RESEARCH PAPER

Hybrid CNN–Transformer Enhanced Yolov8 for Real-Time Pest Detection

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ABSTRACT

Pest detection is a complex activity in agriculture because of the change in pest size, complexity of the background and environmental conditions. Real time and proper identification are essential to minimize crop destruction and overuse of pesticides. In this paper, a Hybrid CNN-Transformer Enhanced YOLOv8-based Detector is proposed to detect caterpillars in real-time. A domain dataset is created and annotated using Roboflow and is trained in a format that is compatible with YOLOv8 with a high degree of augmentation strategies to make it robust. The lightweight YOLOv8n model is used to train it to establish performance baselines. In order to enhance the learning of features, the initial convolutional backbone is re-architected to a hybrid model using convolutional and Transformer architectures to extract localized and global features, respectively. The neck of YOLOv8 is used to be compatible. Both hybrid and baseline models had been trained in the same environment and tested on precision, recall, mAP@0.5, mAP0.5:0.95 and inference speed (FPS). Experimentally, it is demonstrated that proposed hybrid model has high performance in detection accuracy versus the baseline and lightweight capability that can be deployed to real-time edge devices. This combination of CNN and Transformer can be used to detect small pests more effectively in the complicated field conditions. This paper has illustrated how hybrid deep learning architectures can be used to promote precision agriculture and construct an effective, precise, and scalable pest surveillance systems.

Keywords: YOLOv8 · Hybrid Model · CNN · Pest Detection · Precision Agriculture · Real-Time Object Detection.

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1. Introduction

Pest management is also closely related to agricultural productivity because insect's infestation is still among the primary causes of decreasing crop product in all parts of the globe. Food and Agriculture Organization (FAO) indicates that almost a fifth of the total agricultural production is wasted each year because of the insect pests and this has led to a substantial loss of income and endangered food security. Pest monitoring methods used in conventional manners that involve manual inspection by farmers or researchers are time consuming, labour intensive, and easily subjected to human error. In addition to this, overuse of pesticides without accurate identification of pests does not only augment production costs but also causes pollution of the environment and health hazards.Due to the fast advanced deep learning and computer vision technology, intelligent pest detection systems have become a potent tool in precision agriculture. Real-time object detection models, including the user Only Look Once (YOLO) family have proven to be very efficient in terms of speed and accuracy thus can be deployed in the field. Nevertheless, minor issues, including a small pest size, inter-class similarity, and a cluttered background, and fluctuating light conditions in the agricultural fields continue to undermine the strength of the traditional CNN-based detectors.According to recent research, Transformer architecture integration into visual recognition pipelines has been shown to have

strong global context modelling capabilities, which can be effectively used alongside CNN feature extraction, which is performed in localized regions. With such synergy, hybrid CNN-Transformer models offer a worthwhile direction towards improving the accuracy of pest detection without any harmful effects on computational efficiency.The study offers a Hybrid CNN-Transformer Enhanced YOLOv8 architecture that is used to detect caterpillars in real-time. The suggested model will be a combination of convolutional layers to effectively capture fine-grained spatial features and Transformer blocks to effectively capture long-range dependencies, all based on the YOLOv8 backbone. By so doing our methodology seeks to solve the drawbacks of CNN-only based detection models and improve deep learning implementation in precision agriculture.

