SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V9I12P116

Volume 9 Issue 12, 180-188, December 2022

Original Article

The Detection and Identification of Pest-FAW Infestation in Maize Crops Using Iot-Based Deep-Learning Algorithms

D. Sheema[1], K. Ramesh[2], V. K. Reshma[3], R. Surendiran[4]

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

[1]*Corresponding Author : sheemawilson20@gmail.com*

Received: 27 October 2022 Revised: 30 November 2022 Accepted: 15 December 2022 Published: 25 December 2022

Abstract - *In today's world, technology plays an integral role in addressing everyday challenges. Using technology in agriculture allows farmers to increase productivity while managing natural resources. Agriculture has always been plagued by pests, which destroy parts of the crops or even the whole field. Pest control at an early stage of crop development is a challenge for farmers. It eventually has a negative impact on the economy. By examining the odour substance of pests, a novel way to analyze pests is presented in this study. There is a distinct smell associated with every pest. Since odour can identify concealed pests, including deeply buried pests, swirled pests, etc., it is easier to detect than other detection methodologies. In light of this, based on odour as a key consideration, the proposed system evaluates five different odours, such as pungent, musty, misty, and sweet. In this case, gas sensors are analyzed, and then features are extracted using a Faster R-CNN algorithm. Additionally, it can be used to determine the density of infestations and counting. It is possible to develop process accuracy and timeliness using pseudocode. Comparatively, accuracy increased to 6% from Faster R CNN-based pest detection. Samples of the proposed development have been tested for performance metrics.*

Keywords - *Pest detection, Odour detection, Deep learning detection, IoT.*

1. Introduction

Agriculture has changed dramatically over the past 60 years. New advances in machinery have led to more efficient farming equipment, which has resulted in a higher yield. A new agricultural revolution is underway, centered on data, information and connectivity. The benefits of artificial intelligence, analytics, and connected sensors, among other emerging technologies, can lead to further yield increases. India is a land famous for food production. It provides sustenance for a large percentage of the population. Maize is one of the main crops that farmers rely on for their livelihood in the present day. During the past decade, India has become the sixth-largest exporter of maize. It can be grown in a wide variety of climatic conditions in India, and it requires less water than other crops. Unfortunately, pests cause farmers to lose their income. Farmers often use excessive chemical sprays to repel pests. Infestations of pests will be controlled with these sprays. However, animals and humans might be adversely affected. In maize, four pests have been detected, including shoot flies, fall armyworms, spotted stem borers, and pink stem borers. Fall armyworms (FAW) are the most dangerous type of infestation. Their larvae can destroy maize throughout its growth cycle.

IoT involves robots, drones, remote sensors, cameras, and deep learning techniques, combined with machine learning to sort out the problem effectively. Crop monitoring and mapping tools provide data for farmers to make rational farming decisions and save time. Object detection is used by deep learning for accurate object identification. The technique intends to trace objects from images precisely. This methodology will allow farmers to sense pests and mitigate or prevent them at the earliest stage. Utilizing images and computer vision is crucial for identifying and counting insects in plants. The goal behind this method is to reduce labor-intensive manual measurements while also increasing productivity. Here, algorithms were developed to identify pests automatically based on odour detection using image processing algorithms.

2. Review of Literature

The present work investigates a variety of approaches for its implementation. An acoustic sensor integrated into a wireless network architecture which enables detection of ultrasound from pests in the field (Ahouandjinou et.al 2017), Deep learning to detect and classify pests of various classes on a large scale (liu, et al. 2019), Internet of Things-based early cautionary technology for crop diseases and insect pests (wang, et.al 2013), A prediction model based on an iot system is identified and can be used to predict plantation disease outbreaks (Materne et.al 2018), a model for predicting odor's appeal by using CNN (wu, danli, et al 2019), Convolutional LSTM and regression algorithms are used to predict odor descriptor ratings via e-nose indications, which has multiple sibling neural networks (Guo, Juan, et al 2021), a smoke detection algorithm for mobile platforms based on image analysis (Wang et.al 2022), An image is analyzed for the presence of rotten fruits and vegetables (Jana et.al 2021), food spoilage odor identification by deep learning based on convolutional spiking neural network (Xiong et. Al2021), An automation system to detects the shortage of food items (nadar, neethu, et al 2021), Deep neural networks (DNN) are trained with physiochemical properties and molecular fingerprints (PPMF) while convolution neural networks (CNN) are trained with chemical-structure images (img), The smiles notation is used to forecast the smells of chemicals (sharma, anju, et al 2021), Deep learning-based detection of pests and diseases of plants using three aspects: classification, detection, and segmentation (liu et.al 2021), Implementation of improved Faster R-cnn for multiclass fruit detection (wan et.al 2020), Artificial vision and sensing techniques to address fruit counting (Vasconez, juan pablo, et al 2020), An odor sensor platform based on cells (Full, Johannes, et al 2020), Machine learning methods for developing odor perception models based on odorant characters (OC) such as sweet and musky (chacko, rinu, et al 2020).

