Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.98549888

ENHANCEMENT OF VIDEO PROCESSING TECHNIQUE IN INSECT DETECTION

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Abstract
The frequency of insect attacks has been on the rise in recent times. One effective method for identifying and classifying insects is through the detection of these insects within images. This approach is relatively simple and allows for accurate categorization of insects based on the content of the image. Insect infestations can cause significant harm to crops, resulting in financial losses for farmers. However, identifying the specific category of an insect can sometimes be a challenging task.

Different types of insects cause varying degrees of damage to different crops. The impact of these attacks depends on the type of insect and the specific crop being cultivated. Additionally, insect attacks tend to occur during different climatic conditions. It is important to note that climate change can exacerbate the likelihood of insect infestations. These attacks not only lead to economic losses but also result in reduced crop production.

To address the challenge of identifying and classifying insects in video footage, a proposed research approach suggests the implementation of a Convolutional Neural Network (CNN) architecture. This architecture aims to provide an effective solution by leveraging the capabilities of deep learning algorithms. To enhance the accuracy of the model, a confusion matrix can be utilized, allowing for the evaluation and refinement of the results.

Overall, by employing advanced technologies such as CNNs and leveraging tools like the confusion matrix, it is possible to improve the identification and classification of insects in videos. This research has the potential to mitigate the economic damage caused by insect attacks and contribute to higher crop yields.

Keywords---Insect detection, insect classification, Convolutional neural network, video processing, confusion matrix

I. INTRODUCTION

In today's scenario, agricultural land is rapidly diminishing due to various factors. The fast-paced world has led to changes in cultivation methodologies, including the increased usage of different fertilizers and pesticides. Unfortunately, this surge in chemical usage has resulted in a rise in insect populations and subsequent insect attacks on crops. The abundance of insects is influenced by factors such as soil quality and climate. Additionally, water supply quantity and quality play crucial roles in crop production and market value. Even slight damage to crops can significantly decrease their market valuation.

During our research, we extensively reviewed the works of other researchers focusing on relevant topics and issues. Here are some key findings from our review:

Impact of Pesticides: Several studies have investigated the effects of pesticides on insect populations and crop damage. It was found that certain pesticides, while effective in controlling pests initially, can lead to the emergence of pesticide-resistant insects over time.
Integrated Pest Management (IPM): IPM approaches, which combine multiple strategies such as biological control, crop rotation, and targeted pesticide use, have shown promising results in reducing insect damage and minimizing the reliance on chemical pesticides.
Climate Change and Insect Dynamics: Climate change has been linked to alterations in insect behavior and distribution patterns. Warmer temperatures, changing precipitation patterns, and altered growing seasons can influence insect lifecycles, resulting in shifts in their population dynamics and increased insect damage to crops.
Remote Sensing and Precision Agriculture: Remote sensing technologies, including satellite imagery and aerial drones, have been utilized to monitor crop health, identify pest hotspots, and optimize pesticide applications. These techniques enable targeted and efficient pest management strategies, reducing the overall chemical burden on crops.
Insect Identification Technologies: Advancements in computer vision and machine learning have led to the development of automated insect detection and classification systems. These systems utilize image analysis techniques and deep learning algorithms to accurately identify and classify insect species, aiding in early pest detection and precise pest management interventions.
By incorporating insights from the works of other researchers and leveraging emerging technologies, we can develop sustainable and effective approaches to tackle insect attacks, reduce chemical usage, and protect crop production. These efforts will not only safeguard agricultural land but also improve market value by ensuring higher-quality, undamaged crops.
The proposed research paper discusses issues related to the detection and classification of insects in moving videos, specifically focusing on the challenges posed by small-sized insects that often move in groups [1]. Extracting features from such video clips can be difficult as clear and distinct features are not always available for detection and classification.
One particular challenge addressed in the research paper is the classification of insects as either alive or dead in static images. To overcome this challenge, the author implemented a tracking system to maintain a complete track of the insects' movement in the video. Insects that exhibit no activity or movement are considered dead, while those that are stationary in the video are ignored and not included in the total insect count. However, a major issue encountered by the author was differentiating between dead insects and grain particles [2].
Insect attacks on crops, such as rice plants, result in lower crop yields and can contribute to food scarcity. Rice plants, in particular, are susceptible to various types of damage, such as brown spot disease [3]. Researchers have focused on real-time approaches for detecting pests in farms using modern video processing technology. However, one challenge faced by the authors was accounting for the changes that occur in a plant throughout the infection and damage process. This challenge was addressed through the use of segmentation and classification techniques [4].
In summary, the research paper aims to address the difficulties associated with detecting and classifying insects in moving videos. It tackles issues related to the small size and group behavior of harmful insects, as well as the distinction between live insects, dead insects, and

