification is a significant challenge to the study and application of artificial neural networks (ANNs). A growing number of features and categories in a dataset makes it harder to train learning, classification, and transition functions accurately. In this study, we look at the efficacy of different functions when applied to ANN as a classifier and assess their suitability for different datasets.

4. RESULTS

4.1. Artificial Neural Network Results

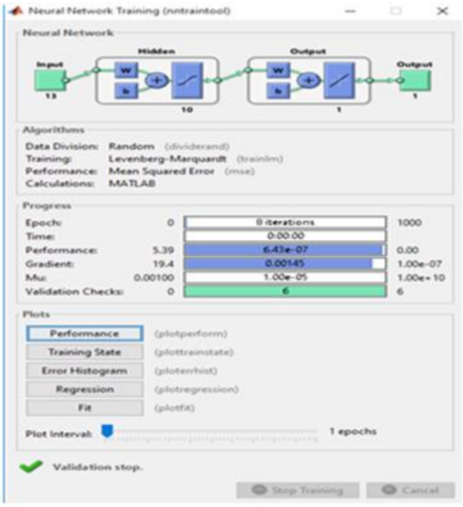

Fig: 4.1 ANN Training

Above a graphical representation of our neural network training process, illustrating input/output components, hidden/output layers, and additional elements

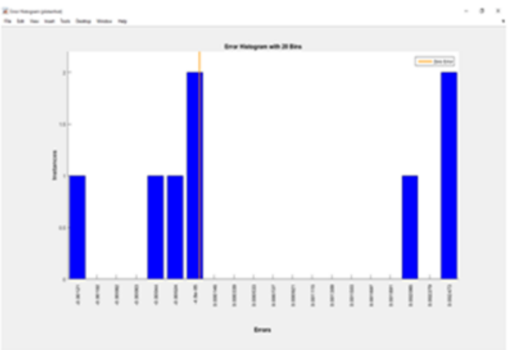

Fig: 4.2 Plot of Error Histogram

In this depiction, we observe the error histogram plot, revealing the disparities between predicted values and target values subsequent to training a feed forward neural network. Negative error values signify substantial room for enhancement between the actual and desired outcomes.

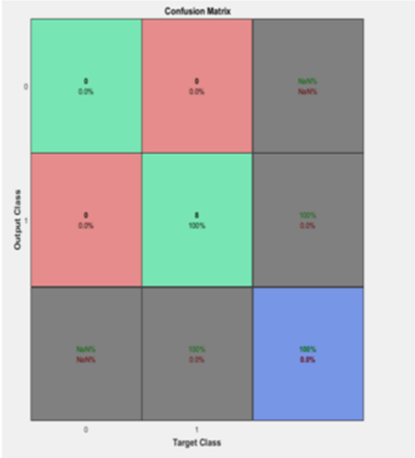

Fig: 4.3 Confusion Matrix

It displays predicted classes in the columns and actual classes in the rows. Correctly classified observations are represented along the diagonal, while misclassified ones are depicted off the diagonal.

In below example showcases the values of the training state utilizing the plottrainstate function.

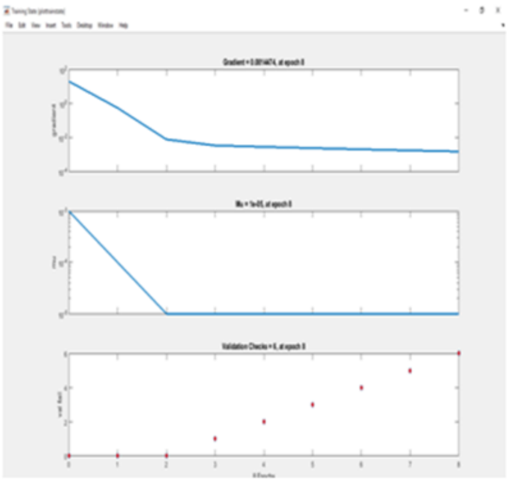

Fig: 4.4 Graph of Training State

4.2. Main Results

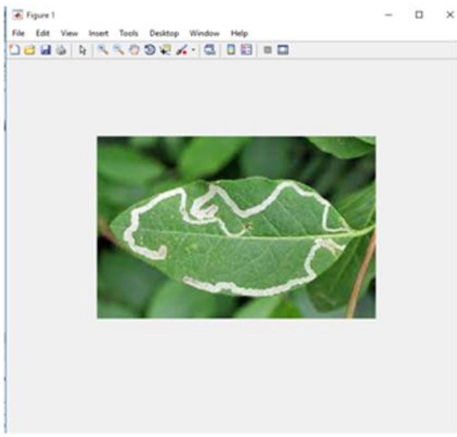

Fig: 4.5 User Input Image

"This figure depicts the pest image utilized as the input in our analysis."