3. Research Methodology

3.1. Pest Detection Analysis Based on a Faster RCNN Algorithm

A method of detecting objects in images or videos is called object detection. Object detection algorithms employ machine learning and deep learning to produce accurate results. Using object detection, we can progress computational models that deliver the most basic information that computer vision applications need: "Where are the objects?". The object detection and tracking methods are the foundation for various downstream computer vision tasks, including image captioning, instance segmentation, and object tracking. In current years, deep learning techniques have greatly increased the speed of object detection. Deep Learning uses Convolutional Neural Networks and CNNs as categories of artificial neural networks to recognize and classify images and objects. Deep Learning uses a CNN to identify objects in an image. By combining deep learning networks and GPU computing power, object detectors and trackers have achieved significant advancements in object detection. Several algorithms perform object detections in deep learning, among that Faster R-CNN provides better accuracy than other models.

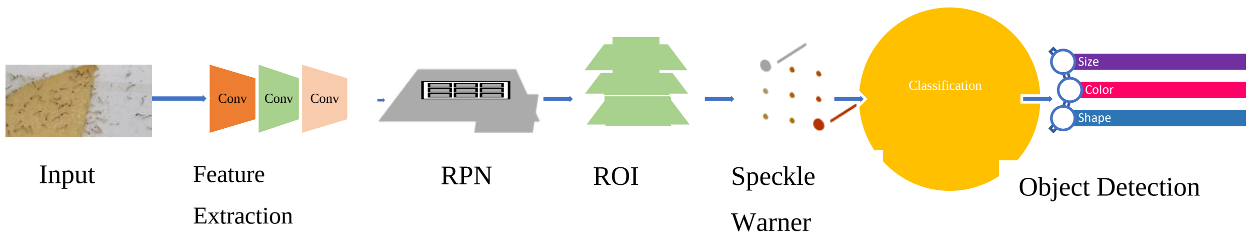


Fig. 1 Architecture of Proposed System

Pests are often detected with object detection techniques; computer vision techniques provide an effective way of analyzing leaf images. Here, three methods have been applied to detect the pest in an image, such as image acquisition, image pre-processing and Feature Extraction, but identification alone is not sufficient. A marked image must also indicate the location, size, and extent of the infection. Hence developed new algorithm Spackle Warner based on Faster R-CNN (SWFRN), is shown in Figure 1. In this algorithm, Convolutional layers are used to extract images' features, and the objects are detected using the Region Proposal Network (RPN). The convolutional and pooling layers are optimized using two loss functions. Several parameters can be automatically adjusted based on the shooting angle, ensuring that each convolutional layer and kernel parameter are within a reasonable range. Loss functions in convolutional layers are as follows:

$$L_f(kl, x^{kv}) = \frac{1}{2\,dn}[\Sigma_{i=1}^{dn}\left(ac - kl * x_{ik}^2\ +\ \lambda\Sigma_{j=1}^{dq}\, w_j^2\right)]$$

The kernel parameters are kl = [kω1, kω2, . . . , kωn] ^{T}, dq is the number of the kernels, multiplication of convolution is *, x $^{(kv)}$ = [x_{1k}, x_{2k}, . . . , x_{mk}] T is the kvth input, database dimension is dm, ac is the actual label of the kvth sample, and regularization penalty factor is λ. Two functions are used in the proposed loss function: a regularization function and a likelihood function. These two functions produce outputs that are identical to their inputs. The pooling layer has the following loss function:

$$L_p(kl, x^{kv}) = \frac{1}{2\,dn}[\Sigma_{i=1}^{dn}\left(ac - pp * x_{ik}^2\ +\ \lambda\Sigma_{j=1}^{dq}\, \mu_j^2\ \right)]$$

