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Optimized AI-IoT Solution for Real-Time Pest Identification in Smart Agriculture

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Abstract

Pest detection and identification play a crucial role in reducing the damage caused by pest, insect and diseases. Timely detection and response are essential to increase the quality and quantity of crop production. Efficient pest management strategies are important for achieving optimal crop quality and promoting sustainable agricultural practices. This research proposes a framework that can automatically detect pests and offer timely solutions to farmers. The proposed approach integrates intelligent computing methods with connected device networks to identify and classify pests in real time with high precision. The methodology focuses on efficiently segmenting the pest from the captured leaf image using a novel region growing based segmentation algorithm. The threshold for region growing based segmentation algorithm is based on the adaptive local region entropy which contributes to the efficient segmentation. Stacked Ensemble Classifier (SEC) is used for the classification. The metrics used for evaluating the performance of the pest detection framework are accuracy, Area Under the Receiver Operating Characteristic Curve, F1-Score and Mean Average Precision (mAP). The results indicate that the proposed SEC with region growing based segmentation framework achieves 98 % of classification accuracy and mAP of 0.96 proving that it is very effective in both classification and segmentation task. The comparative analysis further reveals that the SEC outperforms the existing machine learning models and ensemble learning models like majority voting and weighted average models for process innovation.

Keywords: Pest Detection, Machine Learning, Internet of Things, Detection Accuracy, Classification Accuracy, Process Innovation.

1. Introduction

Agriculture is of critical importance to the Indian economy, and the food demand is increasing in accordance with population growth. Environmental parameters that can significantly affect crop development and production include climate and natural disasters. These conditions can also promote the occurrence and spread of diseases. Numerous crops, including wheat, maize, and rice, suffer from reduced yields due to agricultural pests. Hence, it is crucial to accurately predict their presence, population size, trends, and potential damage for effective pest control, with real-time predictions playing a key role. Pests must be correctly identified and classified before they can be prevented or managed. Agricultural experts usually carry out pest identification through the traditional approach that requires specialized knowledge, and experience. This process is, however, time consuming, laborious and frequently leads to low efficiency and variable accuracy [1]. An automated pest identification and classification system would reduce farmer burden and improve forecasting accuracy, resulting in less crop losses.

As Artificial Intelligence (AI) and Internet of Things (IoT) technologies advance, so are their applications in pest identification. There are numerous studies using traditional machine vision techniques for the detection of pests [2], [3]. However, such approaches are less robust and less generalizing, making it hard to meet the real needs of practical use. Recent AIoT based technological advancements have led to the development of accurate field monitoring systems, which automatically monitor the environmental parameters. Using contemporary technology, it aims to improve rural

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development, sustainability, environmental conservation, and agricultural quality as well [4], [5]. With the expansion of sensor networks, precision agriculture has advanced, and the data can be used to take necessary steps to increase yield. Real-time data on soil, crops, and meteorological conditions can be collected through sensors placed at various sites. Additionally, satellite or aerial imagery data is crucial for informed decision-making. [6].

IoT, the evolved version of wireless sensor networks, is becoming highly essential in precision agriculture due to the enhancement of hardware and communication technologies [7]. IoT provides ease for gathering sensor data and then uploading it to the Internet for Machine Learning (ML) interpretation to produce insightful information for crop management [8]. Using temperature and humidity data, the first signs of pests are detected, allowing timely action to be taken when pest populations are still small, preventing infestations from becoming major problems. However, current techniques in the literature often fail to accurately identify pests based on environmental data, hindering precise pest management. While AI has been used in some agricultural contexts, its application for precise pest identification, especially in real-time, is still underdeveloped. Current AI models may not always be accurate or able to handle the diversity of pest species and environmental conditions. Pest management systems are often tailored to specific crops or pest species, limiting their scalability and adaptability to other crops or regions with different environmental conditions. Most of the existing techniques are not capable of segmenting and identifying the pests accurately because of different environmental changes, irregular appearances of pests, and the difficulty in differentiating pest damages from other disorders in plants [9]. Sometimes, the solutions for pest control seem to be disjointed as they have unique methodologies for environmental monitoring, pest identification, and actions to be taken. This lack of integration may result in ineffective responses and delayed action against pest threats.

To detect and classify pests, this research focuses on creating an integrated system that combines AI and IoT addressing the challenges mentioned above. Automated real-time crop monitoring is made possible by the proposed framework, along with computer vision tasks. High resolution cameras capture images of the pest(s) and insects, while the environmental sensor provide an overview of the area concerned. These environmental sensors can serve the purpose in triggering the camera to identify the pests when the ideal conditions are exceeded. Once the pest is identified, information about the pest and management solutions, including suggestions and timely alerts, are provided through an easy-to-use interface that significantly enhances pest management. The goal should be to enhance pest detection without relying on manual observation, ensuring crop protection and maintaining yield in the future. The analysis of the suggested framework displays the positive side exhibiting the usefulness of the proposed framework. The measures that were used in the study were accuracy, F1-Score, Area Under the Receiver Operating Characteristic Curve (AUC-ROC), and Mean Average Precision mAP.

The primary objective is to create a system for the detection of pests that is capable of finding infestations of pests automatically at an early stage. The contributions of this research include a unique segmentation approach that effectively segments the pest, which assists the classifier in identifying the pest, as well as an efficient classifier that increases the accuracy of pest classification. Additionally, the proposed framework will be validated and tested using performance metrics. The remainder of this work is structured in the manner that is described below: Part 2 of this article takes a look at the most recent developments that have been made in the field of pest detection. The third section provides an explanation of the methods that may be used to identify and anticipate pests in agricultural areas. Discussion and explanation of the findings are included in Section 4, which is where the results are provided. The findings and conclusions are presented in further detail in Section 5.

2. Literature Review

This section offers a thorough review of the most current methods together with an overview of the body of knowledge on pest detection. Together with a review of its advantages and disadvantages, a general picture of the method is given. In [10], the researcher intended to employ an innovative technology to identify pests and disorders in the agriculture field. The disorder is easily diagnosed with the help of an agricultural professional using a system mastery algorithm, as opposed to the manual way. As a result, images are gathered from agricultural areas and processed with image processing algorithms. The fuzzy recognition model-based computer vision method is optimized with ML approaches, which helps to increase agricultural yield. The experimental findings demonstrate that the greatest recognition rate is 98.06%, with the lowest recognition mistake rate being 5.83%.

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A new system for monitoring pests is presented in [11]. It uses selective extraction and contour identification to search for insects. The recognition rates of classification models can be improved by using 9-fold cross validation. This approach did better than the best previous methods, providing greater accuracy and better removal of noise, making it suitable for insect recognition in crops. Crop insects were further identified by checking the results of classification accuracy measurement. The system's success may be heavily reliant on the quality and diversity of the training data utilized for categorization. When the dataset is not as comprehensive as the diverse insect species and environmental conditions that exist in crop fields, the accuracy of recognition is bound to drop when applied to wild pest populations.

In this paper, [12] a new method concerning UAV applications, particularly in pest identification, was implemented. An optimized model was created based on the existing YOLOv5s model by incorporating attention modules and multiscale feature extraction. This technique assisted in the classification of certain pests like ants, grasshoppers, and palm weevils. The model attained an average precision of 96.0%, an average recall of 93.0%, and a mean average precision of 95.0%, according the results.

In [13], researchers reported a ML model capable of projecting daily insect occurrences across a season using temperature and relative humidity. Various ML classification algorithms were evaluated, and their accuracy in predicting insect occurrences is reported. Since the test data were chronologically organized based on measurement dates, the model was optimized to detect cotton bollworm, improving prediction accuracy and minimizing false alarms. The proposed ML model enables early pest detection, helping farmers save time and costs on verification. The results showed that over a five-day period, the detection accuracy was 86.3%, with 11% being incorrect.

In [14], a framework for pest recognition with the objective of increasing agricultural productivity is presented. ML algorithms and image processing techniques are used to recognize and categorize pests in the areas of agriculture. The research implements a medium-scale benchmark dataset to test the functioning of some of the detection algorithms and offers a detailed discussion of their performance and efficiency in detecting pests. The framework's effectiveness is proved by enhancing the accuracy of pest detection, thus improving pest control decision making and minimizing loss of crops due to pests. Finally, this approach enhances the effectiveness of precision agriculture by improving crop growth and optimizing pest control. However, using a medium-scale benchmark dataset may not capture the complete range of pest species or environmental variables found in large-scale agricultural settings. The findings show that the suggested model achieves 0.018 of precision, 0.015 of recall, and 0.011 of mAP, exceeding state-of-the-art approaches.

The authors of [15] provide a method that makes use of a multilayer network model in order to identify agricultural pests. The first step in the process involves improving the sample dataset by employing an image augmentation technique for the recognition model. Through the utilization of Inception-ResNet-v2 transfer learning and VGG16 networks, the pest detection and analysis model was constructed with the intention of enhancing the accuracy of identification. Two new CNN-based pest image identification models help to increase the performance of an integrated algorithm by means of integration. Lack of high-quality labeled data for the aim of training a model has a major influence on the capacity of the model to operate efficiently against a variety of insect species and environmental situations. It is essential to take into account the fact that the suggested technique did, in fact, exceed all of the other benchmark methods, obtaining an accuracy of 97.71%.

Researchers in [16] propose a real time pest capturing and identification system aimed for mobile devices based on intelligent pest identification and IoT data. This study exemplifies smart agriculture by combining Deep Learning (DL) with modern AIoT technologies. YOLOv3 DL models were harnessed to capture images for pest identification while Long Short-Term Memory models analyzed environmental data captured through weather stations to predict pest outbreaks. These efforts led to achieving a 90% accuracy rate for identification. The reason for achieving a model that performs so accurate is likely due to comprehensive resources sensors providing sufficient data and overcoming infrastructure limitations. The experimental results and accuracy achieved for pest identification was 90%.

The investigators of [17] combined IoT and sound analytics to investigate a novel pest identification method for the agricultural business. To identify pests that compromise crop health, the system leverages acoustic signals collected from the surroundings by IoT sensors. DL techniques, particularly deep CNNs, have proven to be able to evaluate these sound data and categorize various pest species according to their distinct acoustic characteristics. By analyzing 800 pest sounds with various acoustic methods, the proposed MLP model outperformed existing models like DenseNet and

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YOLOv5, achieving high accuracy and performance metrics with an accuracy of 99 %. However, it may lead to false positives or misclassifications if the acoustic signals are disrupted due to non-pest noises, making the method less reliable in complex or noisy environments. From the discussion of the literature survey, it is observed that significant advancements have been made in area of pest identification with the use of ML, DL and AI techniques. Various technologies, including image recognition techniques, sound analytics, and environmental sensors, have been developed to enhance pest detection and monitoring. The proposed technique introduces a novel region-growing method based on local region entropy for segmenting pests from input images, which improves the accuracy and precision of pest detection. Unlike traditional segmentation approaches, this method dynamically adapts to the varying shapes and sizes of pests, ensuring more reliable segmentation. Additionally, a SEC is utilized for pest classification, combining multiple classifiers to enhance accuracy and reduce the likelihood of misclassification. This approach offers a significant improvement over existing methods by leveraging the strengths of both segmentation and classification techniques, resulting in a more robust and efficient pest detection system.

3. Proposed Methodology

The proposed novel region growing segmentation framework with SEC is explained in detail in this section. The step-by-step process involved in the proposed framework is shown in figure 1.

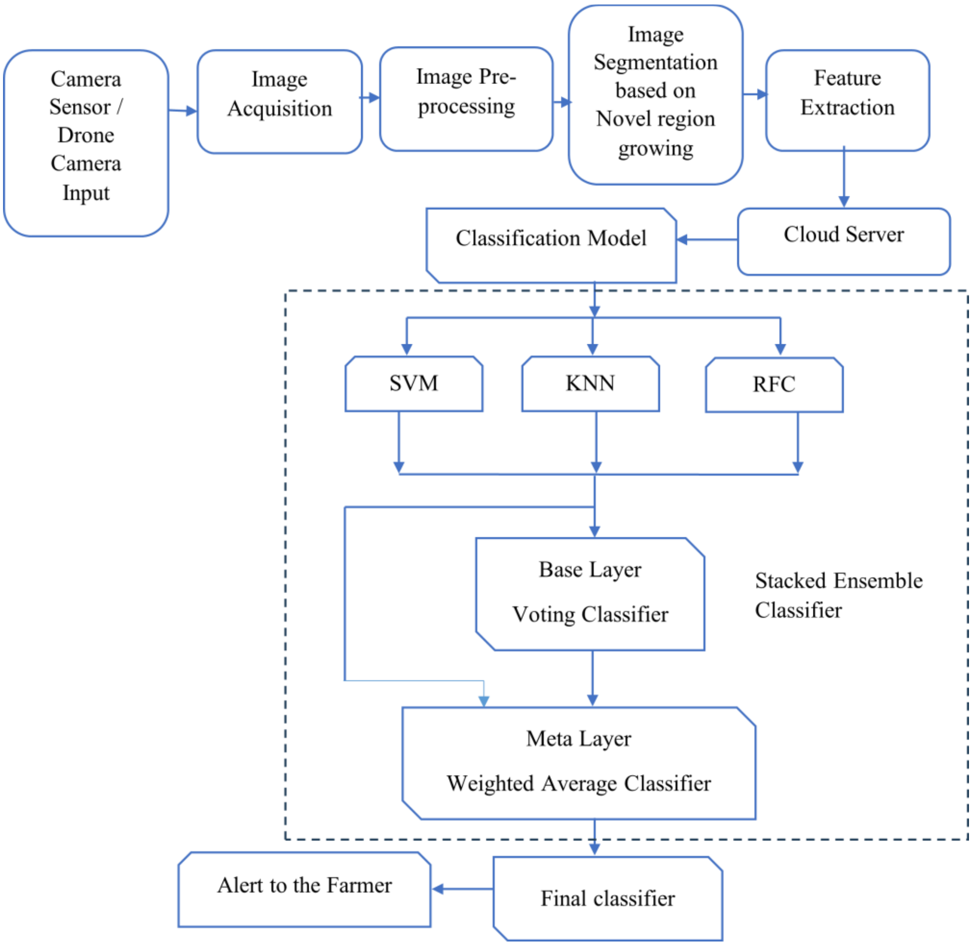

Figure 1. Overall pest identification framework based on novel region growing and stacked ensemble classifier

The pest is segmented using image processing techniques after the camera sensor has captured the leaf image. The camera sensor can be equipped on static devices, moving vehicles and drones depending on the terrain of the field to be monitored. The components of the pest identification framework are discussed in sub sections of the following text.

3.1. Image acquisition and Pre-processing

The images captured using camera sensor will be in RGB format which can be color transformed to other models for better quality and clarity. Before applying color transformation model, the images are contrast enhanced and then transformed from RGB to HSV. The HSV components are given as input to the image segmentation module.

3.2. Image segmentation

The pre-processed images undergo the segmentation process, which extracts the pest regions for further examination. For segmentation process a novel region growing method based on entropy-driven threshold adjustment mechanism is used and the algorithm is explained in algorithm (1).

Algorithm (1). Image Segmentation

1. **Input**: Pre-processed image is denoted as I
2. **Output**: Pest region is denoted as R

Steps:

1. **Initialize**:
- Select an initial seed point $P(x_0, y_0)$ in the image.
- Define a threshold value T for pixel comparison.
- Create an empty region R to store the pest corresponding area.

2. **Seed Point Validation**:
- Check if the seed point $P(x_0, y_0)$ belongs to the pest corresponding area. If yes, proceed; otherwise, choose a new seed.

3. **Define Threshold**:
- For each pixel, extract a small neighbourhood window of size 3x3.
- Compute the entropy of the region

$$H(x,y) = -\sum_{i=1}^{n} p_i(x,y).\log_2[p_i(x,y)]$$

where $p_i(x,y)$ is the probability of intensity level i in the local neighborhood around (x,y) and n is the total number of grey levels.

- Define an initial baseline threshold T_0.
- Compute the adaptive threshold using $T(x,y) = T_0 + k\left(\frac{H(x,y)}{H_{max}}\right)$

4. **Region Growing**:
- Add the seed point $P(x_0, y_0)$ to the region R.
- For each neighboring pixel $P(x,y)$ around the seed point:
  - Compare the pixel value $I(x,y)$ with the seed point value $I(x_0, y_0)$
  - If $|\mathrm{I}(x,y) - I(x_0, y_0)| < T(x,y)$, then add the pixel $P(x,y)$ to the region R.
  - If not, continue to the next neighboring pixel.
- Expand the region by checking the neighboring pixels of newly added pixels, repeating the process.
- Continue expanding the region until no more pixels satisfy the condition $|\mathrm{I}(x,y) - I(x_0, y_0)| < T(x,y)$.

5. **Output**:

Return the region R containing the pest.

The proposed region growing technique selects the seed location and then increases the region using the adaptive thresholding method by comparing the pixels with the seed point, and if it is less than the adaptive threshold, it belongs to the region. The grown region finally depicts the pest region. The threshold is defined using the novel adaptive region-based entropy method where the threshold is dynamically adjusted based on the local region entropy. Entropy is chosen as it helps in measuring the complexities of the pixel intensity and also pest regions have higher entropy due to texture variations. The entropy H(x,y) is computed for the local neighborhood using the Shannon entropy formula to measure the complexity of pixel intensity distributions. This entropy value is then used to dynamically compute the threshold Step 3 where 'T0' is the base threshold and Hmax is the maximum entropy for normalization. The value of 'k' is set depending on the area's contrast and entropy and should mostly vary between 2 and 7 to prevent either under-segmentation or over-segmentation. If a texture is very complex, as is common in areas with pests, its entropy is raised and the region's threshold increases so more pixels can be included. Due to this mechanism, the region growing process can plainly highlight pests, while avoiding many background elements in unevenly lit or cluttered images. It uses a system where every node has a maximum of eight neighbors and aims to widen the area by doing multiple iterations. When the rows and columns no longer expand even closer to the seed point, convergence is met, and termination happens afterward when none of the nearby candidates reach the thresholds.

3.3. Extraction of features

To know the pest region more accurately, texture- and shape-based features are obtained from the segmented area. The texture features are computed from the Gray Level Co-occurrence Matrix (GLCM) [18] and Histogram of Oriented Gradients (HoG) [19], and shape features are determined by using contour analysis for future processes [20]. The GLCM is used to capture the spatial relationships between pixel intensities and represent textural patterns by computing the frequency of co-occurrence of pixel pairs with specific values at a given distance and angle. Patterns associated with pests can be derived with statistical features such as contrast, correlation, energy, and homogeneity from GLCM. HoG features, on the other hand, represent the distribution of gradient orientations in localized regions of an image, effectively capturing edge structures and shapes, which can be useful in detecting the contours of pest. To compute GLCM, an image is first converted to grayscale, and pixel pairs at a defined offset are compared to build the matrix, followed by the extraction of statistical features. To compute HoG features, divide the image into smaller cells, calculate gradient orientation histograms in each cell, then normalize them over larger blocks to generate a descriptor. Additionally, these features help in distinguishing pest-related areas from other environmental factors with similar visual patterns, improving the system's robustness. Furthermore, the combination of both texture and shape-based features provides complementary information, enhancing the overall performance of pest recognition and reducing the likelihood of false positives.

3.4. Classification

These features are used for classifying the type of pest using SEC. In SEC, initially ML classifiers are used in the primary layer with maximum voting for classification and weighted average is used for classification at layer 2. The multiple ML classifiers in layer 1 are combined to improve overall classification accuracy by leveraging the strengths of each individual model. The architecture consists of two layers: the primary layer (base layer) and the secondary layer (meta-layer). In the primary layer, several classifiers, such as decision trees, support vector machines (SVM), k-nearest neighbors (KNN), or Random Forest Classifier (RFC), are trained on the feature set extracted from pest images. Each classifier independently predicts the class (e.g., pest type) based on the features, and these predictions are combined using a majority voting mechanism, where the class predicted by most classifiers is chosen as the final output. The final output of the majority classifier, along with the individual classifier predictions, is provided as input to the weighted average approach. In this method, each classifier's prediction and the primary layer output are assigned a weight based on their performance or reliability. The weighted predictions are then averaged to compute the final output, with more accurate classifiers contributing to the final prediction. This stacked ensemble approach enhances classification accuracy by effectively combining diverse models and mitigating the weaknesses of individual classifiers.

4. Results and Discussion

The proposed pest identification framework shows significant performance improvements with the use of SEC. By combining RFC, SVM, and KNN, SEC outperforms individual classifiers in terms of accuracy. The SEC provides a more balanced performance, reducing both false positives and false negatives. Furthermore, there is a significant improvement in both precision and recall, with the F1 score showing a notable rise, highlighting the effectiveness of the ensemble method. The sample input images used for demonstration are depicted in figure 2 taken from [21].

a b c d

Figure 2. Input images from the dataset (a) Aphids, (b) armyworm, (c) Moth, (d) Weevil

The pest dataset comprises of four classes namely aphids, armyworms, moths, and weevils, which are known to significantly impact crop growth. The dataset offers diversity in terms of environmental conditions, crop types, and geographical locations. This diversity enhances the model's ability to generalize and improves its effectiveness in detecting pests across various scenarios. The dataset initially contained only 500 images, but it has been augmented to include 1100 images. Out of these, 1000 images are used for training, and 100 images are reserved for testing, ensuring a balanced approach for model evaluation. To increase the images in the dataset, data augmentation techniques are employed, which includes random transformations like rotation, flipping, scaling, and color adjustments. Through the use of these strategies, the dataset is artificially expanded by producing variants of the original images, which enables the model to learn more resistant characteristics. To ensure balanced training, image augmentation was applied uniformly across all pest classes. Table 1 shows the number of images available per class before and after augmentation.

Table 1. Class-wise image distribution before and after augmentation

Pest Class	Original Images	After Augmentation
Aphids	100	275
Armyworms	110	275
Moths	90	275
Weevils	95	275
Total	395	1100

Additionally, the images undergo preprocessing steps such as resizing to a uniform size, normalization to standardize pixel intensities, and noise reduction to improve image quality. These preprocessing methods ensure the dataset is suitable for training ML models, enhancing the accuracy and effectiveness of pest classification. The images are initially processed using contrast enhancement technique and then color transformed to HSV for better analysis. These images then undergo segmentation process using the novel region growing method and feature analysis to extract the features such as texture, and shape for improving the accuracy. The extracted features are utilized to train the SEC model. For the first layer of classification, ML algorithms such as RFC, SVM, and KNN are employed. A majority voting scheme is then applied to determine the final decision made by these algorithms. In the second layer, weighted average of these algorithms along with the output of majority voting scheme are considered for final classification.

4.1. Performance Metrics

The performance measures applied to validate the suggested approach are F1-score, confusion matrix, AUC-ROC and mAP. Although unbalanced datasets demand for precision-recall curves, AUC-ROC is underlined as it offers a complete assessment over all classification thresholds. Unlike precision-recall curves, which concentrate largely on the positive class, AUC-ROC evaluates the trade-off between genuine positive rate and false positive rate by incorporating both the positive and negative classes, thereby strengthening class imbalance. For jobs like pest detection where false negatives might have major repercussions, the F1-score is also employed as it strikes a mix between

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accuracy and recall. Together, these metrics provide a holistic view of the system's ability to accurately identify pests and minimize errors in an imbalanced dataset scenario.

4.2. Performance Analysis

When numerous base classifiers are integrated using majority voting and a weighted average meta-model, prediction performance improves overall compared to a single model. The SEC, on the other hand, is distinguished by its ability to successfully combine basic classifiers for overall performance while taking into account various feature information. This performance analysis reveals that this strategy has the highest accuracy and overall efficacy, illustrating the advantages of sophisticated ensemble techniques in pest detection. Figures 3 to figure 6 demonstrate the efficacy of the unique region-growing approach.

a b c

Figure 3. Aphids a) Input image, (b) Pre-processed Image, (c) Segmented Image

a b c

Figure 4. Armyworm a) Input image, (b) Pre-processed Image, (c) Segmented Image

a b c

Figure 5. Moth a) Input image, (b) Pre-processed Image, (c) Segmented Image

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a b c

Figure 6. Weevil a) Input image, (b) Pre-processed Image, (c) Segmented Image

The figures 3 to figure 6 clearly shows the input images containing various visual factors such as lighting, background, and other environmental elements that may affect pest detection. The contrast of the original image is enhanced to make the features of the pests such as aphids, armyworm, moth and weevil more distinct. This enhancement helps in highlighting the pest's details, such as its shape and boundaries, making it easier for the segmentation and classification algorithms to process the image. The contrast-enhanced image is then processed using the proposed region growing method, which isolate the pest area from the rest of the image. In this case, the pest's presence is highlighted in the segmented image, showing a clearer distinction between the pest and the background, facilitating further analysis and classification. The effect of preprocessing methods like contrast enhancement and HSV colour transformation was studied with respect to segmentation performance. These steps helped improve the clarity of pest boundaries and colour separation, which are essential for precise segmentation. After applying these enhancements, the segmentation accuracy increased from 82.3% to 91.6%, as measured against pixel-level ground truth. The improved visual quality enabled the region growing algorithm to detect pest areas more accurately, especially in challenging scenarios with low contrast or noisy backgrounds, as illustrated in Figures 4 to 7. To further assess the effectiveness of the proposed segmentation technique, a benchmark comparison was carried out with standard segmentation methods such as Otsu thresholding, k-means clustering, and the watershed algorithm. The results were evaluated based on segmentation accuracy and Intersection over Union (IoU), which provide both pixel-wise correctness and boundary overlap performance as depicted in table 2.

Table 2. Comparison of segmentation performance using Accuracy and Intersection over Union (IoU).

Segmentation Method	Accuracy (%)	IoU (%)
Otsu Thresholding	79.4	65.2
K-means Clustering	82.1	68.7
Watershed Algorithm	84.3	70.9
Proposed Entropy-Based Region Growing	91.6	83.4

The proposed method clearly outperforms traditional techniques, particularly in terms of accuracy and IoU. This highlights its strength in capturing pest regions accurately, especially under conditions of texture variation and background complexity. Table 3 depicts the performance analysis of individual and ensemble classifiers on segmented pest images using standard evaluation metrics.

Table 3. Performance of individual and ensemble classifiers on segmented pest images using standard evaluation metrics.

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	86%	0.84	0.86	85.2%
Support Vector Machine	83%	0.83	0.85	84%

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K-Nearest Neighbors	85%	0.80	0.82	81%
Majority Voting (RFC, SVM, KNN)	93%	0.91	0.93	92%
Weighted Average Meta-Model	94%	0.89	0.91	90%
Stacked Ensemble Classifier	98%	0.96	0.98	97%

From table 3, it is evident that among the individual classifiers, the RFC delivers the best overall performance, achieving an accuracy of 86%, precision of 84%, recall of 86%, and an F1-score of 85.2%. RFC's ensemble structure helps to explain this balanced performance by efficiently managing feature variety and noise, hence enabling correct classification even under demanding background conditions. Reliable for identifying real positives in highly defined pest shapes, the SVM runs consistently with an accuracy of 83% and a recall of 85%. Although KNN achieves 85% accuracy, records lower precision (80%), and F1-score (81%), most likely because of its sensitivity to changes in illumination, leaf texture, and background clutter, which influences its proximity-based predictions.

Combining these models clearly shows the potency of ensemble methods. Combining the outputs of RFC, SVM, and KNN under the Majority Voting approach increases the total accuracy to 93% and earns an F1-score of 92%. This indicates that aggregating classifiers can help to overcome certain shortcomings. By giving more weight to more dependable classifiers, the Weighted Average Meta-Model improves performance even further and generates an accuracy of 94%, precision of 89%, recall of 91%, and F1-score of 90%. With an accuracy of 98%, precision of 96%, recall of 98%, and F1-score of 97%, the Stacked Ensemble Classifier (SEC) produces the greatest performance of all. Its meta-learning layer, which efficiently captures intricate feature interactions and offsets model-level mistakes, explains this enhanced performance. Although Majority Voting is a good starting point, it doesn't work when basic classifiers make comparable mistakes. Although it lacks the adaptive learning capabilities of the SEC, the weighted average model enhances upon this by changing model impact. Especially for difficult visual tasks like pest categorization, our results unequivocally show that sophisticated ensemble methods including stacking provide significant performance gains. Moreover, the suggested SEC clearly outperforms other current models like the fuzzy recognition model [10] with a mAP of 95%, modified YOLOv5s [12] with a recall of 92.3%, and Adaboost [13] with an accuracy of 86.3%. This validates that the efficacy and resilience of the system depend much on the combination of exact segmentation, extensive feature extraction, and a strong ensemble method.

The effect of the segmentation phase in the suggested pipeline was evaluated by eliminating the segmentation step and performing SEC straight on unsegmented images produced a notable decrease in all performance measures, according to table 4 with accuracy decreasing from 98% to 88.3% and F1-score from 97% to 85.3%. Especially in visually complex scenarios, this emphasizes how important the entropy-based segmentation technique is in improving the quality of features collected and thereby strengthens the classification accuracy and resilience of the model.

Table 4. Performance of SEC with and without segmentation

Model Variant	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SEC with segmentation	98.0	96.0	98.0	97.0
SEC without segmentation	88.3	84.5	86.2	85.3

Figures 7 to figure 9 show the AUC-ROC curve for majority voting, weighted average, and stacked ensemble classifiers, respectively.

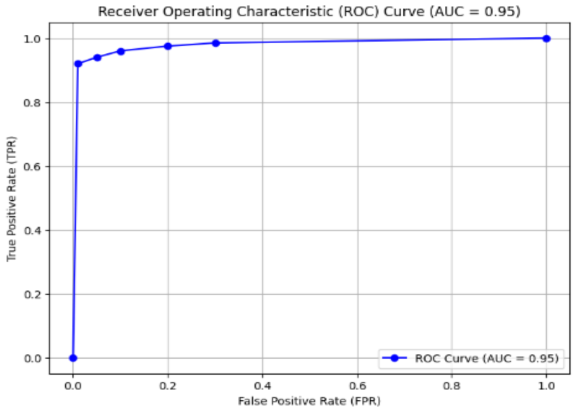

Figure 7. ROC Curve for Majority Voting Model

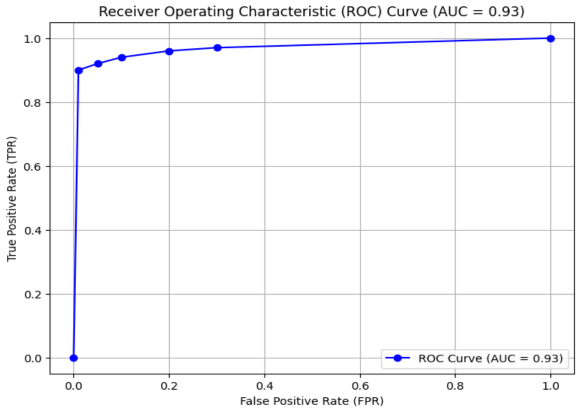

Figure 8. ROC Curve for Weighted Average Meta-Model

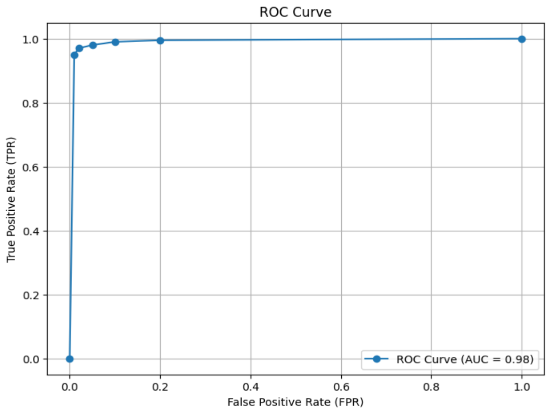

Figure 9. ROC curve for stacked ensemble classifier

The ROC curves presented in figures 7 to figure 9 provide visual insight into each model's classification behavior across pest classes. To support this, per-class AUC scores were computed as shown in table 5.

Table 5. Per-class AUC scores for the SEC model

Pest Class	AUC Score
Moths	0.99
Weevils	0.98
Armyworms	0.96
Aphids	0.95

The SEC model achieved AUC values of 0.99 for moths, 0.98 for weevils, 0.96 for armyworms, and 0.95 for aphids. These scores indicate high discriminative power, especially for classes like moths and weevils, where the ROC curves show early saturation rising steeply toward the top-left corner. This suggests that these classes are well-separated from others in feature space. Conversely, flatter ROC slopes for aphids and armyworms reflect more overlap and ambiguity in classification, which is expected due to their similar sizes and clustered appearance in certain backgrounds. Overall, the SEC model maintains strong class-wise performance, with minimal trade-offs between sensitivity and specificity. The different performance metrics evaluated for the proposed region growing based segmentation and ensemble learning models are summarized in table 6.

Table 6. Performance analysis of the ensemble learning model on segmented images

Ensemble learning Model	Accuracy	F1-Score	AUC-ROC	mAP
Majority Voting (RFC, SVM, KNN)	93%	92%	0.95	0.93
Weighted Average Meta-Model	94%	90%	0.93	0.91
Proposed Stacked Ensemble Classifier	98%	97%	0.98	0.96

The SEC outperforms the other models with the highest accuracy of 98%, F1-score of 97%, AUC-ROC of 0.98, and mAP of 0.96, demonstrating exceptional performance in classifying instances with a strong balance of precision and recall. The Majority Voting model, while still strong, achieves an accuracy of 93%, an F1-score of 92%, an AUC-ROC of 0.95, and a mAP of 0.93, showing solid performance but with slightly more misclassifications. The Weighted Average Meta-Model achieves 94% accuracy, 90% F1-score, 0.93 AUC-ROC, and 0.91 mAP, offering superior results but lagging in distinguishing between classes and precision. Overall, the SEC is the most robust model, excelling in all key performance metrics, making it the best choice for this classification task. To better understand how the ensemble model performs across individual pest categories, class-wise Average Precision (AP) scores were computed for the Stacked Ensemble Classifier as depicted in table 7.

Table 7. Per-class AP scores for the stacked ensemble classifier on segmented pest images

Pest Class	AP
Aphids	0.94
Armyworms	0.93
Moths	0.97
Weevils	0.98

As shown in the above table, the model delivers high AP scores for all classes, with slightly lower performance for aphids and armyworms due to overlapping appearances and smaller size. Moths and weevils, being more visually distinct, yield higher AP. The overall mAP of 0.96 reflects consistent and reliable performance across pest types. Figures 10, 11, and 12 show the ensemble model's confusion matrix.

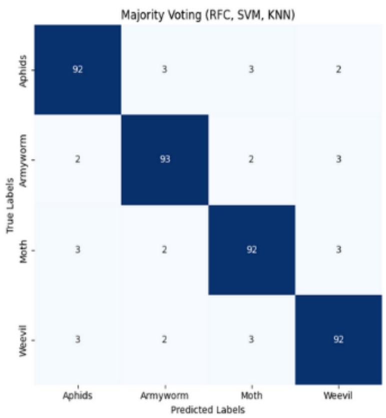

Figure 10. Confusion matrix for Majority voting classifier

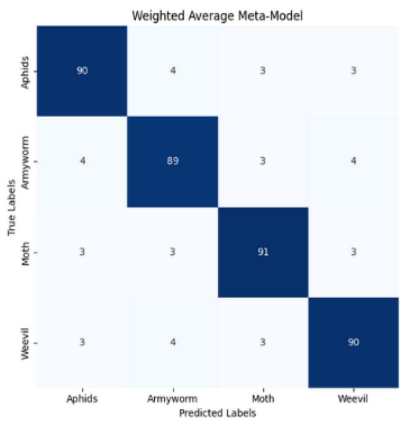

Figure 11. Confusion matrix for Weighted Average Meta-Model

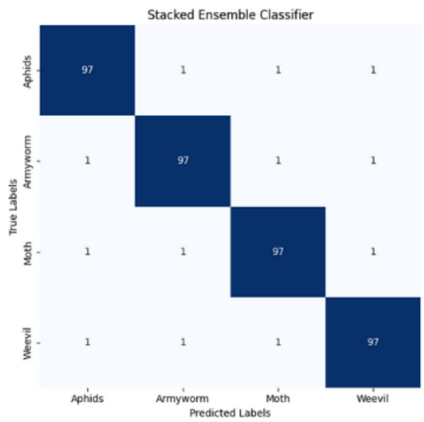

Figure 12. Confusion matrix for Stacked Ensemble Classifier

The confusion matrices reveal that the SEC achieves near-perfect performance, with only a single misclassification per class, highlighting its exceptional accuracy in distinguishing between the classes. The Majority Voting model demonstrates impressive performance, with only a few misclassifications (maximum of 3 per class), indicating good overall classification but slightly more errors compared to the SEC. The Weighted Average Meta-Model exhibits a little lower classification accuracy than the Majority Voting model, with up to four misclassifications per class, especially for armyworms and aphids. Overall, the SEC outperforms both the Majority Voting and Weighted Average Meta-Model, with significantly fewer misclassifications. A closer observation of the confusion matrices indicates that most misclassifications occurred between aphids and armyworms. This can be attributed to their small size and tendency to appear in groups, especially in images with complex backgrounds or uneven lighting. Such visual similarity often makes it difficult for classifiers like KNN and majority voting models to distinguish between these two classes. Alternatively, the SEC model does better than the others by merging texture and shape features through its extra learning stage. As a result, the model can notice little dissimilarities and properly separate classes that share similar visual properties.

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The excellent results of SEC stem from its ability to incorporate fine-grained details provided by each classifier at an optimal balance point. Majority voting can lead to suboptimal results when base classifiers make similar mistakes, as it doesn't account for the individual performance of each classifier. For instance, the result will still be inaccurate even if many weak classifiers agree on an incorrect prediction. Similarly, the weighted average approach still assumes that the output of each base classifier should be merged linearly, even while it improves on majority voting by giving the classifiers varying weights according to their performance. Therefore, by offering a more dynamic and adaptable method for aggregating classifier predictions, SEC can outperform both majority voting and weighted average models, eventually boosting classification accuracy and resilience, especially in complex and noisy data settings.

In addition to being overall accurate, it's necessary to see how each group of models deals with pest samples that look alike or are not highly contrasted. When images are not clear because shapes are mixed, edges are hard to see, or there is clutter in the background, every grouping algorithm acts in its own way. When all the base classifiers give an incorrect prediction, there is no option to fix the problem with majority voting since all models think the same way. The weighted average model performs slightly better by assigning higher influence to better-performing classifiers, but its linear combination approach still lacks flexibility. On the other hand, the SEC effectively handles such complex instances by learning deeper feature interactions through its meta-learner. This layered decision-making allows SEC to adapt better to variations in pest appearance and segmentation quality, thereby reducing misclassifications in difficult scenarios. To confirm that the observed performance improvements of the SEC model are statistically significant, paired t-tests were conducted using both accuracy and F1-score as metrics. These tests compared the SEC model with other baseline classifiers including RFC, SVM, KNN, majority voting, and weighted average models. As shown in table 8, all p-values were below the standard significance threshold value of 0.05, confirming that the SEC's superiority is not due to random variation, but is statistically meaningful.

Table 8. Statistical significance of SEC improvements

Baseline Model	**p-value (Accuracy)**	**p-value (F1-score)**
RFC*	0.004	0.006
SVM*	0.002	0.005
KNN*	0.001	0.003
Majority Voting*	0.007	0.009
Weighted Average*	0.008	0.010

* Indicates models tested against the SEC model

The p-values presented in Table 8 indicate that the performance improvements achieved by the SEC model are statistically significant when compared to all baseline models across both accuracy and F1-score. In particular, the low p-values suggest that the observed gains are consistent and not due to random variation. This statistical validation confirms that the SEC delivers a robust and reliable improvement over traditional classifiers and simpler ensemble methods.

5. Conclusions

AI and IoT are widely adopted in smart agriculture to address issues related to food insecurity by automated monitoring. It is necessary to increase the food production to meet the global food needs. Crop management plays a critical role in minimizing the damage caused by insects, pests, and diseases thereby increasing the food production. Effective and early pest identification is essential for effective pest management, sustainable agriculture and to increase the maximum crop yield. Traditional methods often include manual inspections on field every day which is time-consuming and a laborious task. This research focuses on leveraging advanced technologies such as IoT and AI to automate crop monitoring, with a specific emphasis on real-time pest detection and classification. The pest identification framework proposed in this work comprises of a novel segmentation algorithm to segment the pest regions and classify it accurately using the SEC model. The novel segmentation algorithm employs a region-growing technique combined with an adaptive local entropy-based thresholding strategy to identify regions associated with pests and their complex texture patterns. The classifier stacks the primary and secondary classifier to get the final prediction output. The base classifiers combine ML models such as RFC, SVM and KNN via majority voting. The output of the base layer along with the ML models are fed to the secondary classifier which uses weighted average technique to significantly improve predictive performance. The performance of the proposed work is evaluated using metrics such as F1-Score, AUC-ROC, and mAP. Initially the performance of the individual models is tested which is then fed to the majority voting model and weighted average model for stacking.

From the results of individual ML models, it is observed that RFC leads with an accuracy of 86%, precision of 84%, recall of 86%, and an F1-Score of 85%. SVM achieves an accuracy of 83%, with precision, recall, and F1-Score of 83%, 85%, and 84%, respectively. KNN shows the lowest performance with an accuracy of 85%, precision of 80%, recall of 82%, and an F1-Score of 81%. The Majority voting achieves an F1-score of 92%, an AUC-ROC of 0.95, and a mAP of 0.93 and Weighted Average Meta-Model achieves 90% F1-score, 0.93 AUC-ROC, and 0.91 mAP. It is observed that SEC achieved an F1-score of 97 %, AUC-ROC of 0.98 and mAP of 0.96 demonstrating its exceptional performance and robust nature compared to majority voting and weighted average meta model. The results observed show that SEC can achieve an overall classification accuracy of around 98 % and outperforms other ML algorithms like RFC, SVM and KNN, majority voting and weighted average. In conclusion, the SEC demonstrates superior performance on precisely segmented images, outperforming existing techniques. Although this study focused on pre-processed and segmented images, separate evaluation of ensemble model performance on ambiguous or low-quality pest samples was not conducted. This forms an important future direction to further assess the robustness of the proposed classification system in real-world, uncontrolled conditions.

6. Declarations

6.1. Author Contributions

Author Contributions: Conceptualization, A.N.S., R.K.M., and M.B.; Methodology, A.N.S. and R.K.M.; Software, M.B. and A.N.S.; Validation, R.K.M. and M.B.; Formal Analysis, A.N.S.; Investigation, M.B. and R.K.M.; Resources, R.K.M. and M.B.; Data Curation, M.B.; Writing—Original Draft Preparation, A.N.S.; Writing—Review and Editing, R.K.M. and M.B.; Visualization, A.N.S. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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