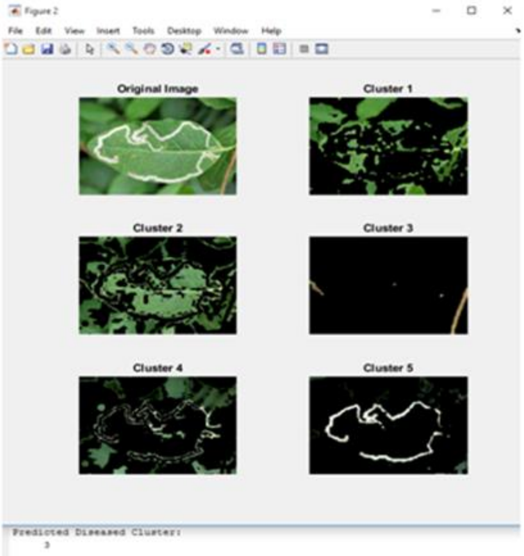

Fig: 4.6 Image After Clustering Process

Within this illustration, both the original image and the segmented image comprising five clusters are visible. Our system discerns cluster 3 as the diseased area.

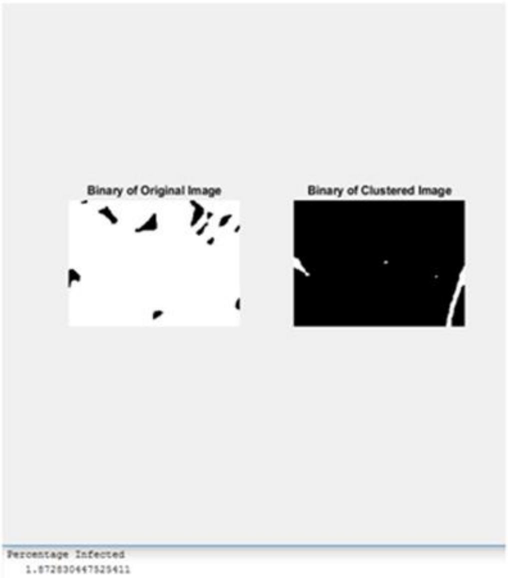

Fig: 4.7 Cluster Image Conversion

Fig: 4.8 Classification Results

Fig: 4.9 User Input Image 2

This figure showcases our second input image.

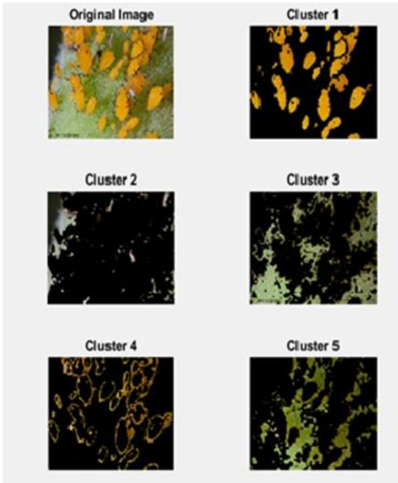

Fig: 4.10 Finalize Cluster Image

This figure showcases both the original image and the image segmented into five clusters.

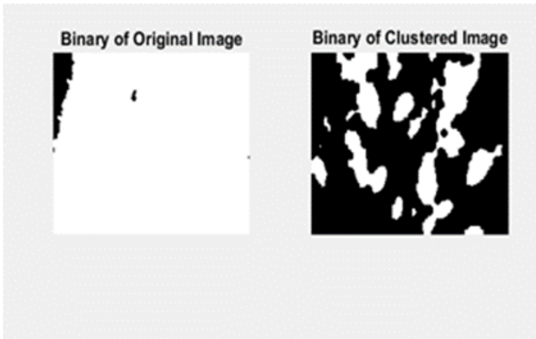

Fig: 4.11 Binary Converted Image

In this figure, we can observe both the binary representation of our original input image and the binary representation of the image segmented into clusters.

Fig: 5.11 Results

In this figure, we observe the image-related data generated by our algorithm.

5. Conclusion and Future Scope

5.1. Conclusion

The use of AI and image processing in agricultural pest management has obvious advantages, but these technologies may have far-reaching uses. Healthcare diagnostics, environmental monitoring, and industrial quality control are just a few of the many areas that could benefit from enhanced detection systems. From abnormalities in natural ecosystems to medical imaging scans, researchers and practitioners can adapt and improve these methods to address a variety of challenges. Because of their adaptability and scalability, artificial neural networks have many potential uses. It is becoming more and more possible to process and analyse huge image data in real-time as computing resources improve. Autonomous systems that can monitor and make decisions in real-time are on the horizon, thanks to this advancement, which can boost production and efficiency in many different sectors.

A new method for detecting pests has emerged with the combination of image processing and artificial neural networks. The use of complex algorithms in this approach shows promise for the accurate detection and classification of agricultural pests. “Our method for early insect detection using neural networks and image processing is practical and can help farmers deal with possible dangers faster”. Future pest management solutions may be more effective and dependable if technology continues to progress and these procedures are optimised.

5.2. Future Scope

The use of these methods and algorithms in real-time hardware is likely to occur in the near future. Our idea is to use a SIM800L module to link Nodemcu to the internet so that data may be transmitted using Thingspeak. In addition, we plan to incorporate webcams so that we can stream video in real-time to keep an eye out for any suspicious activity. Furthermore, our goal is to develop an Android app that can provide notifications and updates about the system's status in real-time. In the future, we want to improve the system's overall performance by making it more accurate and reliable.

Conflicts of interest

The authors declare no conflicts of interest.

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