International Journal of Engineering Trends and Technology
ISSN: 2231 – 5381 / https://doi.org/10.14445/22315381/IJETT-V70I9P224

Volume 70 Issue 9, 240-251, September 2022
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Original Article

An Algorithm for Detection and Identification of Infestation Density of Pest-Fall Armyworm in Maize Plants using Deep Learning based on IoT

D. Sheema[1], K. Ramesh[2*], R. Surendiran[3], S. Gokila[4], S. Aiswarya[5]

[1,2,4,5] Hindustan Institute of Technology and Science, Chennai, Tamilnadu, India.
[*]Sri Krishna College of Engineering and Technology, Coimbatore, Tamilnadu, India.
[3]School of Information Science, Annai College of Arts and Science, Kumbakonam, India.

[1]Corresponding Author : sheemawilson20@gmail.com

Received: 05 July 2022 Revised: 23 September 2022 Accepted: 26 September 2022 Published: 30 September 2022

Abstract *- Information Technology plays a vital role in human lives by dealing with everyday challenges. Technological innovation in agriculture provides farmers with the possibility to increase productivity along with the management of natural resources. Pests have plagued agriculture, destroying a part of the crops or even the entire field. Farmers face immense challenges in controlling pests at the early stage of their crop development. Eventually, it adversely affects the economy. A novel way of analysing pests by examining their odor substance is presented in this study. Every pest has a unique smell. Compared with other detection methodologies, Odor makes the work easier because it enables the identification of concealed pests, such as deeply buried pests, swirled pests, etc. Consequently, the proposed system takes note of Odor as a key consideration and evaluates five different smells, including pungent, misty, sweet, musty, and so forth. Here, gas sensors are utilized to combine these analyses with Faster R-CNN-based algorithm to extract features. It is also used to identify the density of infestation. Pseudocode can be used for further development to achieve accurate and timely processes. Compared with Faster R CNN-based pest detection, accuracy increased to 6%. Performance metrics of the proposed progression have been tested on some samples.*

Keywords *- Pest Detection, Object Detection, Detection of Odor, Faster R-CNN.*

1. Introduction

There are several imperative nutrients in maize, such as minerals, vitamins, fiber, and oil. A key crop in the modern world is maize. A large portion of the population depends on it for sustenance. Maize is one of the primary crops where farmers live in developing countries. The crop of corn grows in different climates and uses less water than other crops in India. It allows farmers to earn a large amount of profit. India is the world's sixth-largest exporter of maize. But due to pests, farmers lose their economy. To repel pests, farmers often use excessive amounts of chemical sprays. The sprays will help to eliminate pest infestations.

Nevertheless, animals and humans can be adversely affected. It is due to four pests found in maize, including pink stem borer, fall armyworm, spotted stem borer, and shoot fly [1]. An infestation of Fall Armyworms (FAW) is the most dangerous. Fall armyworm larvae can attack maize at any developmental stage. To solve this issue, deep learning algorithms are used. Deep learning and the Internet of Things (IoT) can detect objects and things. Deep learning uses object detection to identify objects accurately. In simple terms, object detection is a method that allows a computer to identify, detect, and label objects existing in a video or image to categorize them. Visual representations of objects are named objects. Objects have a limited range of physical characteristics. For an object to be detected and differentiated, it must be semi-rigid. Each object will have its features, which is the main concept behind this process. Separating objects based on their features is possible. These features are used in object recognition methodologies to classify objects.

In the same way, fingerprint detection and face detection use the same concept. Object detection is becoming ubiquitous in real-world applications, including security, image retrieval, and surveillance. Both deep learning and Machine learning are used to detect objects. One of The Support Vector Machines (SVMs) methods in Machine learning is used to describe the features before the features are classified. However, the deep learning approach can detect targets without explicitly defining features. Convolutional Neural Network (CNNs) play a vital role in the deep learning approach. In the classification of images, CNNs have been extensively used. However, detecting an object in an image and drawing bounding boxes around it is challenging. The Region-based (R-CNN) algorithm was developed to solve this problem. R-CNN finds objects from an image by using a method called selective search. A large number of sections are generated and collectively processed using this algorithm. If these collections of regions contain any objects, the objects will be checked. An object's classification accuracy determines the success of this method. The objective of Selective Search is to localize objects by grouping regions based on the intensity of their pixels. Pixels are grouped accordingly based on hierarchical grouping. Farmer uses this technique to access the pest that can be seen, not hidden. An odor-based detection method is used here to detect hidden pests. This technology will eventually enable farmers to mitigate or prevent pests by detecting them at their earliest stages.

Early detection involves detecting symptomatic crops as early as possible, whereas screening involves checking healthy kernels for infestations before symptoms appear. Traditionally, the nose sends signals to the brain when odor molecules bind to receptors inside to detect smells. A gas sensor is used here to apply the same technique. Gaseous reactants heat a platinum coil in a catalytic gas sensor, increasing coil temperature. If the catalytic gas sensor detects a change in temperature in the hazardous range, the alarm will sound.

By using an odor-based object detection technique, more accuracy can be achieved, thereby helping to prevent pest infestation. Various methods exist to detect objects, including Fast CNN, YOLO, Faster CNN, Mask R-CNN, etc. However, all these methods require a whole lot of time to execute. While Faster R-CNN does a better job of modeling relatively to other models, it is time-consuming and would impair the performance. Therefore, a new algorithm was developed, R-SWFRN (Refined Speckle Warner based on Faster R-CNN), which mitigates the period consumption and provides accuracy by using Faster R-CNN. Three patterns are used to analyze the objects in the proposed work: i) Odor-based Recognition, ii) Classification of features, and iii) Detection and Counting.