The first expression shows the reconstruction loss, whereas the second represents the model complexity. The pooling parameters are pp = [µ1, µ2, . . ., µt], whereas the total number of the parameters represents t. λ Usually depends on expert knowledge and testing results. A convolutional feature map can represent each inspection image. Here, The ROI (Region of Interest) was used to shorten the feature map and reduce it to its actual size; then, if an object is present from the target, the ROI is indicated, and it is classified built on three features such as colour, size, and shape of the object. This model produced good accuracy at the perfect time.

3.2. Pest Analysis Using an Odor Based on an Improved Algorithm

According to previous entomology studies, the pest FAW will emit a foul smell from its initial development. Based on ensemble learning, a new model for detecting the pest was proposed based on odor substances. An artificial neural network is used to learn patterns through deep learning. Several problems can be solved without the need for human intervention using it. Sense of odour simulation, also called Machine olfaction, is a remarkable feature of deep learning. Other names for this process include Electronic Nose or E-Nose. There are very few top-notch Indian farmers able to devote more money to external work, but most of them are middle-class. As a result, they developed a concept called POT (Pest odour Tracking) based on Deep Neural Networks to increase their growth. In this work, gas sensors are combined with a thermal camera for the detection of gas absorptions and the imaging of the gas thermal images using improved Faster R-CNN.

3.2.1. Gas Sensor

Detecting the presence of gas involves converting chemical combinational information into electrical information and emitting warning indications in audio or video when hazardous gas levels are present. In addition to detecting and identifying different kinds of gasses, like noxious and combustible, the sensor can also measure gas concentrations. With the support of a gas sensor, this work aims to develop a new model for detecting ammonia odour in pests. According to the study, FAW releases an obscene smell, like a pungent odour. This odour is also called ammonia (NH3), which is pungent. The model used chemical combinations to detect Faw. By using this model, farmers can protect crops from this pest. The location of the pest has been determined by using five-strong odours, including pungent, sweet smell, sting, perfume, and smoke, to detect other pests as well.

Some of the features of the gas sensor which is compact, fast, and long-lasting. Sensors can determine gas concentrations based on analogue output voltages. The following gases are listed as sensors for pungent, sweet, and musty odours; grease/oily and misty odours.

Table 1. The chemical name and molecule formula for the odour of a pest

Odour	Compound Name	Chemical Formula
Pungent	Ammonia	NH3
Sweet Smell	Methyl acetate	NH3
Sting	Formic acid	HCOOH
Musty	Bi-cyclic Alcohol	$C_2H_{22}O$
Grease/Oily	Ammonia	NH3
Minty	P-anisaldehyde	$C_8H_8O_2$

3.3. Thermal Image

Thermal cameras measure temperature using infrared light. Using pixels, every point's temperature is determined at the same time. The images are displayed in RGB format based on the temperature. The application is compatible with all types of environments regardless of their presence, form, and texture. The thermal camera allows us to view about 36 degrees, the temperature range varies from 40^{O}C to 330^{O}C, the frame rate is <9Hz, and the pixels are 32,136. A thermal camera and five sensors were used to collect data for training and validation. In the proposed model, the gas sequence data is retrieved from storage and checked to see if the given gas sequence is the same as the trained sequence. The process calculates the filtration only if yes is selected and does not check if no is selected. Using a gas sensor array and thermal images, improved Faster R- CNN can detect objects more accurately. The following algorithm uses the Inception V3 architecture to extract the features.

Pseudocode for Proposed R_SWFRN Algorithm

```
Begin
    initialize img into ai
        Set store into nw
        Read ai==nw then
        Fx=x0+x1/x0 (1)
        Print "Obj Detected"
        Encode other targets (2)
        if ai >= pxlrs
            Add ai into the object found
        end if
        for
        set ai= ai divided by 9
        ai++
        store i to segvalue
        segvalue into spackle warner (sw)
        calculate with pixel resolution to find the
        position
        store position value (top, middle, bottom)
        to speckle warner
    calculate values speckle warner
    high columns set image found set to value 1 to yes
    if the value is yes
    calculate (size, shape, colour)
    else
    print "no object found"
    end if
End
```

