Vidhyayana - ISSN 2454-8596
An International Multidisciplinary Peer-Reviewed E-Journal
www.vidhyayanaejournal.org
Indexed in: Crossref, ROAD & Google Scholar

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Crop insect classification by combining RGB and Segmented images using SVM and KNN

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Abstract

The Indian economy is badly affected if the crop production for a particular financial year goes down. The two major factors that affect crop production are environmental factors and the other is different types of crop disease caused by various insects. In the current work we have proposed a solution to correctly classify the various crop insect images with the help of fusing RGB and Segmented images. The elbow method has been adopted to correctly identify the number of clusters. The k-nearest neighbor has been used to extract the features by clustering the nearest pixel for segmenting the image, and combination of KNN with support vector machine has been used to fuse the RGB image and segmented image. This approach has streamed line our data and thus the fused image has been feed to pre-trained CNN model Resnet50. The classification accuracy has been observed as 85.5,72.7,88.4 in case of RGB, Segmented, and Fused image respectively. So the proposed method has achieved the highest accuracy, thus novelty has been achieved through the proposed methods.

Significant Statement: The work has been done for the classification of the crop insects, for the classification we have used the fusion of RGB and segmented images of insects. At first we have segmented the image using the K nearest neighbor algorithm. The no of cluster has been chosen with the help of elbow method. Then we have proposed an algorithm to fuse the RGB and segmented image. The novelty has been achieved as the RGB image provide the color

information and the segmentation try to focus on the required object. Fusing both of them leads to better classification with the help of Resnet50.

Keywords: Elbow Clustering, KNN, SVM, crop insects, image segmentation, image fusion.

Introduction

The main goal of the research is to quantify and simulate the effect of invasive insect pests on crop output losses due to climate change. The writers talk on the necessity for efficient pest control methods and the difficulties in anticipating insect outbreaks in light of shifting climate circumstances. They discuss current studies on the topic and emphasize the value of multidisciplinary cooperation as well as the fusion of various data sources and modeling approaches. The authors of the research offer insights into the possible repercussions of climate change on pest pressure and agricultural yields, and they contend that precise and reliable models of pest outbreaks and their effects on crops would be essential for assuring future food security on a worldwide scale [1]. In association to other ResNet models and cutting-edge techniques, the results demonstrate that the ResNet-50 model outperformed them all with an score of 96.33% accuracy and an F1-score of 96.37%. The study illustrates the ability of ResNet models based on transfer learning for the precise and reliable detection of COVID-19 pneumonia from chest X-ray images.[2] The Faster Mean Shift technique, which is GPU-accelerated in this study, clusters data using Euclidean distance metrics. Utilizing parallel programming on GPUs to speed up computation, the suggested method accelerates the widely used mean shift algorithm. Initial cluster seeding and refining of the clusters are the two stages of the procedure. While the initial seeding stage creates candidate modes and reduces the number of data points by grouping them into manageable sizes, the cluster refinement stage improves the candidate modes to produce the final clusters. According to experimental findings on a variety of datasets, the suggested GPU-accelerated Faster Mean Shift method performs better than the traditional mean shift technique in terms of clustering precision and execution time, especially for large-scale datasets [3].

The method for assessing the structure of white brined cheese using image segmentation and median filtering techniques is suggested in the study. The cheese photos are segmented by the authors using a combination of Otsu thresholding and K-means clustering, which is then followed by median filtering to reduce noise and smooth out the edges. Following that, the generated images are examined to extract structural characteristics like porosity, connectivity, and tortuosity. The suggested method is successful in assessing the cheese structure and is applicable to the food industry's need for quality control [4].

This study proposes an innovative method referred to as Auto Elbow. The approach is based on a modified elbow method and determines the clusters by combining the silhouette score and the within-cluster sum of squares. Using a variety of real-world datasets, the authors assess Auto Elbow's performance and compare it to a number of other techniques. The findings of the trial demonstrate that Auto Elbow can perform as well as or better than the currently used techniques while requiring less user input [5].

The segmentation of grapevine regions in RGB photos using a deep learning method is presented. The encoder-decoder architecture of the convolution neural network (CNN) used in the proposed method is based on the U-Net model. The CNN was evaluated on a different dataset of 14 photos after being trained on a dataset of 124 images. The outcomes demonstrate that the suggested method outperformed conventional image processing techniques and obtained a high level of accuracy for grapevine segmentation. The research offers a significant contribution to the creation of automated, trustworthy systems for managing and analyzing vineyards [6].

Using RGB-thermal pictures and a hierarchical residual attention network (HRAN), a novel approach for automatic pavement defect detection and classification has been developed. A coarse fault localization stage and a fine-grained defect classification stage make up the proposed HRAN architecture's two stages. A residual attention network is used in the coarse localization stage to identify areas of interest (ROIs) that may contain defects, and a hierarchical technique is used in the fine-grained classification stage to further categorise the faults. The suggested approach shows improved performance in detection and classification accuracy when compared to several leading algorithms tested on a public dataset. The outcomes show the capability of the suggested HRAN approach with RGB-thermal pictures for automatic pavement defect detection and categorization [7].

Using a mix of one-class support vector machine (SVM) and Laplacian of Gaussians (LoG) algorithms, the research describes a method for identifying aphids in hyperspectral images. The suggested approach starts by applying noise reduction techniques to the photos, then moves on to feature extraction with LoG filters. After that, the SVM model is trained on the retrieved features to distinguish between aphids and other insects. A collection of hyper spectral pictures of plants with aphid infestations is used to assess the proposed approach and to compare it to other pioneering approaches. The results indicate that the proposed approach outperforms alternative methods concerning accuracy and the rate of false alarms.[8].

The efficiency of two feature extraction methods, BERT and TF-IDF, for foretelling persistent defects in free and open source software (FLOSS) projects is examined in this research. The study analyses the effectiveness of the two approaches using ML methods including Support Vector Machine, Random Forest, and Multilayer Perceptions utilizing a dataset of bug reports from 13 FLOSS projects. Precision, recall, and F1-score are the evaluation criteria that are employed. The findings demonstrate that BERT-based feature extraction works better than TF-IDF in terms of recall and F1-score, demonstrating its efficacy in foretelling long-lasting defects in FLOSS projects. The study also sheds light on the traits of persistent defects in FLOSS projects, including their seriousness, complexity, and time to fix[9].

Picture fusion using enhanced (ERBFNN) and (DSWT). Decomposing the source images into various frequency sub bands is done using the DSWT. The ERBFNN is then trained to discover the connection between actual images and the fused output. An input layer, a hidden layer, and an output layer are all parts of the ERBFNN. The input layer is made up of neurons that represent the input images' pixels, while the output layer is made up of neurons that represent the fused image's pixels. The hidden layer uses radial basis functions to model the link between the input and output layers. The research also suggests a technique for ERBFNN parameter optimization [10]. With PCNN and local feature-based fuzzy weighted matrices to present a quick local Laplacian filtering-based technique for fusing medical images. By keeping the key characteristics and decreasing noise. The local features of the images are extracted using a

PCNN, and the features are fused using fuzzy weighted matrices. The findings show that the proposed approach outperforms earlier cutting-edge techniques in terms of both objective and subjective assessments. [11].

The mean shift algorithm, which also involves clustering pixels into regions based on similarity in feature space, is a method for segmenting images that is comparable to k-means + SVM. Mean shift may need more iteration to converge, though, as it is computationally more expensive than k-means. According to the particular application, mean shift may also result in more irregular regions than k-means. The proposed work has used combination of SVM+K-means clustering.

Data Set

The dataset has been taken from the kaggle, Total 9 classes of the insect were chosen for the study [12].80% of the data has been used for training and 20 % of the data has been used for testing.

S.no	No of Images	No of classes
1	3150	9

Preprocessing: With the help of median filtering the noise reduction has been done, contrast normalization using CLAHE has been done, and image resizing using bilinear interpolation to 224x224. K means clustering algorithm has been used for region-based segmentation particularly helpful in finding out the object of interest there are too few clusters, the segmentation may be too rough or simplistic; if there are too many clusters, the segmentation may capture too much information and produce noise or over-segmentation. For Optimal values of the cluster the experiment has been performed with the help of elbow method. Plotting the within-cluster sum of squares (WCSS) against the number of clusters and choosing the number of clusters where the rate of WCSS decline slows down to form an elbow shape in the plot is known as the elbow technique. By viewing the above plot the elbow shape has been obtained at the point somewhere at 3, so the no of cluster has been taken as 3. In the proposed solution the k means clustering has been combined with the support vector machine.

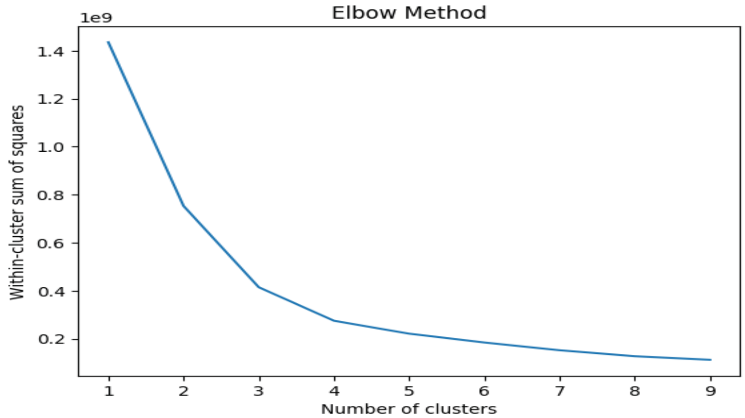

Fig1: Curve for getting the number of clusters

```
1.  Np. array:images=[image 1,image2…image N]//Load all the images from the
    dataset
2.  feature_vector=[]//Compute the feature vector  for each image
3.  loop→for image in images do
4.                  feature _vector=compute_feature(image)
5.                  Feature_vector. append(feature_vector)
6.  data_matrix=np.vstack(feature_vector)//combine feature vector for all image into a
    single matrix
7.  kmeans=KMeans(n_cluster=k)//Perform k means clustering on the data matrix to
    obtain the cluster centroids
8.  kmeans.fitdata(data_matrix)
9.  cluster_centroids=kmeans.cluster_centers
10. loop→image in images
11.         binary_masks=[]
```

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12. loop→centroid in cluster_centroids

13. binary_mask=create_binary_mask(image,centroid)

14. binary_ masks.append(binary_mask)

15. svm_classifiers=[]//train svm classifiers

16. loop→binary_mask in binary_masks

17. do

18. X_train,y_train=extract_feature_label(binary_mask)

19. svm_classifier=train_svm_classifier(X_train,y_train)

20. svm_classifiers.append(svm_classifier)

21. segmented_image=[]

22. loop→image in new_images//segment image using SVM classifier

23. segmented_image=[]

24. loop→svm_classifier in svm_classifier

    - binary_mask=create_binary_mask(image,cluster_centroids[svm_cla ssifires.index(svm_classifiers.index(svm_classifier))]
    - X_test=extract_feature(binary_mask)
    - Y_pred=svm_classifier.predict(X_test)
    - segmented_image.append(y_pred)
    - segmented_image.append(segmented_image)

25. Return segmented images.

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Multi Resolution image fusion using Laplacian and Gaussian pyramids

Let X be a matrix of size m by n that represents an image, with each pixel being represented by a vector of size n (for example, n=3 in a color image for the Red-Green-Blue channels). Let K represent the desired number of clusters.

K initial cluster centroid, c_1, c_2,..., c_K…………………..………………(1)

Each pixel in X should be mapped to the nearest centroid, with r_ij being set to 1 for cluster j-related pixels and 0 otherwise. The Euclidean distance can be used to settle the separation between pixel i and centroid j:

||x_i - c_j||2 = d_ij……………………………………………..………………. (2)

Image data contains total 3150 image and total classes of crop insects are 9 that is Armyworm, beetle, Aphids, mosquito, stemborer, bollworm, grasshopper, mites, sawfly.

The no training images are taken 300 image per pest.50 image per pest has been taken for testing purpose. Images were taken from ip102 dataset and we have consider 9 classes for our research

1. G_i = G(i-1) * h L_i = G(i-1) - expand(G_i)// Create Gaussian pyramids by recursively applying Gaussian filter and down sampled each level where G(i-1) is the (i-1)th level of the Gaussian pyramid, h is the Gaussian filter kernel, and L_i is the Laplacian pyramid of image i.

2. M_i = mask * G_i + (1 - mask) * H_i//Mask creation for finding region of overlap and Combine the Gaussian and Laplacian pyramids where H_i is the Laplacian pyramid of the second image.

3. F_i = M_i + expand (F (i+1))//Up sampled recursively by adding Laplacian pyramid for each level where F (i+1) is the (i+1) th level of the fused image pyramid.

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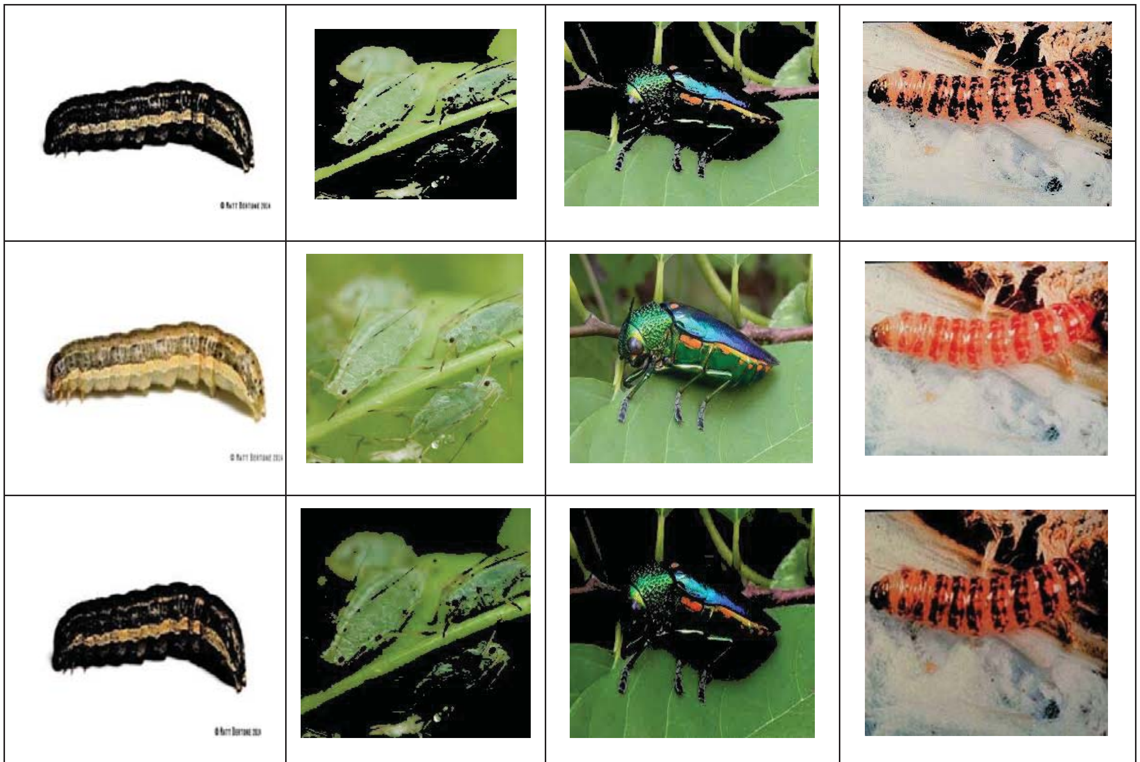
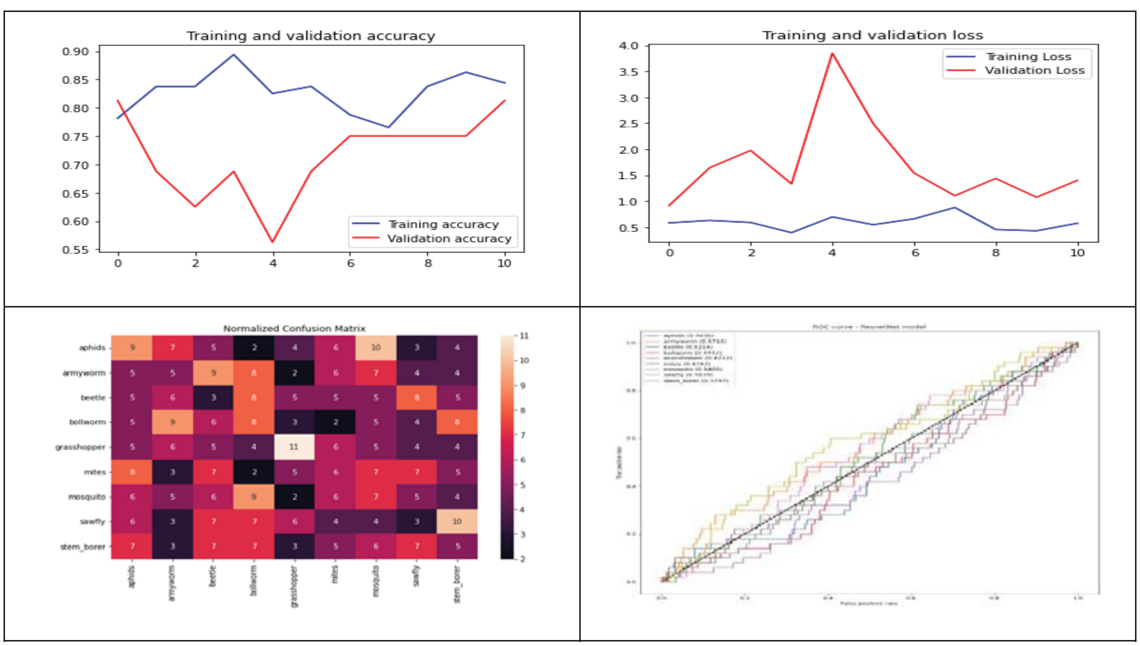


Fig2:Row1 (Segmented Image), Row2 (Original image), Row3 (Fused image)



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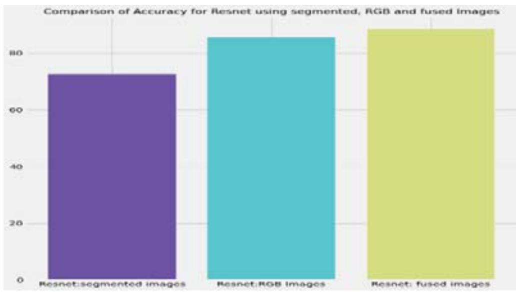

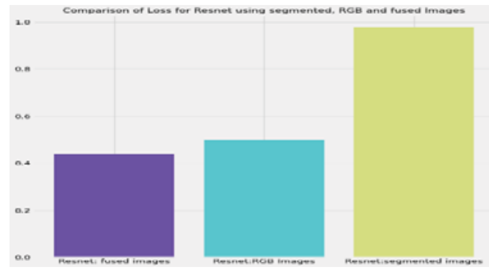

Figure3: The accuracy metrices

	precision	recall	f1-score	support
aphids	.16	.18	.17	50
armyworm	.11	.10	.10	50
beetle	.05	.06	.06	50
bollworm	.15	.16	.15	50
grasshopper	.27	.22	.24	50
mites	0.13	.12	.12	50
mosquito	0.12	.14	.13	50
sawfly	0.07	.06	.06	50
stem borer	0.10	.10	.10	50
accuracy			.13	450
macro avg	0.13	.13	.13	450
weighted avg	0.13	.13	.13	450

Accuracy: 0.8844444751739502

Loss: 0.44716864824295044

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Model	Image Type	Val_Acc	Val_Loss
ResNet	RGB	85.5	.5
ResNet	SEGMENTED	72.7	0.98
ResNet	FUSED	88.4	0.44

Table 1:validation loss and accuracy

Conclusion

Identifying image class using image fusion, the segmented mask and the original image's color information are combined to create a complete representation of the insect body area from the background image and classifying using Resnet50 provide a more accurate classification of insect class, which is more accurate from only a RGB or only a segmented images. Hence the proposed model has performed better and provides the novelty in the work. The end of the work can be done with the assistance of diverse profound deep-learning model.

Acknowledgement

WE are thankful to the Devi ahilya university administration for providing resources to complete this research task.

Conflict of interest

We do not have any conflict of interest and all the study has been referenced in the paper to the resource from where the data has been taken.

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