Each task will have a pattern; every pattern will extract characteristics for classification. An odor-based detection method allows pests to be detected based on their foul odors, which is more reliable than earlier object detection methods since they are small pests that can blend into the field crops. Consequently, this odor-based detection method is efficient for identifying camouflaged pests. Several chemical combinations have been proven to identify the pest, including ammonia, which smells pungent like the pest. The feature classifier can also identify whether a pest has been transpired because previous methodologies isolated occurrences but did not indicate if an object transpired or a second object was present. The refined version of Faster R-CNN, known as R-SWFRN, is used for identifying features based on shape, size, color, and other characteristics. As a result of this automation, hidden objects can be identified to a greater extent. In addition to their physical characteristics, this process involves identifying pests. Currently, the process relies on manual labor and the human visual system. During the last twenty years, the process of identifying agricultural pests has evolved from manual classification to automatic grading. Today, several greenhouse cultivation companies use automated classification. It was designed to develop algorithms for image processing that can be used to automate pest identification using odors. According to the following structure, the work is divided into 4 sections. Section 2 discusses related work on Object detection and feature extraction. The proposed work is discussed in section 3. The results and discussion are contained in Section 4. This section concludes with the conclusions.

2. Related Work

A thorough literature review has been conducted toward correctly identifying the Pest-related problem. A diversity of approaches is investigated for implementing this current work. Accordingly, the analyzed literature has been bifurcated into 5 primary headings for comprehensive analysis. This classification will enable the study of literature in its context. Image processing is being used on the following agricultural products: Fukuyama et al. present a deep learning technique for odor identification. An ARNN embedding with an autoencoder is used in the deep learning model to visualize and deal with the six types of fragrance oils [2]. In their study, Chacko et al. evaluated how well data analytics and machine learning algorithms predicted the odorant composition of sweet and musky odorants [3]. Deep learning architectures with CNNs and prediction models were proposed by Sharma A et al., which could be used to classify smells and gain information about the relationship between chemical structure and preparation of smells [4]. A comprehensive study was conducted by Full et al. utilizing a customized methodology to identify the potential market for odor sensors. It is possible to compare and deduce biosensors' performance profiles and their suitability for different applications [5].

Recognition of pomegranate fruits in an orchard is the objective of this paper. Utilizing a k-means clustering algorithm, the image is segmented according to its color feature. The K-Means algorithm generates accurate segmentation results when applied to images with similar texture and color attributes. The pixels are clustered according to their color and spatial features before segmentation begins. Each cluster of blocks is then divided into a set of regions. It enables retrieving images. Hence this paper shows the imitative results obtained using the algorithm [6]. It is critical to consider lighting conditions, occlusions, and clustering to detect and localise objects accurately in an orchard environment. It discusses the various methods of detecting fruit in canopy vegetation and their pros and cons. Researchers have developed sensors and systems to geolocate fruit, and in the paper, they discuss the advantages and limitations of those devices and systems [7].

Yizhou et al. proposed an algorithm based on bionic olfactory theory, which detects odors with a sensor array and a machine learning algorithm. Using convolutional spiking neural networks, a novel odor recognition algorithm is proposed to detect food spoilage odors [8]. In this study, Borowik P et al. designed an e-nose with an optical sensor array to solve the problem of developing e-noses for specific applications and reduce development costs. This paper proposes a method for extracting and selecting E-nose modeling features to optimise E-nose performance. This study shows that the e-noses' ability to recognise odors can be improved using the information in the desorption curve. [9]. Danli Wu et al. projected a model for forecasting the pleasantness of an odor by using a convolutional neural network. In a study comparing pleasant and unpleasant odors, a convolutional neural network model performed better than one with manual feature extraction and achieved 99.9% accuracy [10]. Sheema et al. developed an innovative method to detect pests through odor substance analysis. Different types of smells were detected by five sensors, including pungent, misty, sweet, and musty. Even hidden pests could be identified with the help of this technique. A feature extraction process using Faster R-CNN was then added after the process was completed [11].

Withington et al., medical detection dogs sniffing biological samples have been studied using artificial neural networks to process pressure sensor data. Sample pots contained pressure sensors that collected information on how dogs searched for samples as they snorted [12]. The CNN-based algorithms both detect objects and segment them semantically. They can be applied to a variety of images, and one such example is radiation images. FCN and UNet are bifurcated into several branches, such as FCN and UNet, SSD, DeepLab, and YOLO V5. These branches represent specific applications in various areas of medical image analysis [13]. Two prevalent architectures were compared. The R-CNN, built on

Inception V2 and the Single Shot Multibox Detector (SSD), built on MobileNet. Video-based counting based on Gaussian estimation is made easier using a multi-object tracking approach [14]. Real-time detection of crop diseases in videos is achieved using a deep learning-based detection architecture and a custom backbone. A video frame is created by converting a still image into a video frame; then, the video frame is detected by an image detector and created by the video synthesizer. The still-image sensor is based on a faster-RCNN framework [15].

Using gas sensors with different smells, odor-based detection has been applied to identify the fruits or food in the above study. A new algorithm is formulated to identify the bad-smelling pest using this methodology with just a few modifications.