Table 2. Experimental results of mean accuracy precision (map) in percentage for the detection of pests for both day and night

Objects\	Pest		Leaf		Corn	
Algorithms	Day	Night	Day	Night	Day	Night
Faster R-CNN with Inception_V3	70	72.3	78	73.3	81.2	76.3
Faster R-CNN _ResNet	69.9	58.6	62.54	74.56	70.4	83.4
Faster R-CNN _VGG 16	70.4	70.2	79.9	75.5	80.7	79.4
Proposed with Inception_V3	82.5	83.1	89	81.1	85.6	88.2
Proposed with _ResNet	72.4	79.2	79.4	76.8	78.8	80.2
Proposed with _VGG 16	82	82.1	88.2	80.4	83.5	82.6

Foregrounds and backgrounds can be categorized based on their features. High-resolution values are called foreground classes, while low-resolution values are called background classes. Four parameters were used to extract the position value: top, bottom, width, and height. The process can confirm that the object exists by analyzing the size, shape, and colour of the pixels.

A Concentration estimation model is also evaluated by calculating the mean square prediction error (MSPE), which helps to find out unobserved data.

$$Mean\ square\ \ prediction\ error = \frac{1}{\mathrm{M}_2}\sum_{i=1}^{\mathrm{M}_2}\left(\mathrm{Y_i}^{\ te} - \mathrm{T_i}^{\ te}\right)^n X\ 100$$

To understand the concentrations of gases, a thermal camera provides the images. The name of the odour, as well as its compound name and molecular/chemical formula, are provided in table 1 for further formulation efforts.

3.4. Pest Analysis in Image on Both Day and Night

Pests will usually destroy plants during the tertiary stage, when they are plump, green, garden-fresh, etc. However, this kind of pest can eat plants at any stage. Detection of this pest should be precise because it has four stages, from eggs to moths, so that the size may differ. Intersection over Union (IoU) is used to detect objects more accurately and is also known as an evaluation metric.

The custom dataset is implemented to measure IoU (Intersection over Union) and NMS (Non-Max Suppression) to measure the effective object detection accuracy. Pest detection was analyzed for both day and night time scenarios. For this study, the proposed algorithm and the Faster R-CNN algorithm were applied to thermal camera images, and the VGG16, ResNet, and InceptionV3 architectures of CNN were tested for their performance. Three architectural methods are compared to identify the object detection result. The Inception V3 method is the most reliable, and it is fast. The camera achieves a perfect accuracy rate of 8.96% during the day and 10.17% at night at approximately 3 frames per second.

3.5. Pest Detection and Counting

Object counting in images is a primary function of computer vision. Computer vision algorithms face a challenge when attempting to count objects, especially when different instances' shape, colour, texture, and size vary significantly. Digital image processing is currently performed using deep learning methods. The annotation of large amounts of data can be tedious and prone to error, making these studies time-consuming. In deep learning, counting objects is typically done by detecting them first using convolutional neural networks and then counting any instances found. Despite being effective, this method requires annotations; therefore, it is trained on data with point-like annotations instead of bounding boxes. A fixed filter size of 3*3 is used with three downsamplings, and three upsampling in the convolutional blocks are implemented to process the data more quickly (image) by reducing its dimensionality.

4. Result and Discussions

4.1. Analysis of Pests Based on a Faster RCNN Algorithm

To novelty the best algorithm for generating accuracy as well as reducing time interruption, major object detection algorithms were compared. Using the new technique SWFRN, time delays can be avoided. Various object detection methods have been compared using mean average precision (mAP) to afford an average precision.

Table 3. Accuracy comparison of prediction models

Algorithm	mAP	FPS	Dataset
SSD	78.09	3	2567
Faster R-CNN	95.02	0.2	2567
R-FCN	85.50	1	2567
SWFRN	**96.98**	**0.053**	**2567**

4.2. Analysis of Pests Based on Odor Detection

TensorFlow and Python 3 are used to implement the proposed model. Five chemical values can be used to identify the pest locations. Model performance is measured by Accuracy (A), Precision (P), Recall (R), and F1 scores (F1). Ground truth and false objects are predicted with this method.