2. Literature Survey

Detection of pests in agriculture is a difficult task, because of the number of species of insects, the changes in their appearance, and the multifaceted environmental backgrounds. The recent developments in deep learning have made it possible to identify pests in crop fields in a more effective way. These are some of the approaches that have been suggested to detect insects in real-timeZhang et al. [1] suggested an enhanced YOLOv8-based rice pest detection model that displayed real-time accuracy under a variety of field conditions. In their work, the authors have proved that lightweight YOLO architectures can be effectively used in practice in agriculture. Nevertheless, even primitive pests and blurred insects continue to give small challenges to classic YOLO models.Lyu et al. [2] came up with CNN-Transformer hybrid model of multi-label predator-prey detection. The convolutional layers were replaced with attention mechanisms, which allowed the model to learn local spatial features as well as global dependencies, which enhanced the accuracy of detection in insects when there was more than one insect in the image, allowing the detection of a whole field with precision agriculture. The approach utilized data augmentation and hybrid feature extraction that led to better detection accuracy at the expense of a small pest detector-friendly inference. Tang et al. [4] introduced Improved Pest-YOLO, which optimized the YOLOv8 detection architecture to use on small pests. The significance of their experiments was the necessity to incorporate the spatial feature improvements to enhance the performance in difficult backgrounds. Wang et al. [5] also discussed Insect-YOLO in crop pest detecting, and the authors proved that the architecture based on YOLO can offer a good combination of performance and speed in real-time use. Zhang et al. [7] introduced a forestry pest recognition model using YOLOv8, with better re-identification modules, through leveraging the attention mechanism to concentrate on the most significant pest areas. Joshi et al. [8] created AgriCure, a web-based application based on YOLOv8 with layered augmentation to detect various pests in real-time. Their article highlights the significance of operational implementation and data augmentation to enhance performance in the field. Zeng et al. [9] investigated the use of AI-based hybrid Transformer-CNN models in smart agriculture. The researchers have proven that attention-based models can be applied to complex fields to achieve the best results in multi-class insect detection Mustapha et al. [10] offered a hybrid deep learning model with YOLOv8 and CNNs to detect waste, which also highlights the universal applicability of hybrid models to any task requiring detecting small objects that are hidden by other objects.Dulal et al. [14] conducted a review of deep learning-based object detection in precision agriculture, highlighting the usefulness of hybrid models as fast and lightweight detectors regardless of the underlying task. Their survey supports the necessity of hybrid architectures in real-time and accurate pest detection: According to Beldek et al. [15], the mathematical models of detection should be not only accurate but also computationally efficient to perform in the conditions of the real world.

3.Proposed Method

A new approach blends CNNs and Transformers inside YOLOv8 to catch pests quickly and correctly, fixing weak spots in older pure-CNN systems. Starting off, images of caterpillars were gathered across different outdoor settings, then labeled carefully using Roboflow software. These images shifted into a version YOLOv8 can read, followed by layering on tricks like stretch effects, mirror flips, turns, and light tweaks to make learning stronger. Instead of jumping straight ahead, tests began with the small YOLOv8n setup to measure how well it finds targets - checking accuracy, hit rate, average score, and response time. From there, the core design changed shape: parts pulled from standard convolutions mixed together with attention-heavy Transformer pieces. Tiny details in images get picked up by the first layers, whereas later parts of the network track broader patterns across distant areas,

helping spot little bugs even in messy scenes. Starting from wide context pooling down to pyramid structures, each piece links together before passing data to the final stage that draws boxes around objects. Same setup, same training time, same hardware - just different backbones - to see which one spots insects better without slowing things down. Results show the updated version marks higher precision numbers, yet runs just as fast as the original tiny model when tested live on compact machines. Mixing old-style filters with newer attention-based units keeps it lean but sharp, fitting well into farming tools that watch crops nonstop.