3. R-SWFRN (Refined – Speckle Warner based on Faster R-CNN)

Agricultural products should be updated with new technology to improve their quality and quantity. In India, maize is a major cereal crop. Many Indians depend on it for their staple food. Farmers in developing countries, many of whom lack resources, are highly dependent on maize as their main source of income. The farmers lose their economy due to pests. They often spray excessive amounts of chemicals to repel pests. Pest infestations can be lessened with the sprays. Algorithms based on deep learning are used to resolve this issue. A wide range of objects and things can be detected using deep learning and the Internet of Things (IoT). Object detection is used to identify objects in deep learning accurately. Tracing objects from images is the primary objective of the method. In the future, this technology may allow farmers to thwart, mitigate, or prevent pests at their earliest stage of development. Also, it is possible to increase object detection accuracy using an odor-based technique, thereby preventing pest infestation. This approach to image processing is non-invasive, reliable, time-efficient, and cost-effective.

Fig. 1 shows a block diagram representing a generalized approach to defects and pest detection. It consists of various levels, such as image classification, image segmentation, preprocessing, and extraction of features. It has been used to extract the exact features. Image files can be converted into understandable formats through pre-processing within the database. Segmenting an image involves defining small areas on the image that should not be divided. Seeds or areas are these regions, and their position on a tile defines that tile. Feature extraction networks use input images, and neural networks use the extracted features for classification.

Several issues and factors must be considered while developing a system for defect detection and tracking pests using image analysis.

3.1. A Faster R-CNN-based Odor-based detection method using R-SWFRN

Deep learning techniques are used to execute many amazing tasks by neural networks. Nowadays, deep learning can perform extremely complex tasks automatically. In deep learning, the next step is a sensory olfaction simulation, also known as E-Nose, which uses a device to give a sense of smell. But most Indian farmers are relatively average and poor in economics, so this device will not suit them, as the exterior work will be too costly in this country. Consequently, the tracking of pests using the odor functionality of pests was developed as a conceptual process.

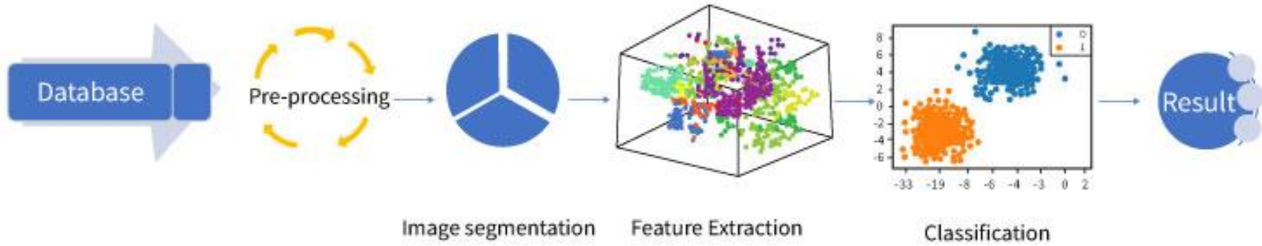


Fig. 1 A generalized block diagram for the detection of pest

A new method is based on Faster R-CNN called Refined Speckle Warner. It was specially developed to identify FAW (Fall Army Worm). At any stage, this pest feeds on maize and spreads rapidly.

Pesticides, poisonous food, and Traps were used for hunting down pests in the olden days of pest control, but these methods could harm domestic animals and humans. Frequent monitoring is essential to solving this problem. Implementing the proper techniques will assist in getting rid of an infestation of pests. An ensemble learning method is implemented here to identify the pest using odor-based methods properly. Object detection can usually detect only visible objects, not camouflaged ones. Even in dense areas, it will be easier to locate the hidden object using these techniques. Pests emit a foul odor from the early stages of growth, a pungent odor. In this method, it is possible to identify pests even from small, twirled leaves, and it is possible to inform the exact location of the pest at regular intervals. In this case, the gas sensors identify the smell using the chemical formula. The digital analysis was conducted on five chemical combinations, which included pungent, sweet, stingy, perfume, and smoke. Thermal cameras and gas sensors detect thermal images of gas and gas concentrations. A method for extracting pests is depicted in Figure 2. a. It shows how pests are identified according to their smell and b. It shows how Odor can be employed to extract features from thermal camera images. It depicts the pest according to the concentration level and the five sensors that measure infrared light. The steps are given in Figure 3 that illustrate data collection and the process of training the data.