4.3. Analysis in Image on Both Day and Night

Day and night images were captured for the parameters of the pest, leaf, and corn. The Inception V3 model has exhibited better performance, leading to better detection performance and reduced computational complexity. Experimental results are expressed as percentages based on mean average precision (mAP), recall, F1 score, and IoU.

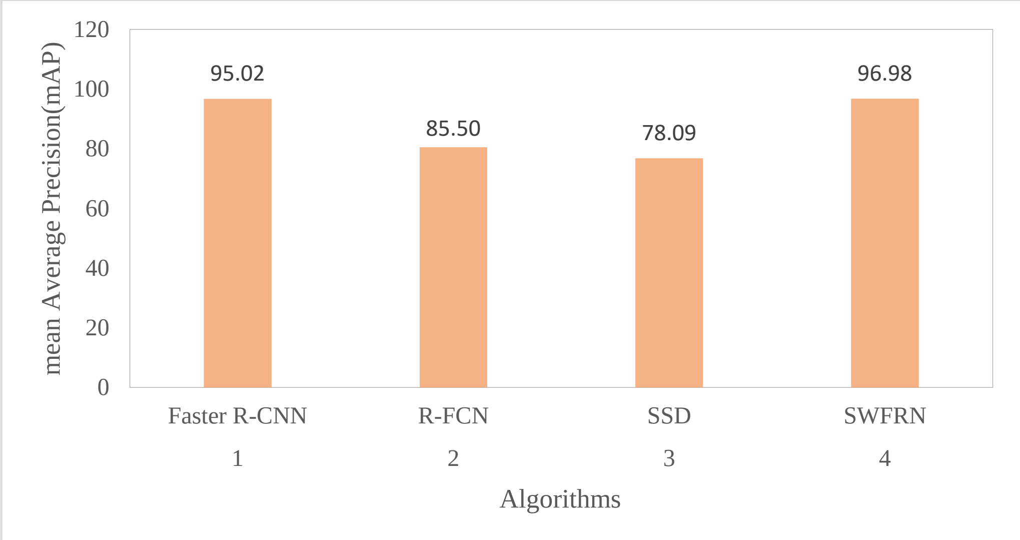


Fig. 2 Comparing SWFRN's Accuracy to Other Algorithms

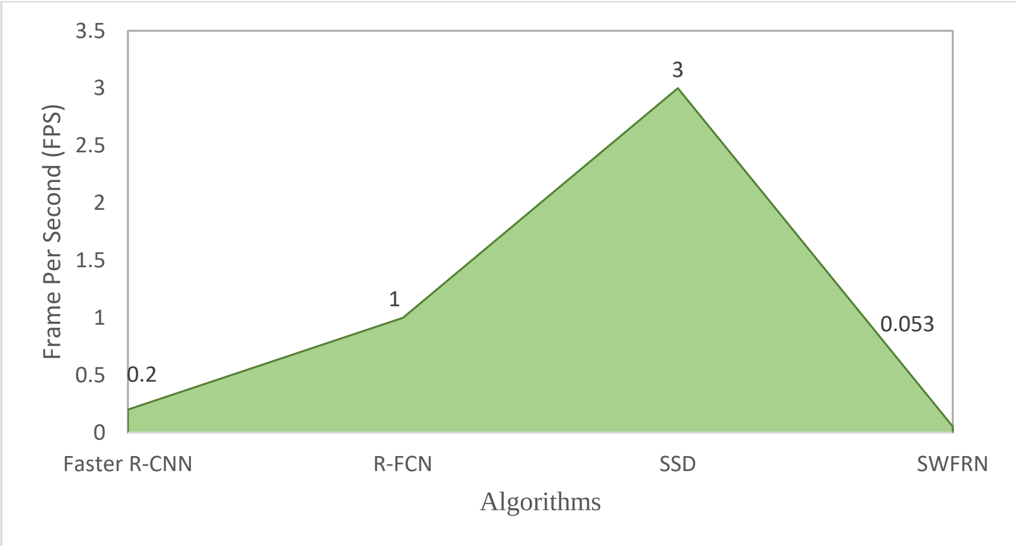
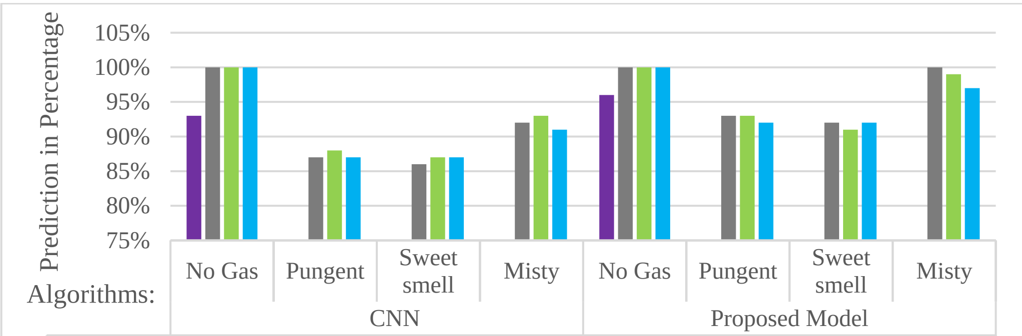
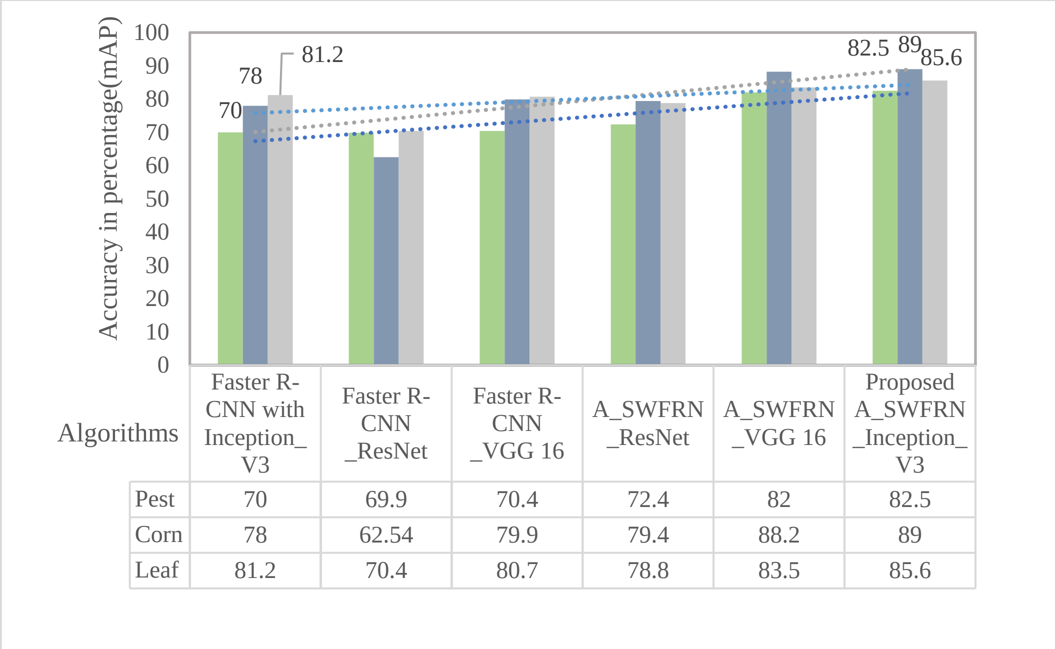