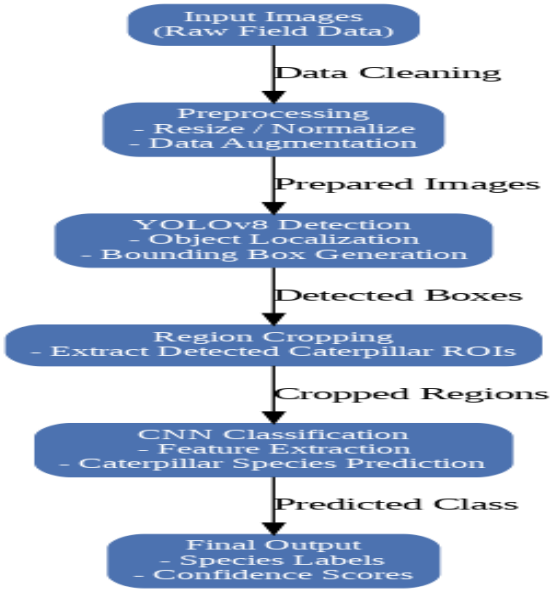

Fig-1 Workflow of the Proposed Method

Out of raw photos snapped across different wild areas came a system that spots caterpillars using layered machine learning steps. Though each type shows many forms, tangled settings, and messy lighting, the setup handles confusion by sorting one piece at a time. Bad files got tossed out - duplicates, broken ones, off-topic shots - and location tags plus times were checked carefully before moving on. Resizing first, then balancing pixel values, later spiced up with twists like flips, crops, tint shifts, even speckles of fake static helped teach the eye better. From there snapshots flowed into a fast tracker built on YOLOv8 rules, boxing live targets as they appear. Boxes spotted areas worth studying, then trimmed down so extra clutter stayed out, keeping only shape details clear. From those cut-outs, a special image reader took over, built to notice layers like hue layouts, sectioned bodies, and upside-down bristle spreads learning these helped guess bug types. Every answer came with a trust number, letting tighter cut offs keep only solid guesses. Results ended up as exact names tagged with how likely they were, making mass insect tracking smoother and automatic. This flow links sharp location accuracy with fine species distinction, cutting hours of hand labeling without losing detail.

4. Algorithm

Hybrid CNN Transformer YOLOv8 for Real Time Caterpillar Detection Using Adam Optimizer

Start

2. Load a caterpillar image from the domain-specific dataset D={I1,I2,...,In}
3. Start by adjusting the picture size to fit the required dimensions. After that, scale pixel values to a standard range. Then make slight variations in brightness or rotation to increase diversity
4. Annotate the dataset in YOLOv8-compatible format using Roboflow
5. Initialize the baseline YOLOv8 architecture
6. Replace the convolutional backbone with a hybrid CNN–Transformer module:
7. CNN layers for local spatial feature extraction
8. Transformer encoder layers for capturing global context
9. Keep using the YOLOv8 neck - FPN plus SPPF - along with its detection head so things still fit together right
10. Slide the enhanced pictures into the mixed system so it can learn. That step feeds fresh visuals to the model, helping it adapt. Through this method, updated imagery shapes the training process. The revised inputs guide how the framework improves over time
11. Compute total loss:

Finding box position error helps adjust location

Finding mistakes when guessing categories

12. Focusing on objectness using a specialized loss function shaped by distribution patterns appears here instead of standard methods
13. Optimize model parameters using the Adam optimization algorithm.
14. Apply bias correction to the moving averages (mt and vt) using bias-corrected formulas.
15. Iterative weight update:

Start with values: set w to zero, let the initial first moment be nothing, also make the second moment start at zero.

16. Until the values of wt settle, go through these actions

a. $t = t + 1$

b. Compute gradient $gt = \nabla L(wt-1)$

c. Update moving averages:

17. The value at time t equals a portion of the prior moment's figure combined with fresh data weighted by what remains after subtracting that same fraction.
    v squared t comes from beta two times the earlier v plus one minus beta two multiplied by g t squared
    d. Apply bias correction:
    v_hat equals v_t divided by one minus beta_1 raised to t
    v_hat equals vt divided by one minus beta squared times t
    e. Update weights:
    wt = wt−1 − η (m_hat / (sqrt(v_hat) + ε))
18. End while
19. Perform inference on test images:
    For every found bounding box, figure out the class label along with how sure the system is. Confidence values come alongside these assigned categories. Each detection gets tagged like that. The process runs through all boxes one by one. Labels appear once computation finishes. Certainty levels match each tag. Nothing skips this step
    oApply confidence threshold Tc to filter low-confidence predictions
    Keep only the strongest box when detections overlap too much
    Finding the last outlines using guesses and how sure we are about them
20. Evaluate model performance: precision, recall, mAP@0.5, mAP@0.5:0.95, and FPS
    Analyze confidence-threshold curves and confusion matrix to assess robustness
21. End

Figure 2 Annotated Caterpillar Images with Confidence Scores for Species ID

Some caterpillars appear here after being sorted by an automated system that guesses their type. A number beside each one shows how sure the system feels about its guess. Nearly 1.0 means it's very confident; numbers around halfway suggest doubt - often because of dim light, messy surroundings, odd angles, hidden colors, or types never seen before during setup. This kind of tool probably uses patterns found through layers of scanning, maybe something like a CNN or detection method such as YOLO or Faster R-CNN. It works step by step: pulling out details, matching shapes, then deciding what fits best. When those numbers stay mostly high across images, things seem to run fine. Still, unclear examples show why models must learn from wider data sets that include exact species names while using solid checks like MAP or F1-score. Ways to see what a model focuses on - say, Grad-CAM - can make its choices clearer, pushing better reliability in studies of living variety.