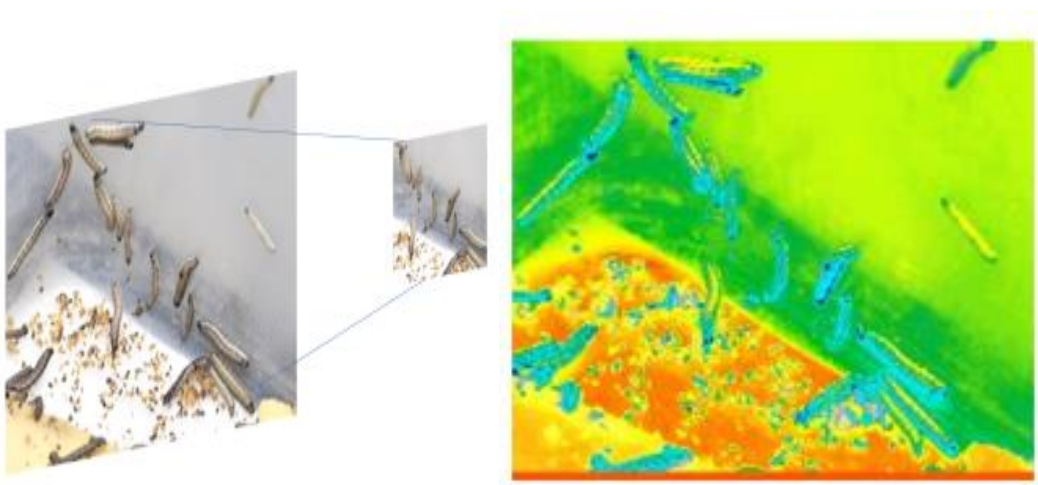


Fig. 2 Detection of Pest a. Classification of Feature and Extraction b. Thermal Image

The methodology helps to illustrate the appearance, shape, and texture of RGB images will be shown. It is possible to view up to 60 degrees with the thermal camera. By computing gas concentration, the sensor can extract the features of compactness, speed, and long-term serviceability. During the process, data will be pulled from the storage, and a prediction will be made. A mathematical formula can be used to compute the chemical substance concentration.

$$f(ax) = \frac{ax_0 + ax_1}{ax_0}$$

In the example, an odorous sample would be represented by f(ax), and an odor-free sample would reach the odor threshold in odor units per cubic meter (ou/m3).

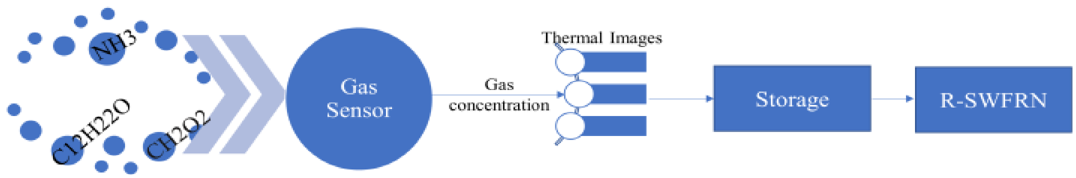


Fig. 3 The training process for data

Pseudocode for identification of Odor Occurrences

```
Begin
        Input con
        if con==high | medium
            oc = ob+ob1/ob
             output "object Found"
        else
            oc=0
            output "No Object Found"
End
```

3.1.1. Acquisition of Thermal Image

Pests were placed at a 50 cm distance to simulate farmland at a known location in the test area, as shown in Fig. 2(a). A thermal camera is used to acquire images of the pest object (ThermaCAM-T420 by FLIR, Wilsonville, OR, USA). It measures wavelengths between 7.5 m and 13 m and can measure temperatures between 20 ºC and 650 ºC with a precision of 2% and sensitivity of 0.05 ºC. This current work constructed an extensive thermal image set with 1000 thermal images with and without pest objects. Fig. 4(a) illustrates the thermal image with marking. Color changes indicate temperature variations. Because the odor-based pest object is more heat-carrying than the surrounding area, the marked regions show a greater temperature in blue than the surrounding area. During grayscale conversion, pixel color information is removed, leaving only luminance information.

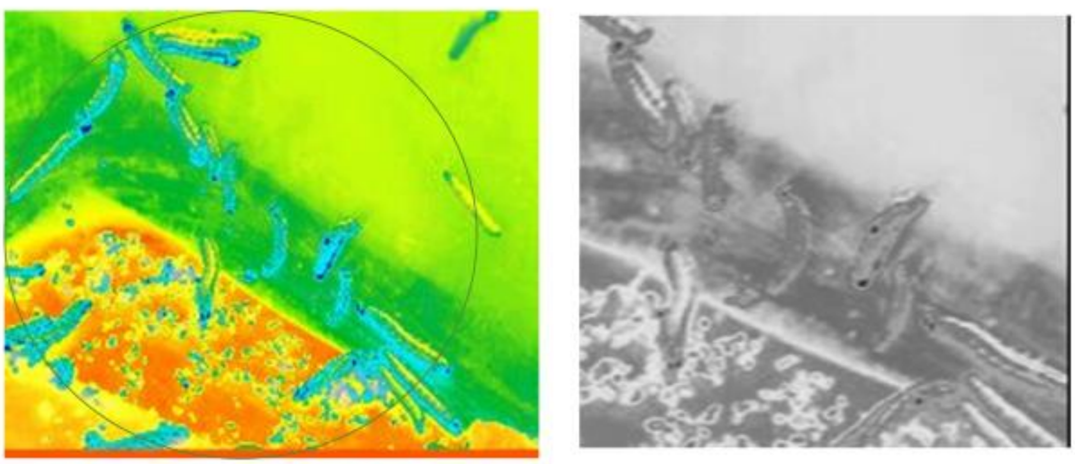
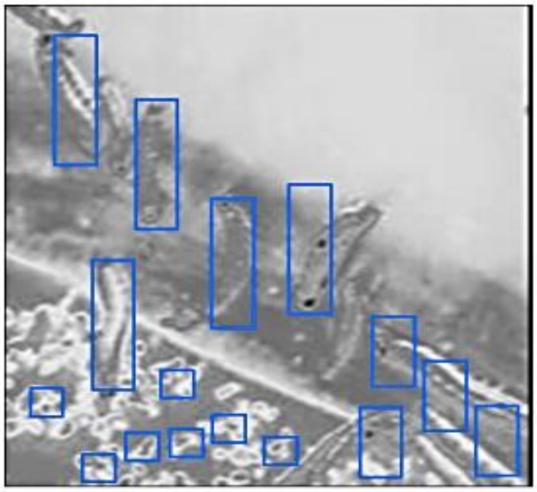


Fig. 4 a) Thermal image with Marking Fig. 4 b) Gray Scale Image

3.1.2. Pest Detection using Grayscale Images and Thresholding

When the grayscale image of the pest object is thresholded using a grayscale image processing method, it can be distinguished from the background image based on the intensity variation in the grayscale image, as shown in Figure 4 (b). Using the non-max suppression, the bounding box is generated as shown in Figure 4(c) It is used in these object detection algorithms to select the most precise bounding box from a set of multiple predicted bounding boxes by applying the Non-max suppression algorithm. When using this technique, only the most likely bounding boxes are retained, and the less likely ones are suppressed. Figure 4(d) demonstrates how to determine the maximum and minimum temperatures of a region in a thermal image and how to set the threshold based on the mean temperature. It also compared the level of density based on the gas concentration for three parameters: FAW (Pest), Leaf, and Corn. Thermal images are classified into foreground and background parts by dividing pixel values by a threshold so that objects can be detected in the foreground.



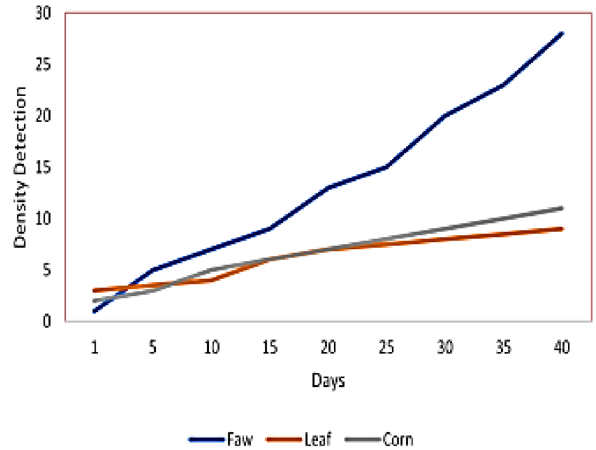


Fig. 4 c) Pest object with Fig. 4 d) Ammonia gas concentration the bounding box for different parameters

Fig. 4 Thermal Image Processing for Object Detection using Grayscale

Pseudocode to convert Grayscale

Begin

```
    Input img
    Img= read file
    Imggray= call color.rgb2gray(img)
end
```

3.2. Classification of Features

According to a previous analysis, pests are small objects that can camouflage within the crops. Therefore, the Faster R-CNN model is insufficient to identify the pest in maize fields. Faster R-CNN has the main drawback of training 256 sizes of anchors mined from a solitary image, so it takes a long time for the network to converge. Faster R-CNN is improved in this complex view to detect pests at any process stage. Using R-SWFRN, the number of feature maps increases through feature fusion, which reduces computation time and speeds up processing. In this case, the boundaries of each box are also suppressed using non-Max suppression. Using this technique, it is easier to extract images with the supported parameters such as shape, Colour and size. The following steps illustrate the steps of the Refined-SWFRN network.

Steps of the R-SWFRN Process

Step 1: Extraction of the thermal image
Step 2: Perform Preprocessing
Step 3: Using CNN, extract the features of the image
Step 4: Using the Region Proposal Network, the foreground (featured) areas are extracted from the image.
Step 5: Reduction of background noise
Step 6: The conversion of Region on Interest Pooling occurs from variable vectors to fixed vectors.
Step 6: Each cell will be assigned a class based on the pool.
Step 7: In non-max suppression, detection overlaps are eliminated
Step 8: Classify the objects to generate bounding boxes
Step 9: Parameters (Color, Shape, Size) are used to detect the object.

4. Results and Discussion

To locate the pest objects, Python's computation environment searches the area of interest in the image to determine their location. A Windows 10 computer is used for training using an Intel Core i5-8265U CPU @1.6GHz 1.8GHz, 8GB RAM, and labeled data sets of selected regions over time. Validation and testing are conducted using pre-trained data sets. This section's results demonstrate the proposed Refined SWFRN to predict areas of a bounding box that can detect a pest based on a gas concentration in a thermal image.

4.1. Refined SWFRN Counting and Detection

To reduce labour-intensive manual measurements of phenotypic data, detecting and counting crop pests using images and computer vision is critical for advancing automation. A neural network model is proposed and trained based on labeled images and the bounding box of the proposed region. A neural network is trained using 70% of the dataset, and the hyperparameters are optimized using 30% of the dataset. The following figure illustrates the neural network's loss function for a given number of training data sets. Increasing the number of training samples reduces the magnitude of the loss function.

The bounding box predicts the object based on the trained R-SWFRN. To train the proposed R- SWFRN for objects with shapes, as indicated in Figure 4(c). A 90% accuracy rate for detecting and classifying pest objects in bounding boxes has been found. By updating the neurons' weights during the neural network training, more accurate predictions for pest objects can be made in thermal images. Thermal images show that Refined SWFRN can identify pest objects of various shapes and sizes. Implementing the proposed approach for detecting surface farms is feasible by using a gas sensor by thermal vision.

4.2. Performance Matrix

The precision, accuracy, F1 scores, and recall of Faster R-CNN and R-SWFRN are calculated with different backbone networks in Tables 2 and 3.

$$\text{Precision} = \frac{T_{Pv}+T_{Nv}}{T_{Pv}+T_{Nv}+F_{Pv}+F_{Nv}}\ x\ 100\% \quad \text{--------------} (1)$$

$$\text{Recall} = \frac{T_{Pv}}{T_{Pv}+T_{Nv}}\ x\ 100\% \quad \text{--------------} (2)$$

$$\text{F1 Score} = 2\ x\ \frac{\text{Precision x Recall}}{\text{Precision + Recall}} \quad \text{--------------} (3)$$

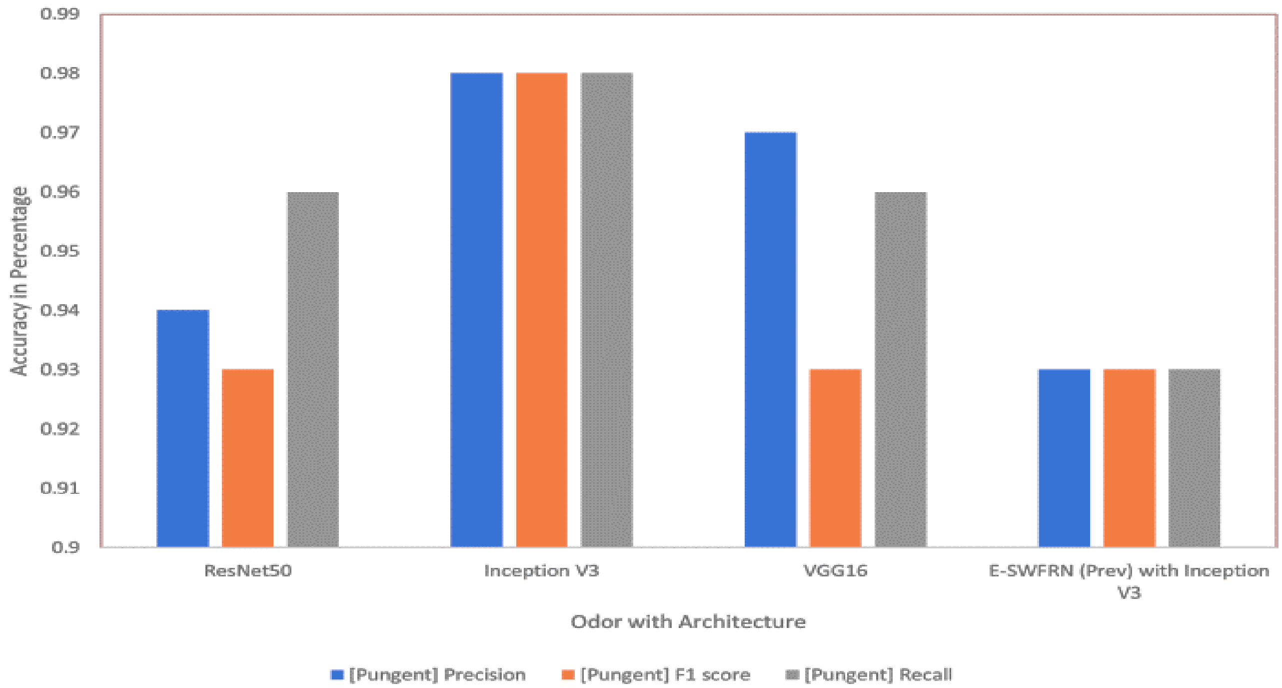
Table 1. Detailed Detection results based on counting at a different angle

Backbone/Architectures	Number of parameters		FAW on the edge
	Perfect	Imperfect	
Faster RCNN VGG16	98	5	3
R-SWFRN **VGG16**	**101**	**3**	**5**
Faster RCNN ResNet50	98	4	4
R-SWFRN **ResNet50**	**100**	**4**	**6**
Faster RCNN InceptionV3	99	6	5
R-SWFRN InceptionV3	**105**	**3**	**8**

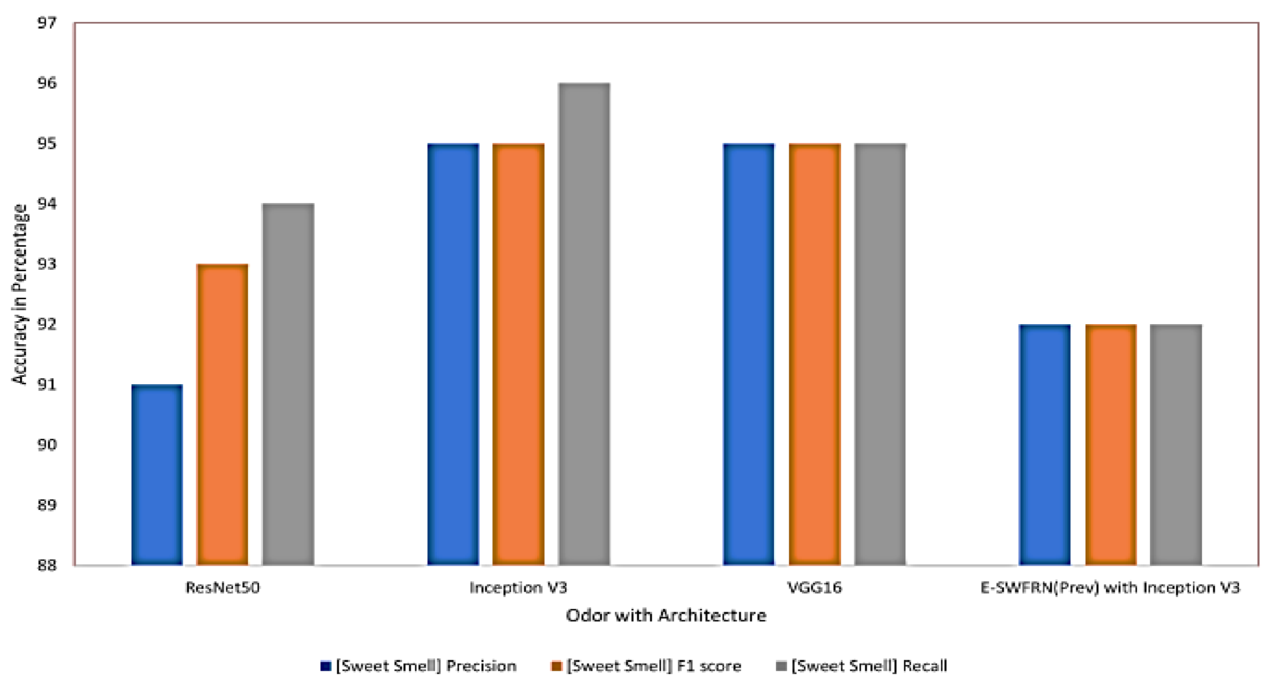
Table 2. Detection results for the different backbones for each Odor with the Previous Model

			E-SWFRN			**Refined-SWFRN**	
Odor	Backbone/Architectures	AP	F1 score	Recall	AP	F1 score	Recall
No gas	ResNet50	98	99	99	1	1	1
	Inception V3	98	98	98	1	1	1
	VGG16	99	99	99	1	1	1
Pungent	ResNet50	90	91	92	94	93	96
	Inception V3	93	93	93	98	98	98
	VGG16	88	90	89	97	93	96
Sweet Smell	ResNet50	91	92	0.9	91	93	94
	Inception V3	92	92	92	97	98	98
	VGG16	93	94	93	95	95	95
Misty	ResNet50	95	95	95	96	95	95
	Inception V3	94	94	94	97	97	96
	VGG16	93	94	94	96	96	96

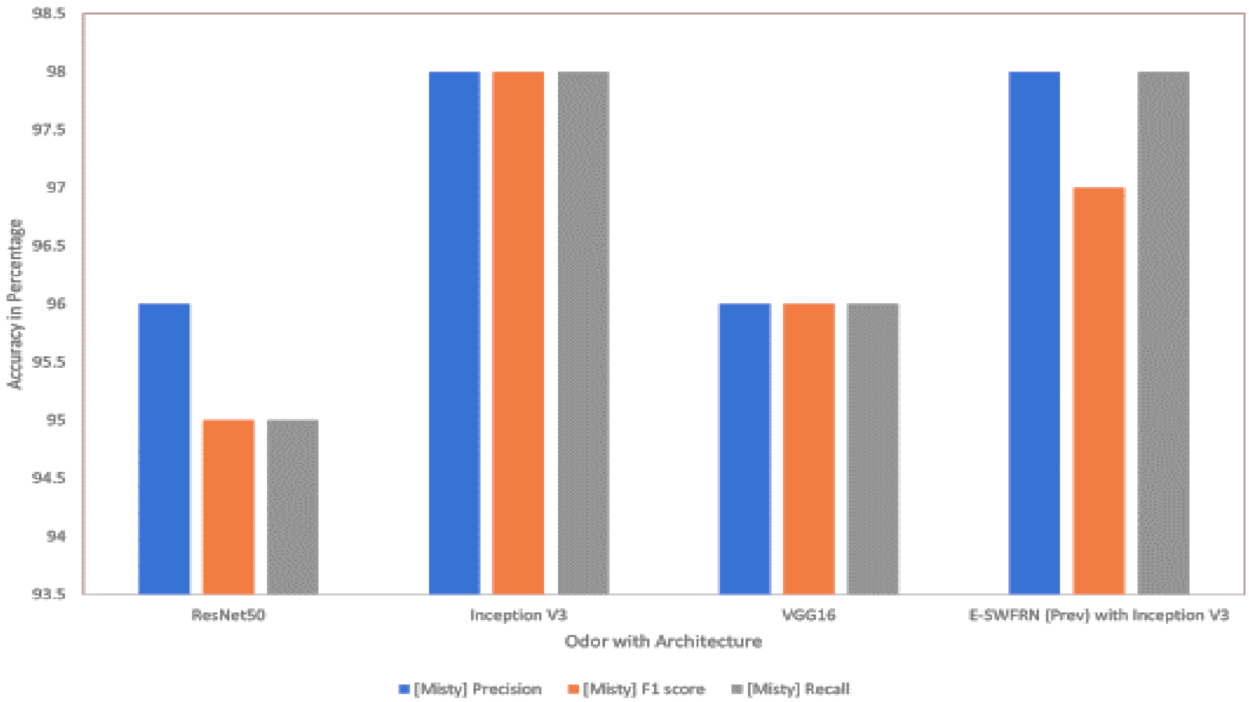
True Positive (TPv), True Negative (TNv), False Positive (FPv), and False Negative (FNv) describe objects that are predicted to be true or false, respectively. Table 1 shows various backbones' parameters, training time, and inference time. Detection results for the different Odor of Existing and proposed values are shown in Table 2. The graphical representations are shown in Figures 5 and 6 of Faster R-CNN and R-SWFRN, illustrating the accuracy performance metrics.



(a) R-SWFRN for Pungent Gas



(b) R-SWFRN for Sweet Smell Gas



(c) R-SWFRN for Misty Gas

Fig. 5 (a), (b) and (c) are Accuracy Comparison for different Odor with Architectures for R-SWRFN with Previous Model E-SWFRN

A graphical representation of the accuracy and precision with decreased time delay is displayed in the following figures, which describe the existing algorithm performance with R-SWFRN. The accuracy and timing of previous work with Faster R-CNN, SWFRN [16], E-SWFRN [17], and R-SWFRN are shown in Figures 6 and 7, respectively. An overall prediction was made.

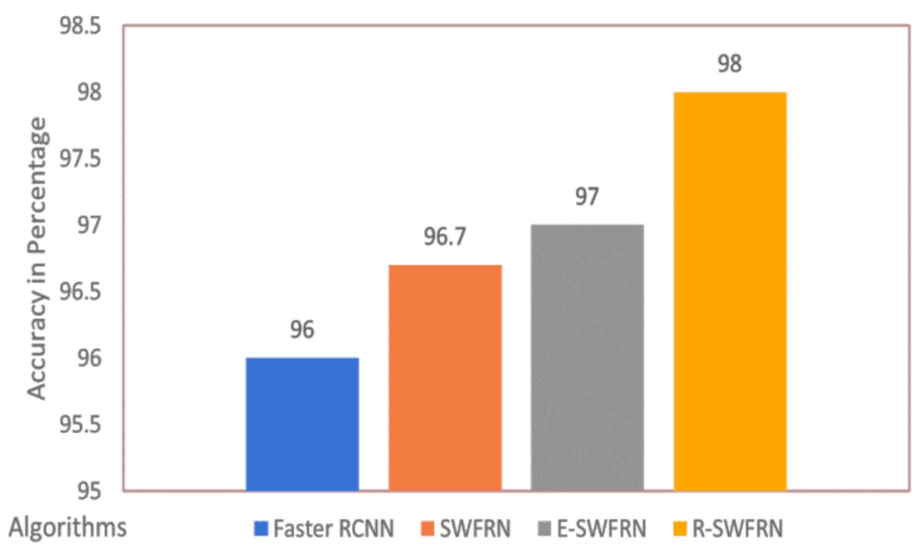


Fig. 6 R-SWFRN compared with the previous algorithm in terms of accuracy

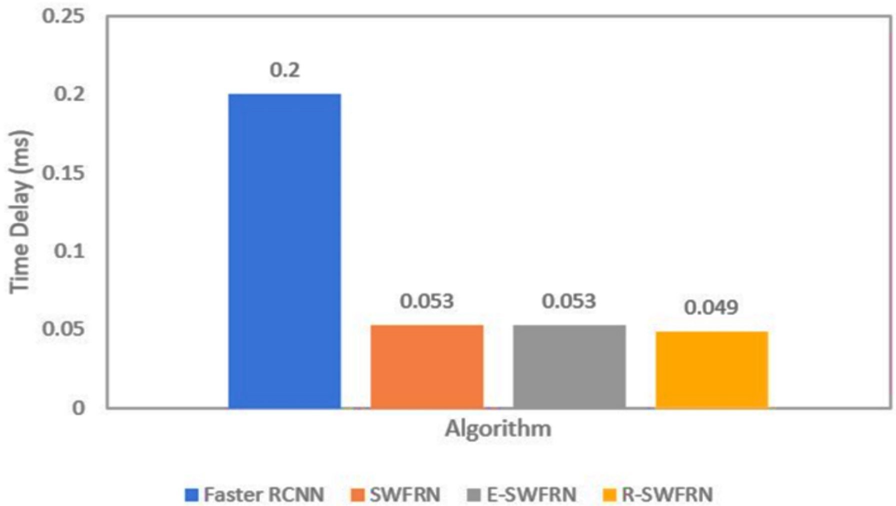


Fig. 7 R-SWFRN compared with Previous Algorithmin in terms of Time delay

5. Conclusion

The largest industry in the world is agriculture. More than one billion people are employed in it, producing more than $1.3 trillion worth of food every year. Agriculture is essential for human life, as it provides us with necessities like food to sustain us. Due to crop pests, the Indian economy is slowing down as it gets more revenue from agriculture. With this method, agriculture productivity will be improved, and the spread of pests will be reduced. An automated system for detecting pest infestations based on Odor has been developed. Using this system, infestations can be prevented at an early stage. Automating the processes of identifying and counting insects in plants using images and computer vision is critical for reducing labor-intensive manual measurements and improving productivity. With R-SWFRN, the speed and accuracy can be improved by 6% compared to the previous model with Faster R-CNN. The model achieved 98% accuracy with a time delay of 0.049 fps. Despite the differences in pest sizes, Inception V3 can access different filters simultaneously. The findings of this study encourage further enhancements to Inception V3 architecture.

Conflicts of Interest

This manuscript has not been submitted to, nor is it under review at, another journal or other publishing venue.

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