Fig. 3 Training Time Comparison of SWFRN and Other Algorithms



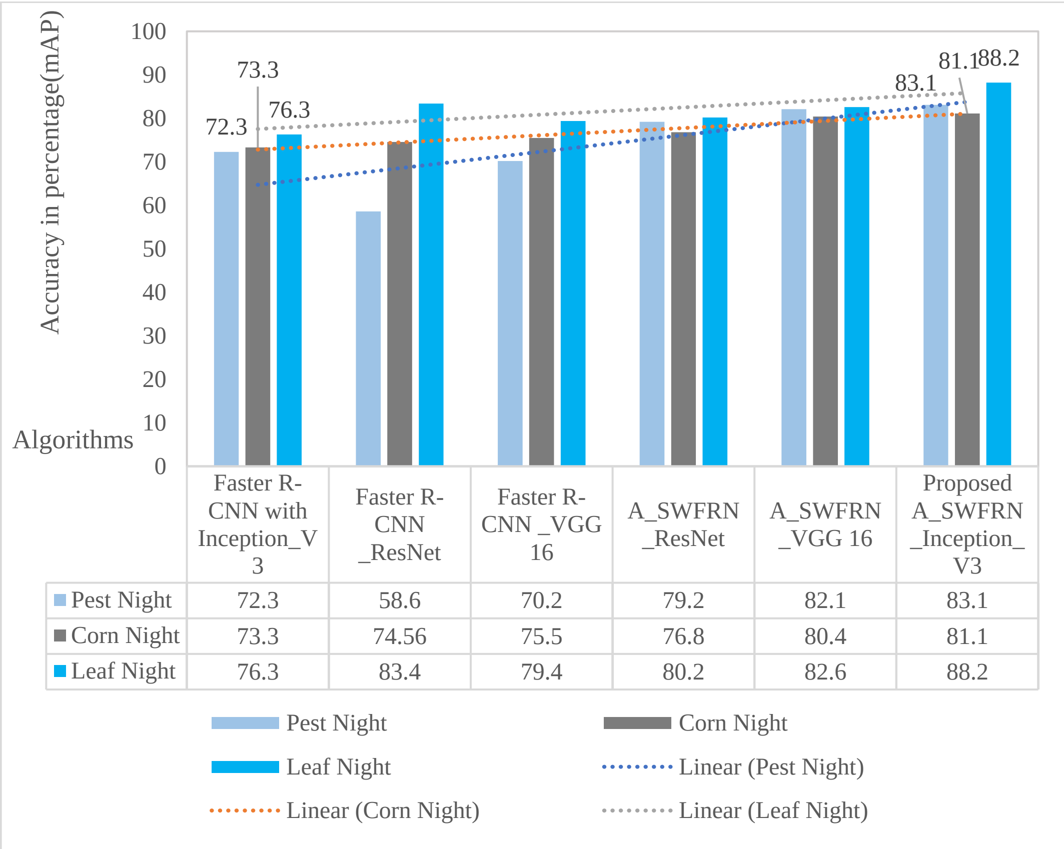
Algorithms:	No Gas	Pungent	Sweet smell	Misty	No Gas	Pungent	Sweet smell	Misty
	CNN				Proposed Model			
Accuracy	93%				96%			
Precision	1	0.87	0.86	0.92	1	0.93	0.92	1
Recall	1	0.88	0.87	0.93	1	0.93	0.91	0.99
F1	1	0.87	0.87	0.91	1	0.92	0.92	0.97

Fig. 4 Comparative analysis of models' accuracy



Algorithms	Faster R-CNN with Inception_V3	Faster R-CNN _ResNet	Faster R-CNN _VGG 16	A_SWFRN _ResNet	A_SWFRN _VGG 16	Proposed A_SWFRN _Inception_V3
Pest	70	69.9	70.4	72.4	82	82.5
Corn	78	62.54	79.9	79.4	88.2	89
Leaf	81.2	70.4	80.7	78.8	83.5	85.6

Fig. 5 For the detection of daytime objects, A_SWFRN is compared with Faster R-CNN



Algorithms	Faster R-CNN with Inception_V3	Faster R-CNN _ResNet	Faster R-CNN _VGG 16	A_SWFRN _ResNet	A_SWFRN _VGG 16	Proposed A_SWFRN _Inception_V3
Pest Night	72.3	58.6	70.2	79.2	82.1	83.1
Corn Night	73.3	74.56	75.5	76.8	80.4	81.1
Leaf Night	76.3	83.4	79.4	80.2	82.6	88.2

Fig. 6 For the detection of Night-time objects, A_SWFRN is compared with Faster R-CNN

4.4. Analysis of Pest Detection and Counting

Pest objects in point-like annotations can be detected and classified with 90% accuracy. In thermal images, more accurate predictions can be made by updating the neurons' weights during training. Based on thermal images, Refined SWFRN can differentiate pest objects of several shapes and sizes. This proposed method for spotting surface farms with a gas sensor can be implemented by thermal vision using a gas sensor.

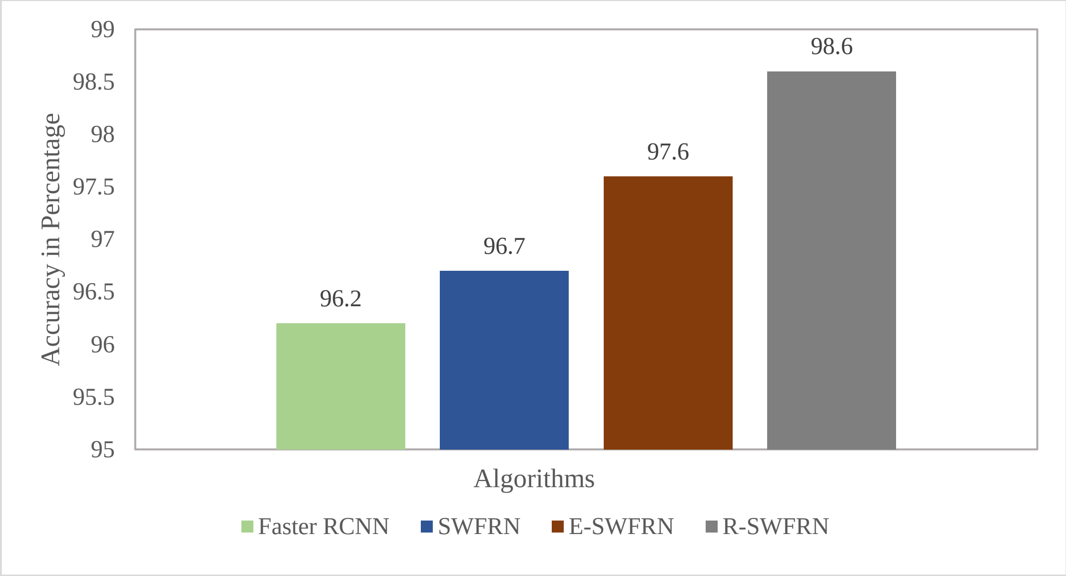


Fig. 7 Algorithm accuracy comparison with previous algorithms

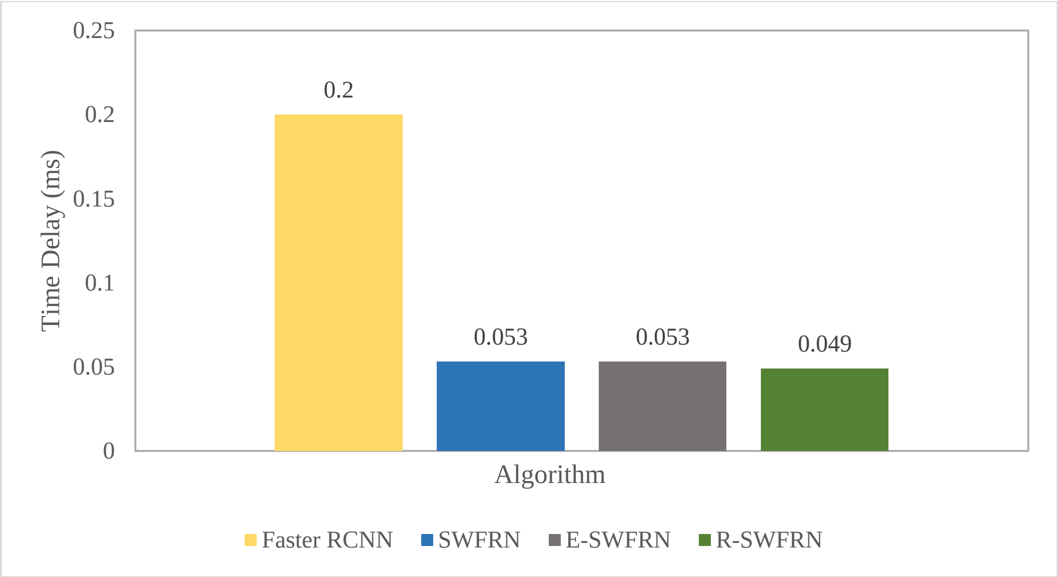


Fig. 8 Algorithm Time delay comparison with previous algorithms

5. Conclusion

Agriculture is the most important industry in the world. It produces more than 1.3 trillion dollars' worth of food every year, employing more than one billion people. Agriculture is important for human life since it provides basic needs like food. Despite its growth in agriculture revenue, India sees its economy slow down due to crop pests. As a result of this method, agriculture productivity will be increased, and pests will be less spread. The odour of pest infestation can be detected using an automated system. A deep learning algorithm can detect objects based on their odour. