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An Automatic Insect Detection Framework Using Deep Learning Strategy Based Mask R-CNN Classifier

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Abstract: Insect infestation affecting fruits and vegetables causes huge production losses and financial losses for the global food and agriculture industries. Farmers are already experiencing a loss in crop productivity for a wide range of reasons, with insects being one of the main issues. This is a sign of lack of information about the condition and the insecticides or pesticides that can be used to control the condition. But in order to manage the condition, it's important to recognize the underlying illness and offer the most effective solutions. The design and development of a model for an efficient insect detection system for agriculture are described in this research paper. The insect related data is gathered from the agricultural area in the form of images. Three phases comprise the proposed methods are input images processing, preprocessing, and mask RCNN-based insect detection. The input data is gathered from the agriculture area, here the insects present in the plants are captured for processing this detection. Then to enhance the quality of the images, pre-processing is performed after data gathering which comprises image resizing, noise filtering and contrast enhancement. In order to achieve better outcomes for the detection of agricultural insects, the final detection is carried out using a deep learning-based Mask RCNN classification model. Some of the prior insect detection techniques applied to evaluate the effectiveness of the proposed technique are RCNN, CNN, Fast RCNN, and Faster RCNN. The presented Mask RCNN classification model obtained 98% accuracy, 93% sensitivity, 90% specificity, 2% error, 95% precision, 4% FalsePositiveRate, 89% F1 Score, and 86% Kappa. Consequently, the deep learning strategy proposed in this paper, comparable studies between Insect and insider manual counting indicate that the method is accurate enough to inform detection systems for integrated insect control of cockroaches.

Keywords: *Deep learning, Agriculture area, Insect identification, CNN, Fast RCNN and Mask RCNN.*

1. Introduction

One of the most significant industries in the history of humanity, agriculture has a significant influence on quality of life. With the development of smart technology, there is a growing need to decrease the use of energy and water resources, which will also lessen agricultural labour [1]. Early detection of plant diseases through automatic diagnostic is possible to stop further plant deterioration, which will certainly boost production [2]. Experts in agriculture typically identify insect infestations by hand [3]. In order to anticipate, prevent, and manage insect pests in agriculture and increase the effectiveness of prediction and control activities, insect pest identification is a crucial first step [4]. The identification of insect pests is essential to agricultural pest forecasting. The codling moth, a specific insect with similar characteristics to those of a butterfly, is a pest that harms cherry kinds of crops [5]. These systems, albeit undoubtedly a step forward in automated insect monitoring and management, still rely on sentinel points inside the crop field. Insecticide use issues, overuse of natural resources, increased global trade, rising human population, shifting consumer patterns, and technological advancements are all contributing to a new agricultural revolution [6]. Insects usually hidden under leaf tissue throughout the day to avoid the warmth, then come out to rest on the plants in the evenings or at night time [7].

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When utilizing insect photos to detect insect pests, traditional image processing techniques produced acceptable results and performance. As deep learning has transformed computer vision, particularly picture categorization and object identification and recognition [8]. The most recent advancement in artificial intelligence and machine learning, deep learning (DL), has significantly improved both fields [9]. DL is now widely utilised in the agricultural sector. Deep convolutional neural networks, in addition to being used to identify insect pests, are also applied to other aspects of image processing and computer vision in agriculture [10]. Deep Learning methods are already frequently used across many different industries. For computational tasks like plant identification, flood control, grain quality, diagnostic testing, and pest detection in agricultural, these are extremely creative. [11]. One of the numerous industries that frequently uses Deep Convolutional neural networks related object recognition and selection is insect controlling [12]. Deep learning framework for counting and recognizing bugs on trap sheet photos. Typical two strategies are Path Aggregation

Feature Pyramid Networks (PAFPN), Mask R-CNN, Faster R-CNN, and Regions using Deep Neural Network Features (R-CNN) [13]. The efficiency of object recognition, pattern recognition, and neural supervised learning for insect detection in tomatoes fields. An image detection method utilizing deep learning is used to identify the insects on the catch [14].

The health and environmental risks associated with existing agricultural sprinkling methods have led to their identification as being irreversible. In agricultural production management, the detection of insect pests has always been a critical problem. However, errors in judgement and other issues can arise for a range of factors, which has a major impact on crops [15]. Finding insect pests is a very hard job in farming picture processing. Traditional picture recognition methods have some flaws that deep learning can fix. Because of this, it is getting more and more attention in the area of finding farming bug pests. If these issues were fixed and made less of a problem, the sector as a whole would grow economically. This would make it possible to grow a lot of food with fewer environmental impacts. The challenge of agricultural pests and insects makes up the majority of the different components. In agriculture, image identification of vegetable infections and caused by pests can decrease the need on improved planting experts, enabling farmers to address issues quickly. Three different processes, comprising input images, preprocessing, and insect detection using a mask R-CNN, are included in the proposed model. Data collection is the initial stage in this process, and images are used to gather data from agricultural land on insect and crop damage. The preprocessing stages includes image resizing, noise filter and contrast enhancement. RCNN classifier-based deep learning strategy to identify the agricultural insect. The research's main contribution is listed as follows.