other particles. By employing advanced techniques such as tracking systems, segmentation, and classification, the research contributes to more effective pest detection and management in agricultural settings.

II. RELATED WORK

In recent years, there have been numerous studies aimed at enhancing video processing techniques for insect detection. The primary objective of these studies is to improve the accuracy and efficiency of insect detection algorithms, particularly in agricultural settings where insect damage can have significant implications for crop production. Researchers have recognized the importance of accurately identifying and classifying insect species to effectively manage pest populations. In their study, Ikhlef Bechar et al. [1] focused on the whitefly species, a harmful insect species. The researchers successfully recognized this insect species in offline mode, achieving a significantly higher accuracy. They collected a video dataset by installing video recording cameras in the farm and processed the videos into frames. Frame-based insect detection was employed, where RGB frames were converted into grayscale images. Insects appeared as bright objects in the grayscale images, making them easily visible and identifiable. Connected components algorithms and local conquer and merge segmentation strategies were utilized for insect detection.

Ying Yang et al. [2] addressed the challenges of noise in images and errors caused by moving insects. They also tackled the issue of distinguishing between live and dead insects since only live insects have the potential to damage crops. Their proposed method focused on video analysis and included insect recognition, counting, and avoidance of recounting and missing insects in the video frames. They employed a video collection subsystem with components such as grain sampling, conveying, illumination, and cameras. Clustering techniques were applied to consecutive frames to avoid recounting and missing pests. Additionally, multi-frame verification and support vector machine (SVM) classification were employed for better accuracy and pest type classification.

Understanding the various factors causing damage to rice plants, such as humidity, fertilizers, water management, and climate conditions, can be challenging. Dengshan Li et al. [3] employed CNN, R-CNN, VGG, and YOLOv3 in their research. CNN was used for feature extraction, while YOLO models were responsible for insect recognition in videos. Weather changes often result in unclear videos, necessitating preprocessing steps. Deep learning methods were utilized to recognize the type of insect. The dataset primarily focused on rice plant-based insects such as rice stem borers, rice sheath blight, and rice brown spot. Video detection metrics were used for counting spots where insects were identified, comparing them with true spots to determine accuracy. The researchers used three different video detection systems: frame extraction, still-image detection with a custom DCNN backbone, and video synthesis module. Different colored boxes were used to signify different insect species, and a confusion matrix was employed to improve accuracy. The proposed systems had some limitations, including long detection time, motion blur, irregular shapes, and defocusing of videos.

Madhuri Devi Chodey et al. [4] focused on identifying and classifying pests. Their methodology involved image and video frame acquisition, preprocessing, object tracking, segmentation, feature extraction, and classification. The research covered twelve different insects.

Xi Cheng et al. [5] proposed a system that utilized deep convolutional neural networks for pest image classification and R-CNN for videos. The system was capable of identifying insects regardless of background coloration. They considered ten different species of insects in their model development. Asaf Gal et al. [6] proposed a system for identifying groups of insects and multiple groups of different insect species. They employed the anTraX algorithm, which involved multi-object tracking algorithms, insect classification algorithms, and identification of unclassifiable insects in frames. Unique IDs were assigned to the identified insects.

Overall, these studies contribute to the advancement of insect detection and classification methods using various techniques such as frame-based analysis, deep learning algorithms, and tracking systems.

Table 1: Related Work

SR. NO.	TITLE OF PAPER	METHODOLOGY	RESULT	LIMITATION
1.	On-line video recognition and counting of harmful insects	Video are converted into frames. These colorful R-G- B color frames converted into Gray images. Connected components algorithm and Local Conquer and merge segmentation strategy.	Insect species: *Whiteflies* Insects in thebright background are clearly visible	Objects(here insects) in the darker background are not clearly visible
2.	A system for detection and recognition of pests in stored grain basedon video analysis	SVM Classifier is used to classify the insect. Continuous frames from the video are collected along with tracking of insect count.	Counting of moving objects(here insects) and avoidance of recounting of the sameinsect	At times unable to detect insects in b lured background.
3.	A recognition method for rice plant diseases and pests video detection based on deep convolutional neural network	CNN, R-CNN, VGG, YOLOv3 and DCNN Backbone. Confusion matrix is used for better accuracy.	Inesct species: *rice steam borer, rice sheath blight, rice brown spot.* Different colored spots are detected and insects are detected and classified.	Longer processi ngtime, not useful for blur motions and irregular shapes and defocusing ofvideos.
4.	Pest Detection inCrop using Video and Image Processing	Images and videos frames acquisition is done followed by pre-processing and objecttracking.	Research consisted for twelve different species. Segmentation was taken into for	Useful only for higher quality of videos and images

			extraction a nddetection	
5.	Agricultural Pests Tracking and Identification in Video Surveillance Based on Deep Learning	Deep Convolution Neural Network - Alexnet and VGG16.	Insect species: 10 different ins ect species Mo del capable of detecting the insect type in the frame.	Frame loss in thevideo 0.83%
6.	anTrax, a software package for high throughput video tracking of color tagged insects	Multi-object tracking algorithms and segmentationof frames.	anTraX trac ks individual ants with near-human accuracy over a wide range of conditions	

III. METHEDOLOGY

The proposed method addresses the challenge of identifying and classifying insects on crops by leveraging video processing techniques. Video processing technology involves extracting data from videos and their frames. In this method, Convolutional Neural Networks (CNN) are utilized for feature extraction. CNN is effective in capturing even the smallest visible features of insects by employing multiple layers for extraction.

To detect insects in moving videos, the You Only Look Once (YOLO) algorithm is employed. YOLO is a pretrained model that recognizes insect types based on previously provided information. By utilizing YOLO, the system can easily detect moving objects, specifically insects, in both video and image frames. YOLO has the capability to process approximately 150-160 frames per second, allowing for real-time analysis. Running the algorithm on multiple frames simultaneously facilitates tracking the movement of objects, in this case, insects, within the video.

The proposed model demonstrates the ability to identify different types of insects. Since the videos may contain multiple types of insects in a single frame, pre-processing techniques are applied to accurately identify the specific type of insect present.

Overall, the proposed method employs CNN for feature extraction and YOLO for insect detection in moving videos. By combining these techniques, the system can effectively identify and classify different types of insects on crops.

The proposed model is capable of accurately identifying and classifying the type of insect present in each frame of the video. It can perform real-time detection and classification without any noticeable time lag. The model is designed to process videos of regular mobile camera quality, eliminating the need for high-quality videos.

The workflow of the process is illustrated in Figure 1. It begins with capturing real-time video footage from the field. The video is then converted into a series of continuous frames representing the movement. During frame extraction, background noise from the video is reduced to enhance the clarity of the frames. Insect detection and classification are performed using the YOLO algorithm. By considering multiple frames simultaneously, the model calculates the insect count. If the count matches specific conditions, an alert message is sent to the user.

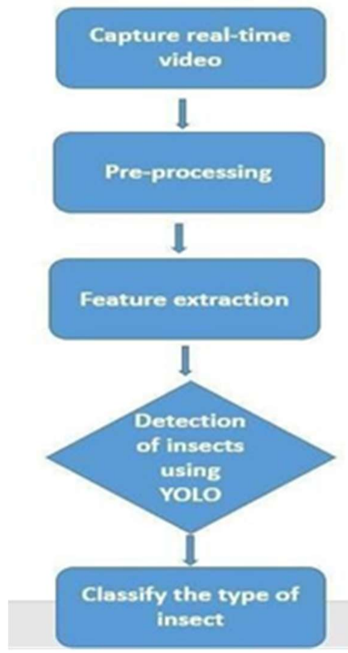


Figure 1: Process Workflow

The initial step in the process involves video processing techniques to achieve higher accuracy by extracting features from the video frames. Video processing is a form of signal processing, where a video serves as the input and the output can be either a video or an image. The video processing approach includes the following steps:

- Importing a video
- Reducing background noise
- Calculating the results and indicating the objects in the video

Video processing can be performed in two ways: static processing, where frames are extracted from the video and used for analysis, and live processing, where real-time video is processed. In some cases, continuous frames from the video are used for analysis.

Overall, the proposed model incorporates video processing techniques to accurately identify and classify insects in real-time video footage, with the ability to handle videos of regular mobile camera quality.

Figure 2 and Figure 3 provide visual representations of the output generated by the working model. In Figure 2, the model predicts the presence of a Honeybee in the frame, while in Figure 3, it identifies a Butterfly in the frame. The outputs showcase the effectiveness of the model in accurately recognizing and classifying different insect species. These visual representations help users understand the model's performance and provide a clear indication of the insects detected in the frames.

Figure 2: Output - Honeybee Prediction

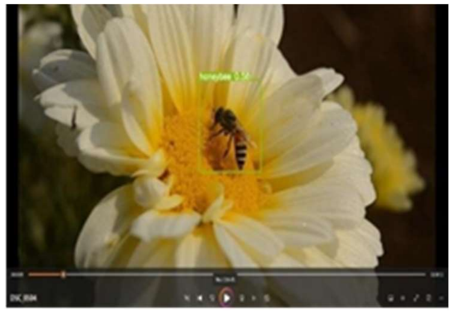
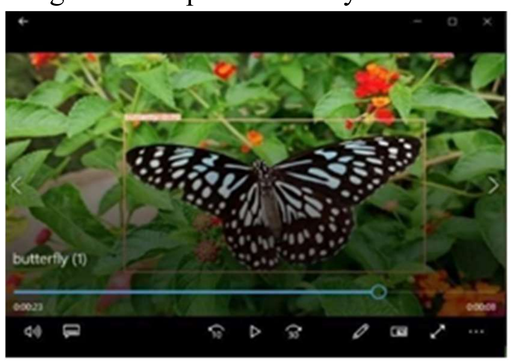


Figure 3: Output - Butterfly Prediction



These figures demonstrate the model's ability to identify and classify specific insects within the frames, further validating its effectiveness in real-time insect detection and classification.

IV. CONFUSION MATRIX

A confusion matrix is a valuable tool for analyzing the outcomes of a classification problem and visually representing the predicted and actual values of a classifier. It presents a table layout that showcases the different outcomes of the predictions and results.

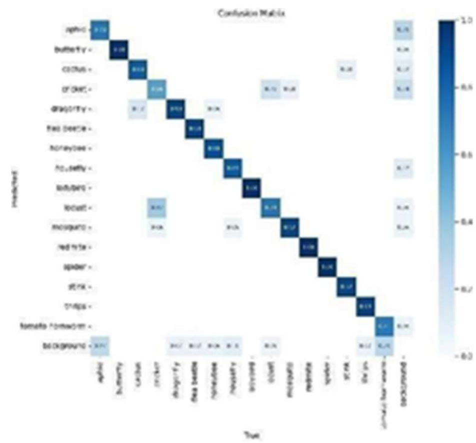


Fig 4: Confusion Matrix

The confusion matrix typically consists of four main components: True Positive (TP): The number of correctly predicted positive instances. True Negative (TN): The number of correctly predicted negative instances. False Positive (FP): The number of instances that were incorrectly predicted as positive. False Negative (FN): The number of instances that were incorrectly predicted as negative. The confusion matrix provides a clear and concise summary of the classifier's performance, enabling a deeper understanding of the prediction outcomes. It helps in assessing the accuracy, precision, recall, and other evaluation metrics of the classification model. By analyzing the confusion matrix, one can identify any patterns or trends in misclassifications and gain insights into the strengths and weaknesses of the model. It is a valuable tool for fine-tuning and improving the classifier's performance. In summary, the confusion matrix is an essential visual representation that aids in the evaluation and analysis of a classification problem, facilitating a comprehensive understanding of the predictive outcomes of a classifier.

V. RESULT AND DISCUSSION

As the size of the training and test datasets increases, the model achieves higher accuracy. Precision measures the similarity or reliability of values, indicating how many similar elements are present. Recall refers to the retrieval of information that satisfies certain criteria. Accuracy measures the correctness of the working model. Increasing the dataset size leads to significant variations in the output results of the model. Utilizing a confusion matrix aids in achieving better accuracy in both precision and recall for insect count and attack status based on the provided video.

Figure 5: Model indicating the detected insects.

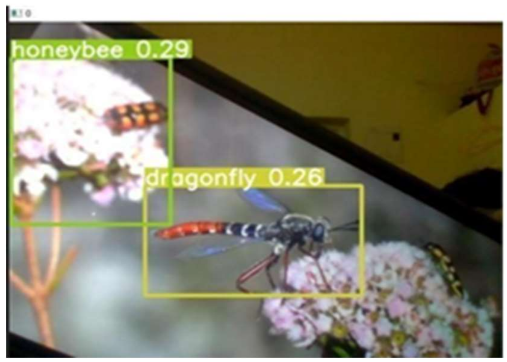


Figure 6: Model indicating the detected insects

Figure 7: Model indicating the detected insects.

Figure 8: Model indicating the detected insects.

Figure 9: Model indicating the detected insects.

Figures 5, 6, 7, 8, and 9 display the output for real-time video, where insects of different species present in a single frame are identified and classified based on their distinguishing features. Insects from multiple species are detected, and the model is capable of detecting and classifying insects regardless of the background variations.

Figure 10: Train/Loss Graph 1

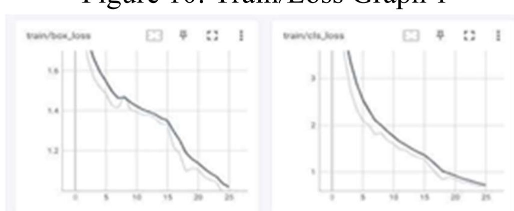


Figure 11: Train/Loss Graph 2

Figure 12: Metrics/Precision and Recall Graph

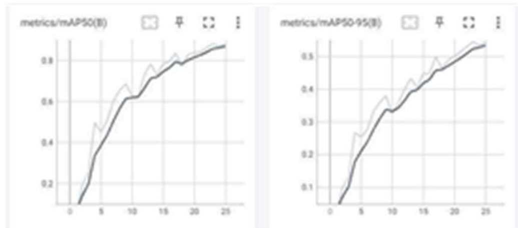


Figure 13: Metrics Graph

Figures 10, 11, 12, and 13 illustrate various graphs related to the model's training and performance metrics. These graphs provide insights into the model's training progress, loss reduction, precision, recall, and overall performance.

VI. CONCLUSION

In conclusion, the proposed model demonstrates its effectiveness in insect identification and classification. By utilizing a confusion matrix, the accuracy of the model is significantly improved, enabling it to identify and classify insects of different types without confusion, even when dealing with similar-looking species. The model is capable of processing videos captured by regular mobile cameras, making it accessible and practical for real-time video analysis. It successfully detects and identifies insects in both video and image input formats. Overall, the proposed model shows promising results in insect detection and classification, providing a valuable tool for monitoring and managing insect attacks in agricultural settings. With further refinement and optimization, this model has the potential to contribute to crop protection and enhance agricultural practices. Further research can focus on expanding the dataset to include a wider variety of insect species and refining the model's accuracy in challenging environmental conditions. Additionally, integrating the model with a real-time monitoring system can enhance its practicality and usability for farmers and agricultural professionals. In conclusion, the proposed model offers a valuable solution for insect identification and classification, with potential applications in agricultural pest management and crop protection.

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