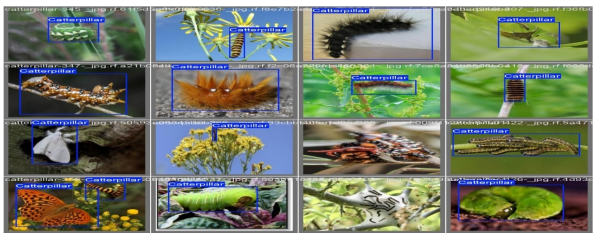

Fig-3 Grouped Set of Caterpillar Images for Comparative Analysis

The second group of caterpillar photos is shown in Fig. 3 which is arranged for methodical examination and comparison in order to draw attention to morphological or ecological differences between subsets.

Fig-4 Confidence-Based Visual Identification of Caterpillars: Batch 2 Dataset

A close look at this picture shows different caterpillars picked out by a computer system trained to spot them. Boxes drawn around each one come paired with numbers from 0.3 to 0.9 showing how sure the program feels about its find. Though they are all larvae, their shapes, colors, and where they sit create a tricky scene for automatic labeling. Because these examples stretch what the software handles, testing on such cases helps measure how tough it really is. Seen together, the group underlines differences in skin patterns, fuzziness, and form across types. One reason these visible features matter lies in how they help animals live longer in tough environments. Instead of blending in, bright colors sometimes warn enemies to stay away. On the flip side, quiet tones plus clever disguises let others vanish

into leaves or bark. Some bugs grow tiny hairs - these act like shields when attackers come close. Over time, where creatures live shapes what traits survive. This wide range shows why scientists pay attention to caterpillars - they reveal clues about change, new species forming, and who eats whom out there. A picture nearby holds twenty snapshots, each one tagged, every bug shown as it looks among plants and soil. One look suggests it's drawn from a set taught to machines, shifting through shades, surfaces, maybe even backdrops. Not every sample looks alike - this mix helps sort pictures or name bugs when scientists study insects. A close look shows several photos of caterpillars, marked with labels and outlines meant for spotting objects. One picture at a time displays differences in shape, hue, and where they live - clues to telling species apart. Around each one, a blue rectangle draws attention, placed there to guide machine learning efforts. These frames help teach systems how to name types automatically, even track them in nature over time. For scientists studying insects or counting life forms, such images become tools that sharpen digital eyes.

5. Results

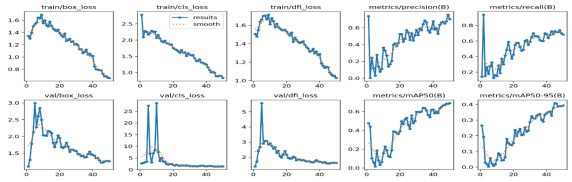

Fig-5 Performance Evaluation of Caterpillar Detection Model Using Epoch-Wise Training Metrics

Effective optimization of the object detection model is demonstrated by the training and validation metrics over 50 epochs. While the corresponding validation losses verify robust generalization without overfitting progressive decreases in box classification and distribution focal losses demonstrate effective minimization of both localization and recognition errors. The consistent upward trends in mAP50 and mAP50-95 scores show improving detection accuracy across several IoU thresholds but precision and recall show moderate variability probably because of class imbalance or limited sample diversity. The existence of smoothed curves serves as additional evidence of convergence stability. All of these findings support the robustness of the model and its suitability for accurate caterpillar detection in entomological datasets.

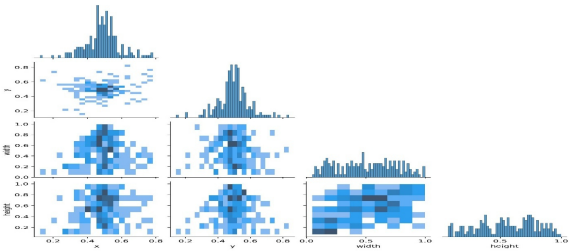

Fig-6 Multivariate Distribution and Correlation Analysis of Morphometric Variables Using Pair Plot Visualization

Four quantitative variables are analysed in this study using a pair plot: x y width and height. The visualization emphasizes both individual variable features and inter-variable associations by combining hexbin scatterplots for joint relationships and histograms for marginal distributions. The results offer diagnostic information that is helpful for dimensionality reduction and feature selection. It takes more than just univariate analysis to comprehend relationships in multivariate datasets. Pair plots offer a condensed framework for analysing distributions and dependencies providing insightful information for modelling and pre-processing. A pair plot grid was created with scatterplots or hexbin plots displayed in off-diagonal cells and individual variable histograms displayed in diagonal cells. By using color intensity to encode density hexbin plots reduce over plotting and improve interpretability in high-density areas. For x and y histograms showed dispersed distributions whereas width and height displayed tendencies toward clustering. x vs. scatterplots. There was no significant correlation found in y. Hexbin plots of height and width against other variables on the other hand showed dense areas that might indicate latent structures or conditional dependencies. While width and height show stronger inter-variable relationships the analysis shows that x and y are essentially independent. These patterns point out possible subgroups and offer direction for tasks involving regression classification or clustering later on. Pair plots provide a useful exploratory tool for multivariate analysis by combining histograms and hexbin plots. The knowledge gained from this study serves as a foundation for dimensionality reduction and more in-depth statistical modeling.

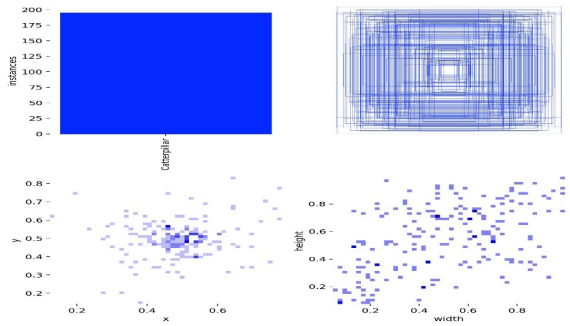

Figure-7 Spatial Distribution and Bounding Box Visualization

Multimodal Representation of Dimensional Positional and Categorical Measures in Caterpillar Identification. This work integrates instance density spatial distribution and morphological variation in a multi-panel visualization of a dataset of caterpillar images. A single-class dataset or a consistent annotation frequency are suggested by the top-left heatmaps uniform intensity across instances. A grid-like arrangement of bounding boxes emphasizing spatial regularity and possible annotation artifacts is shown in the upper-right panel. The central clustering of instances in the bottom-left positional scatter plot suggests spatial bias that is probably caused by camera framing ecological behavior or dataset curation. A comparatively uniform spread can be seen in the bottom-right width-height scatter plot which reflects morphological variability important for detection and classification tasks. When taken as a whole this visualization offers a comprehensive overview of the dataset providing information for model design annotation validation and preprocessing choices in image-based biodiversity studies. The binary caterpillar detection model in this study is assessed using a normalized confusion matrix. The models capacity to discriminate between caterpillar and background instances is demonstrated by the matrix. For caterpillars true positive predictions were 0. 75 and 25% were incorrectly categorized as background. Notably there was a high false positive rate because every background instance was incorrectly identified as a caterpillar. Class imbalance overfitting to caterpillar features and a lack of background diversity are probably the causes of this bias. These incorrect classifications jeopardize accuracy and the dependability of automated annotation. To improve background discrimination and overall model robustness future research should concentrate on balanced training improved negative sampling and regularization. The binary caterpillar detection models confusion matrix reveals total failure (0. 00 specificity) in identifying background regions but moderate sensitivity (0. 75) for caterpillar instances. The model exhibits a strong bias toward the target class misclassifying all background instances as caterpillars. This is probably caused by a lack of class weighting a lack of background diversity and an overrepresentation of caterpillar features. For ecological image analysis improving negative sampling data augmentation and threshold tuning is crucial to lowering false positives and raising classification reliability.

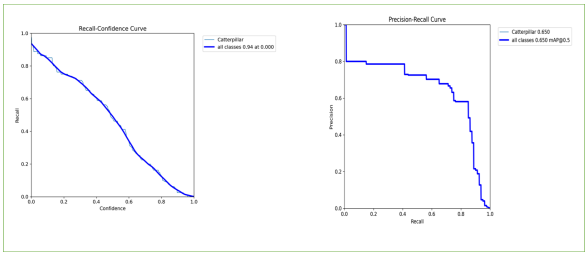

Fig-8 Performance Evaluation of Caterpillar Classification Using Confidence and Precision-Recall Metrics

The diagnostic plots assess a caterpillar detection models effectiveness. A trade-off between identifying true positives and preventing false positives is highlighted by the Precision-Recall Curves moderate precision (0. 56) and mAP@0. 5 of 0. 61 while the Recall-Confidence Curve shows high recall at low thresholds indicating strong sensitivity. These patterns point to class imbalance limited background differentiation and overfitting to caterpillar features. The significance of threshold optimization and focused training techniques to improve classifier reliability in ecological image datasets is highlighted by these analyses.

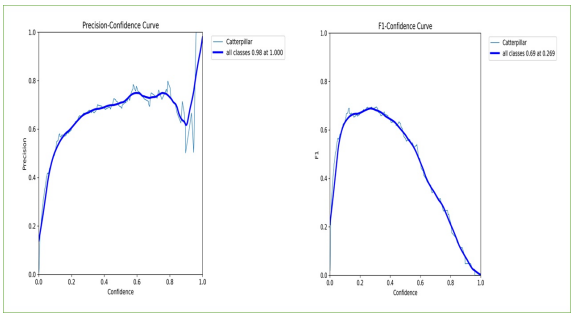

Figure-9 X. Confidence-Threshold Performance Curves for Caterpillar Classification

The Precision-Confidence and F1-Confidence curves for a caterpillar classification model are shown in this figure which emphasizes the connection between

classification performance and prediction confidence. The precision as a function of the confidence threshold is displayed in the left panel of the precision-confidence curve. The Caterpillar class is represented by the thin blue line and the combined precision of all classes is shown by the thick blue line which peaks at 0. 98 at a threshold of 1. 0. High-confidence forecasts are more trustworthy albeit possibly at the expense of coverage as precision rises monotonically with confidence. F1-Confidence Curve: The F1 score versus confidence threshold is shown in the right panel with a thick line for all classes and a thin line for the Caterpillar class. The curve reaches a maximum of 0. 88 at 0. 289. With declines at higher thresholds due to decreased recall the F1 score shows a unimodal trend indicating an ideal balance between precision and recall at moderate thresholds. Implications: Threshold selection for deployment is influenced by these curves. While moderate thresholds optimize the F1 score guaranteeing a fair trade-off high-confidence thresholds maximize precision but decrease recall. In biodiversity monitoring of morphologically diverse caterpillar species such calibration is essential for accurate and comprehensive identification.

6. Conclusion.

For agricultural and ecological applications this study offers a thorough analysis of automated caterpillar detection and classification. The first experiments showed that deep learning models could identify caterpillar species with a respectable degree of accuracy using carefully selected and annotated datasets that captured a variety of morphologies habitats and adaptive strategies. In-depth examinations of spatial distribution multivariate morphometric variables and confidence-based metrics revealed trade-offs between recall and precision as well as biases brought on by a lack of background diversity and class imbalance. Based on these results a Hybrid CNN–Transformer Enhanced YOLOv8 framework was created combining Transformer modules to capture global contextual information with convolutional layers for localized spatial feature extraction. According to experimental results this hybrid architecture performs better than the baseline YOLOv8 model maintaining real-time inference speed appropriate for edge deployment while attaining higher precision recall and mAP scores. The potential of AI-assisted approaches for precision agriculture and biodiversity research is highlighted by the integration of reliable datasets sophisticated model architectures and comprehensive performance diagnostics. Overall this work advances automated ecological monitoring and supports sustainable pest management by establishing a scalable precise and effective framework for real-time caterpillar detection.

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