- The noise filter is removed, images are resized, and contrast enhancement is done using preprocessing techniques.
- Mask RCNN is performed for the dectection of the insect in the classification model.
- The performance of the proposed insect's detection model is evaluated by comparing its performance with measurements considered with existing techniques.

The structure of the study is as follows. The study paper discussed in Section 2 is related to the prior agricultural insect detection systems. The proposed methodology of insect identification is briefly described in Section 3 of this article. The proposed framework's results and performance metrics are described in Section 4. Entire study work is covered in Section 5 through the conclusion.

2. Related Works

Several studies have been done in this area, and one of them used tracking and control methods used in farmland to find the bug. News stories in the past used CNN, R-CNN, Fast R-CNN, and faster R-CNN as methods. So, here is a review of some studies that are connected to this suggested work.

To improve this method, Junioret al. [16] added two new factors that could be used to change the lengths of the CNN model's grounding sides and the ratio of false positives by class. This was done to improve the accuracy of finding low entities. For the 2019 and 2020 growing season, 580 pictures were used to test the model. These pictures came from field-exposed traps set up in Coxilha and Passo Fundo, north of Rio Grande do Sul State. The model fits well in figuring out the changes in population levels for these insects when compared to counting them by hand, as shown by the coefficients of determination. There are some small differences from the growth curve in the beginning stages and when the shape stays the same. According to Ozdemir and Kunduraci [17], they used a deep learning model to make a mobile-based decision support tool that could find and sort insects by order. Aside from that, they talked about the outcomes of comparing the order-level bug segmentation deep learning systems YoloV4, Faster R-CNN InceptionV3, and SSD Mobile NET. After looking at how well different models work with this kind of problem, we found that faster R-CNN InceptionV3 is the best at finding and sorting insects at the order level. They also helped studies being done in this area by adding 258,220 training data sets and 1,500 test data sets to the Kaggle library.

The work of Ullahet et al. [18] created a full DeepPestNet framework for finding and labeling bugs. The suggested model is made up of eleven learnable layers, three fully connected (FC) layers and eight convolutional layers. They used techniques for rotating images to make the data bigger and show that the DeepPestNet method can be used in many situations. We used the well-known Deng's crops data set to test the suggested DeepPestNet system. Using the suggested method, 10 groups of insect pests were found: Locustamigratoria, Euproctispseudoconspersa strand, ChrysochusChinensis, Empoascaflavescens, Spodopteraexigua, Laspeyresiapomonella larva, parasalepida, acridacinerea, and S. exigua larva.

Albattah*et al.* [19] had developed a basic drone-based approach, specifically a modified CornerNet approach employing DenseNet-100 as the base model. Three phases make up the newly presented framework. By creating sample annotations that will subsequently be used for model training, the region of interest is initially collected. The DenseNet-100 is used in the following step to compute deep keypoints in a custom CornerNet. The one-stage detector CornerNet's final step involves identifying and classifying a number of insect pests. The DenseNet network improves feature extraction capability and supports the CornerNet model in identifying insect pests as paired key points by merging the image features from all of its preceding layers.

Kavitha Lakshmi &Savarimuthu [20] had created one of the biggest and most significant risks to precision farming is plant disease identification, which seeks to identify unhealthy instances in plant leaf photos of particular categories. Despite numerous recent initiatives, there is still potential for study to build models to identify and categorise plant diseases at various growth phases in agricultural fields. The training of the two suggested models takes into account a total of 9,304 hand annotated photos from two datasets that are accessible to the general public.

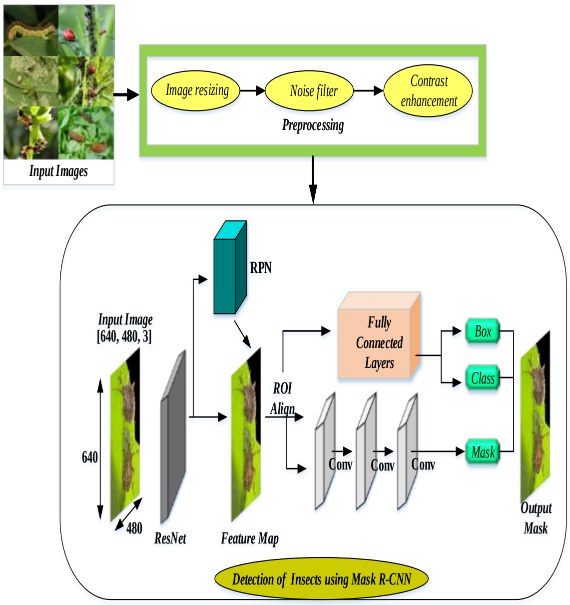
Mourseye*et al.* [21] had introduced a G. gryllotalpa's impact on sugar beet output, vegetative traits, and sugar quality. The refectance features of sugar beet plants, both infested and untreated by G. gryllotalpa, were evaluated using hyperspectral remote sensing data. Sugar beet plants that were 80 days old were experimentally infected with 5, 10, and 15 adults of Gryllotalpa per replicate. The infested rate, losing weight, vegetal properties, and glucose quality traits were assessed at all G. gryllotalpa infestation levels. It was also able to analyse the harm caused by various Gryllotalpa infestation levels at three different stages of sugar beet plant growth using hyperspectral remote sensing technologies.

Butera*et al.* [22] had described the capacity of state-of-the-art (SoA) object detection models based on convolutional neural networks (CNN) to recognise harmful insects that like insects on heterogeneous outdoor images taken by different sources. Additionally, they concentrate on differentiating a nuisance insect from related innocuous species. Designers take into account both needed processing resources and the detection performance of various models. A baseline model for these types of tasks is what this work tries to provide. Their results indicate how Faster RCNN with a MobileNetV3 backbone is a particularly strong starting point for precision and inferences processing latency, showing the suitability of existing SoA model for this application.

According to the above reviewed articles several concerns are arise during the detection process. In authors [1], it work offers a new automatic deep learning approach for insect monitoring that employs hybrid and regionally activated features to tackle this issue. In authors [2], data augmentation techniques were used to improve the models and address the overfitting problem by enlarging the photos of the data up to fourfold beyond their original size. In authors [3], Food safety thus seems to be one of the most urgent challenges in the future. One approach to solving this problem is to increase agricultural output productivity, which is one of the expanding study disciplines. In authors [4], to solve problems with manual inspection, they have offered an automated framework for the recognition and classification of insect pests. In authors [5], this covers the as-yet-unsolved issue of identifying insects in photos taken under uncontrolled circumstances. In authors [6], in order to address this problem, effective multi-task automatic leaf disease of plants detection and classification systems are built using the deep learning techniques EfficientDet and Mask RCNN. In authors [7], furthermore, by enabling local insect elimination even before problem spreads, can aid in lowering the expense of scout, limiting environmental risks, and enhancing precise farming methods. In order to address these issues in this proposed work introduce an automatic insect detection model using a deep learning based Mask RCNN in agriculture application.

3. Proposed Methodology

The detection of insects in the agriculture industry, which helps in the creation of intelligent farming, has gained a great deal of attention. Farmers can analyse crop development trends and avoid insect damage in the early days with the help of deep learning and insect identification. Insects that feed on stored grain must be found and identified in order to protect the food during storage. Numerous advancements in agriculture, like the detection of insects, are the result of scientific progress and research. Image detection also has significant scientific relevance in the area of spotting insects in different plants. Lizards, insects that crawl and fly, like cockroaches, ants, and flying, are commonly occur in any developed environment. Insects commonly seek cover from the sun behind plant leaves during the day, emerging on the leaves at dusk or dawn. However, another problem with remote trap monitoring techniques is automatically detecting the insects or pests. In order to mitigate these issues in this work proposed an automatic insect detection framework for using deep learning strategy based mask R-CNN classifier.



A design of the automatic insect detection framework using mask R-CNN based deep learning methods is shown in Figure 1. The proposed method consist of three phases such as, input images, preprocessing and classification. The input images are collected from the dataset this is the initial phase. Secondly this stages includes preprocessing like image resizing, noise filter and contrast enhancement. The obtained picture data is then used in the preprocessing stage to enhance the photos' brightness and get rid of any potential noise. One can resize an image without removing any material to make it smaller or larger. Noise can be reduced by fusing a smooth operation mask or low-pass filter with the actual picture. To enhance the picture quality, processes like contrast enhancement must be performed. In order to detect agriculture insects, the mask R-CNN classifier can be used. Finally, these classification outcomes are presented in order to achieve the final detection result. These are the specific processes that compose our proposed method.

3.1. Data gathering

Data gathering is the initial phase of this method, here the agriculture images is gathered to make a dataset which comprises plant related information, insect related information and so on. The considered image dataset is taken from [27], which is in the folder insect classes contains 1000 synthetic images for each insect class.

Table 1. Sample Input Images

3.2. Preprocessing

Data collection is followed by preprocessing to improve the quality of the images. Thus, preprocessing techniques are applied to the raw pictures. The raw photographs are downloaded from many sources, however they shouldn't be processed right away because of the various types of noise they represent. In order to study it, it must first go through preprocessing. Preprocessing is done to reduce the load during identification by resizing the images, removing noise, and improving the image quality.

Image Resizing: image scaling is the process of changing the size of a picture so that it can be sent in a similar pixel format for further processing. Picture down-sampling and image up-sampling are two image replacement methods that must be used to convert the data to fit the output display or the communication route [23]. It may be more efficient to give people copies with lower resolution, but the end display of visual data may need to be as close to the original high quality as possible.

Noise Filter: After resize the images that is given as the input of the noise filter and here, the noise filters is referred to as the median filter. A dynamic signal processing method called the median filter is based on statistics. The median value of the neighbourhood is used to replace a noisy value in a digital photo or series. This median value of the group is preserved in place of the noisy value, and the pixels of the mask are sorted according to their relative grey levels. The following equation (1) represents the median filter's output.

$$g(x,y) = med\{f(x-i, y-j), i, j \epsilon W\} \quad (1)$$

$f(x,y), \mathrm{g(x,y)}$ in equation (1) stand for the input and output pictures, respectively. The two-dimensional mask is described as W, for instance, and its size is $n \times n$, for example, $3 \times 3, 5 \times 5$, and so on [24]. Another is the design of the mask, which might take the form of a circle, line, square, cross, etc. It can be challenging to mathematically analyse the thresholding for a picture with random noise because it is a nonlinear filtering. The noise level of the average filtering for a photo with no mean noise is roughly, based on a normally distributed.

$$\sigma_{med}^2 = \frac{1}{4nf^2(\bar{n})} \approx \frac{\sigma_i^2}{n+\frac{\pi}{2}-1} \cdot \frac{\pi}{2}$$

(2)

Equation (2) specifies the noise function variance as $f(\bar{n})$, the input noise power as σ_i^2, and the mask size of the median filter as n.

$$\sigma_0^2 = \frac{1}{n}\sigma_i^2 \quad (3)$$

The benefits of average filtering rely on both the size of the mask as well as the frequency of the noisy, and it is shown from (2) and (3). Whenever it relates to this, the median filter frequently outperforms average filtering performance, even though impulse noise, particularly narrow pulses that are spaced farther apart and have pulsed width lower than $\frac{n}{2}$, are better at reducing impulse noise than random noise. The effectiveness of median filtering should be improved if it is possible to adaptively increase the mask size in response to the noise density.

Contrast Enhancement: One way to improve the contrast of a picture is to use adaptive histogram equalization after the photos have had their noise removed. The method only uses small parts of the picture. The contrast change function for each tile is found and then applied to the tile to make the contrast better. In this case, the output region's histogram is very similar to the histogram of a distribution like uniform, Rayleigh, or exponential. Bilinear interpolation is then used to mix neighboring tiles together to get rid of borders that were made by humans. Histogram equalization, also called global histogram equalization, makes the picture more contrasty, but it may lose information because it doesn't limit to a certain area. When it comes to the HE, this method works to improve the picture, but it could mean losing some important info [25]. AHE is often used to fix this problem with data loss. It works better than the standard histogram-based way for improving edges and local contrast in certain parts of the picture. In the next few lines, they will talk about how the AHE is used on the picture. To fix this problem, the AHE is used.

Step 1: In this case, the picture is broken up into "Tiles" called mall blocks, and HE is then applied to each block.

Step 2: The histogram is therefore limited to short blocks in this instance. Imagine that if there is noise in the block, it will be amplified. Contrast limiting is employed in order to solve this problem. The images negatives are reduced by applying the CDF before applying the AHE to the gray-scale image.

Step 3: The neighbouring pixel or the size of the image's histogram affect this threshold value.

Step 4: Before performing histogram equalisation and after it has been completed, bilinear interpolation is used to reduce artefacts in tile boundaries whenever a histogram value rises beyond the given contras threshold.

3.3. Detection of insect using Mask R-CNN

The input of the classification phase is receive from the pre-processing phases. Additionally, this technique finds the output using Mask Region based convolutional neural network. In this method Mask R-CNN is used to detect the insect in the agriculture field.

3.3.1. Mask R-Convolutional neural network

Images can be segmented using mask R-CNN, among the most cutting-edge and powerful learning applications. The four primary stages of the mask R-CNN architecture are image enhancement, region proposal, region of interest, and prediction. A classifier and a boundary offset are the two outputs of faster R-CNN for every eligible object. They incorporate a third element that produces the photo mask. Depending on Neural and fully linked networks, its design allows convolutional feature extraction, RBC and WBC regions of interest (RoI) detection by extending bounding boxes, and eventually mask construction for the discovered cell. Thus, the idea of Mask R-CNN is reasonable and obvious. The extra mask output, however, differs from the classes and boxes outputs and calls for the extraction of a considerably more precise spatial configuration of an objects. The same two techniques, with an identical first stage, is used by Mask R-CNN. For each RoI, Mask R-CNN generates a binary image in the second stage, along with predictions of the class and box offset. In contrast, the majority of modern systems rely on mask estimates for identification.

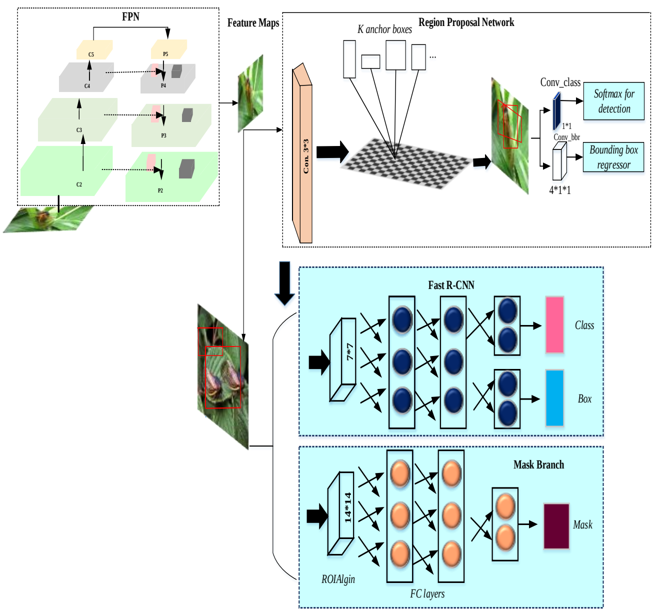


Fig 1. Architecture of Mask R-CNN

Feature Pyramid Network

After Res-Net offered a solution to the declining gradients problem in Figure 2, the large majority of shallow extraction techniques, along with the Subsurface Extracting

Features Network, FP-Net, have been improved. As stated in the ResNet Building Block equation:

$$Y = F(X, \{W_i\}) + X \quad (4)$$

Where Y is the result, X is the input, W_i are the ith convolutional layer's learning parameters, and $F(X, \{W_i\})$ is the residual mapping that has already been acquired.

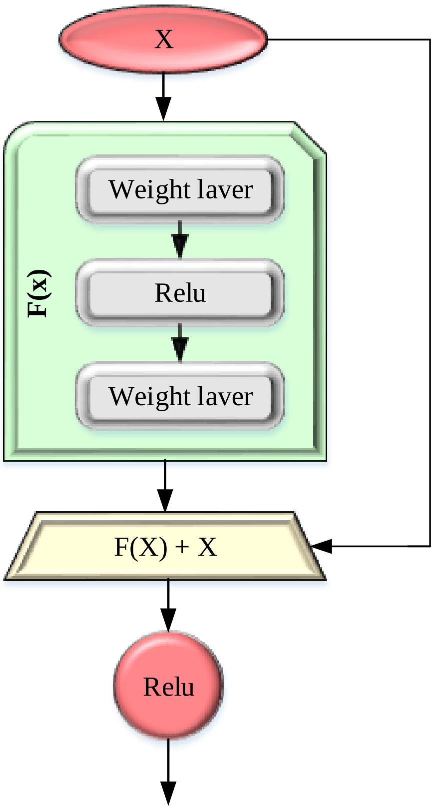


Fig 2. Structure of the residual block of Res-Net

FP-Net bottom-up technology has been used to develop Res-Net-50 in this experiment. The architecture must employ a proper feature extraction which can balance and extract more features because it deals with photos of many various scales and resolutions. To recover FMs that describe the image as input at various scales and features, use FP-Networks. Increasing the depth of multi-scale extracting features only leads to a significant semantic information, which is frequently beneficial for classification methods but ineffective for detection. Strong resolution values at the lower levels of FMs are crucial for pinpointing the locations of objects. FP-Net provided two additional paths to the reinforcing FMs with resolution values as a result. The feature maps P5, P4, P3, and P2 are created after input image has been analyzed by the FP-Net layers. When these FMs are transmitted into the RP-NET to recover RPs, a complete estimate is then generated by passing them into the second phase.

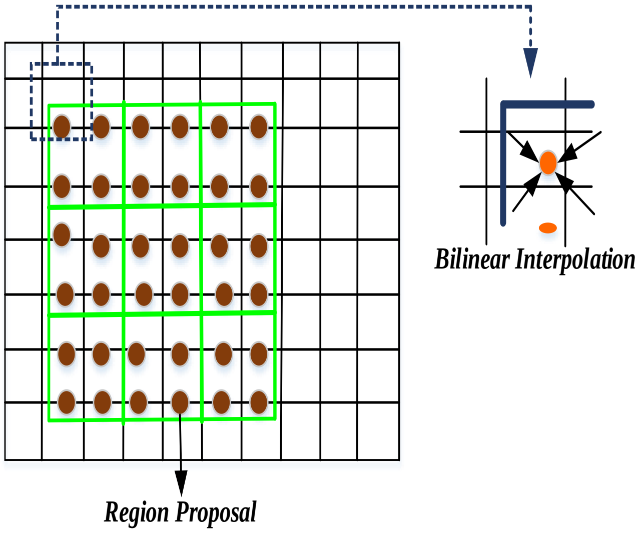


Fig 3. Operation of bilinear interpolation and pixel values in each region box.

Region Proposal Network

The RP-NET develops anchors over each FM prior to the FM inserting through it. Every point is actually and each FM's size and amount of ratio and scales determines how many and what kind of anchors are placed there. To produce the different sizes of anchors, three ratios (0.5, 1, 2) and five scales (32, 64, 128, 256, and 512) were combined. Furthermore, in an effort to select the most accurate box, each anchor is categorised using Intersection-over-Union (IoU). Whereas if IoU value is IoU ≥ 0.7, the anchoring is given a great label (1), indicating there is an entity within and that it matches the flooring BBX well; if, the anchoring is given the lowest label (0). Therefore, BBXs (RPs) and their class are both part of the output of RP-NET (1 or 0). IoU can be calculated as follows:

$$IoU = \frac{area(B_{pb} \cap B_{gt})}{area(B_{pb} \cup B_{gt})} \quad (5)$$

The union of the projected and actual BBX is represented by$area(B_{pb} \cap B_{gt})$, where $area(B_{pb} \cup B_{gt})$ is the area.

$$L(X, Y, B_{bt}, B_{rb}) = L_{cts}(p(X), Y) + \lambda[Y \geq 1]L_{bbr}(B_{gt}, B_{rb} \quad (6)$$

The cross-entropy losses is $L_{cts}(p(X), Y) = -logP_y(X)$, where X is the predicted likelihood anchoring with $\lambda = 1, [Y \geq 1]$ is 1 when Y ≥ 1 and 0 and the regression area of BBX. The bounding box's loss of regression is calculated as follows:

$$L_{bbr}(B_{bt}, B_{rb}) = Smooth_{L1}(xB_{gt} - B_{rb}) \quad (7)$$

$$Smooth_{L1}(x) = \begin{cases} 0.5x^2, |x| < 1 \\ |x| - 0.5, otherwise \end{cases} \quad (8)$$

Fast R-CNN and Mask Branch

The identification process of the Mask R-CNN consists of the two elements known as Fast R-CNN and mask branch. Faster R-RoI-pooling CNN's is being replaced by RoIAlign in Mask R-CNN. Instance segmentation's lack of RoIpooling has an impact on mask production and leads to misaligned. RoIAlign was employed to address the aforementioned RoI pooling drawbacks in this industry. Due to the fact that the object proposals boxes of RP-NET have varying width, RoIAlign employs the "Nonlinear Interpolation" method to obtain image values on the pixels with positions of floating-point numbers and also to create a stable size for every region box. When resize generated FMs are used, objects' sizes drop without sacrificing quality [26]. Researchers must simply apply bilinear interpolation in two circumstances. When switching from one cell size to another, which is the first. If somebody wants to display the data in a distinct coordinate, use the second. The final cost is computed using the four closest input value centres using interpolation. The new cell produced from this output produces an ultra-smooth answer from the weighted average of the four closest values, as shown in Figure 3. RoIAlign's result was supplied into FC-Net for categorization and localized operations as well as the mask branch, which used it to create a mask for every input region. The dimension of RoIAlign in the present employment is 14 ×14 in the mask branch and 7×7 in the Fast R-CNN stage, as shown in Figure 1.

While the Fast R-CNN identifies the variables taking into account all objects, the RP-NET classification layer predictions only two classes, the optimistic and the negatives [37, 26, 10, and 6]. Each object's position is identified by Mask R-CNN, and it also offers the object's distinctive shape. Multi-task loss is used by Mask R-CNN and is defined on each sampled RoI:

$$L = L_{cls} + L_{box} + L_{mask} \tag{9}$$

Mask loss (L_{mask}), also referred to as the mean binary cross-entropy loss, is defined in [9] along with classification loss (L_{box}) and BBX loss (L_{cls}). The three losses are combined to enhance performance and accelerate.

4. Result and Discussion

This study presents the suggested agricultural insect identification framework for utilising Mask RCNN classifier in deep learning. The proposed model is tested using the MATLAB software. The initial phase involves capturing information from input images in a collection of agricultural insects. The second process, known as pre-processing, involves resizing the image, applying a noise filter, and enhancing the contrast to detect insects. Moreover, this technique identifies the output using a Mask Region based convolutional neural network. This approach employs Mask R-CNN to detect insects in agricultural fields. The proposed Mask RCNN classifier's effectiveness is assessed using performance metrics including accuracy, sensitivity, specificity, error, precision, false positive rate, F1 score, and kappa. The performance classifiers are CNN, RCNN Mask RCNN, Fast RCNN and Faster RCNN. An efficient performance analysis of the suggested method is provided in this section. The following process is shown in Figure 4.

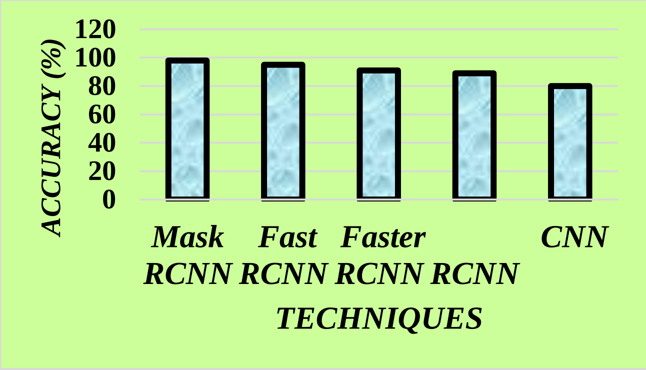


Fig 4. Analyzing the accuracy of suggested and prior methods

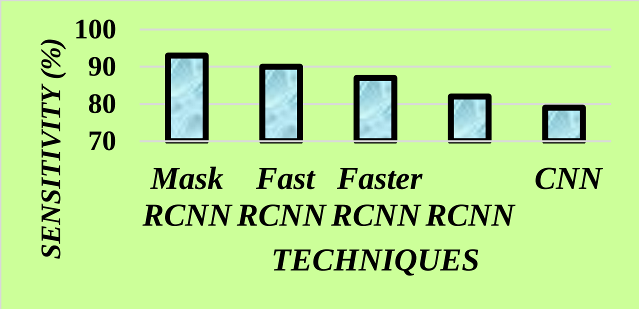


Fig 5. Analyzing a sensitivity

The accuracy comparison analysis among deep learning and different previous classifiers is shown in figure 4. For any performance analysis of the suggested model, accuracy is a crucial parameter. Prior classifiers like Fast RCNN, Faster RCNN, RCNN, and CNN obtained accuracy values of 95%, 91%, 89%, and 80%, respectively. The Mask RCNN model achieved 98% accuracy, which is higher than the prior methods. Figure 5 provides comparison analyses of the sensitivity (%) of the suggested and existing techniques. It is observed that the specificity is higher for the suggested data analysis. The proposed method is proved to be 93% higher when compared to the previously used methods. According to the results, Fast RCNN gain 90%, Faster RCNN gain 87%, RCNN gain 82%, and CNN gain 79%.

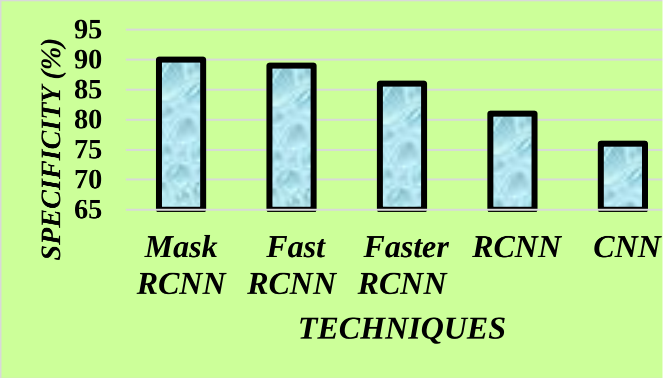


Fig 6. Analyzing a specificity

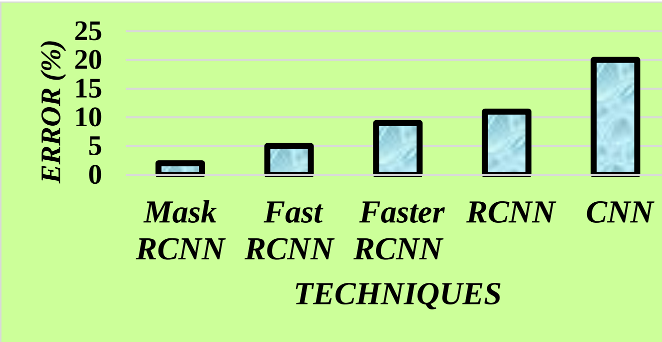


Fig 7. Analyzing an Error

Based on specificity (%), Figure 7 compares and evaluates suggested and existing approaches that entail comparison analysis. It is found that the proposed data analysis has a greater specificity. Among DL methods several classification approach are considered such as, Fast RCNN, Faster RCNN, RCNN and CNN. Mask RCNN model is found to have more specificity than others, according to estimation. 90%, 89%, 86%, 81% and 76% are the achieved specificity values of Mask RCNN, Fast RCNN, Faster RCNN, RCNN and CNN. This figure 7 compares suggested and existing strategies based on error (%). The error is observed to be less for the proposed data analysis. When compared to the current methods, the proposed solution is shown to be 2% less effective. Fast RCNN is 5%, Faster RCNN is 9%, RCNN is 11%, and CNN is 20%, according to results.

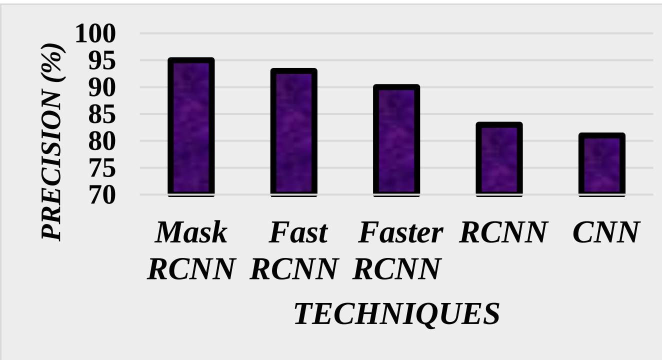


Fig 8. Analyzing a Precision

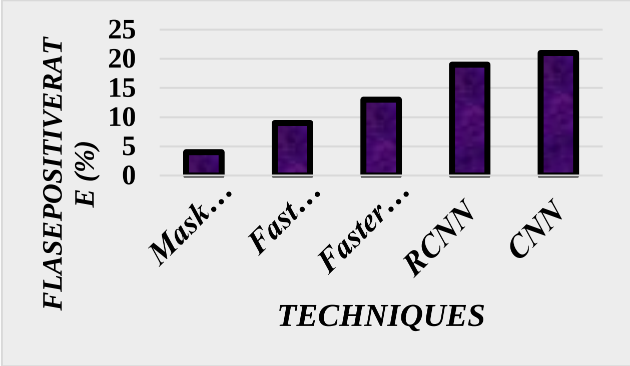


Fig 9. Analyzing a FalsePositiveRate

Figure 8 presents comparative analyses based on Precision (%) among existing and suggested techniques. It is determined that the precision is higher for the proposed data analysis. The proposed technique has been shown to be 95% higher when compared to the previously used techniques. The results indicate that Fast RCNN is 93%, Faster RCNN is 90%, RCNN is 83% and CNN is 81%. Figure 9 shows the comparison study of FalsePositiveRate for the proposed Mask RCNN with the prior classifier. The FalsePositiveRate value attained for Fast RCNN, Faster RCNN, RCNN and CNN classifier are 9%, 13%, 19% and 21%. The proposed Mask RCNN model attained 4% of FalsePositiveRate, the FalsePositiveRate value of the proposed model attained better value than the existing methods.

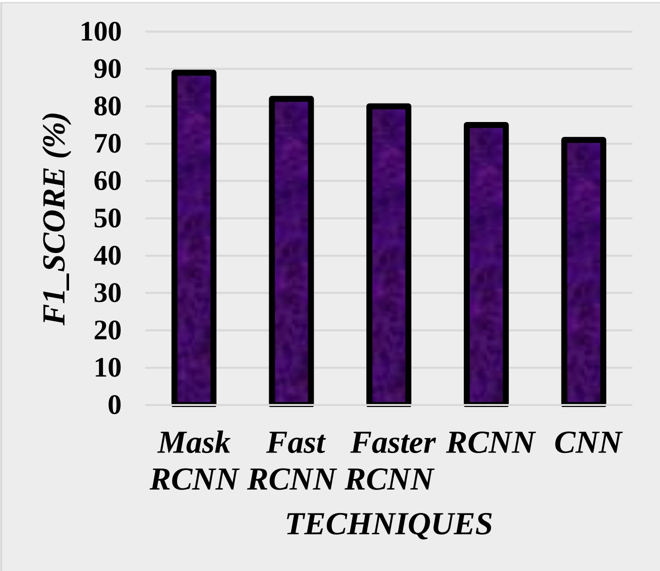


Fig 11. Analyzing a F1_Score

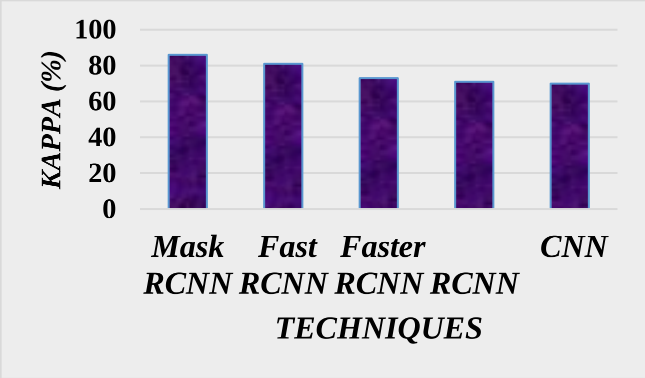


Fig 12. Analyzing a Kappa

Comparative analyses between the existing and suggested methodologies are shown in Figure 11 based on F1 Score (%). The F1 score is higher according to the suggested data analysis, it is observed. When compared to existing approaches, the proposed method exceeded existing by 89%. The analysis shows that Fast RCNN is 82%, Faster RCNN is 80%, RCNN is 75%, and CNN is 71%. The evaluation of kappa for suggested Mask RCNN and existing approaches is shown in Figure 12. Several classification approaches, like Fast RCNN, Faster RCNN, RCNN, and CNN, are taken into consideration when using DL methods. The kappa values achieved using existing methods such as Fast RCNN, Faster RCNN, RCNN, and CNN are 81%, 73%, 71%, and 70%. The kappa of the proposed Mask RCNN classifier is 86%.

5. Conclusion

A deep learning-based approach for identifying agricultural insects is established in this paper. The proposed method is divided into three phases such as, input picture, preprocessing, and mask RCNN-based insect detection. Images of insects are used to gather data on them from the agricultural region. Image resizing, noise filter and contrast enhancement are the methods involved in the preprocessing phase. The size of all photos must be fixed before uploading them to the CNN because neural networks only accept inputs of the same size. The effectiveness of the image pre-processing filters for removing noise in real-time photos of transformer oil taken at various temperatures. By altering the input data, more of the available range can be utilized, enhancing the contrast between the backgrounds of the objects. A Mask RCNN classifier used to detect agricultural insects offers the final outcome. The suggested monitoring and controlling system for agricultural applications is tested using MATLAB software. In accordance with the Mask RCNN classifier there is 98% Accuracy, 93% Sensitivity, 90% Specificity, 2% Error, 95% Precision, 4% FalsePositiveRate, 89% F1_Score as well as 86% Kappa. In comparison to previous models, the suggested model achieved better results. The proposed scheme to detecting insects enables accurate monitoring and management of the condition of the plants in the agricultural system.

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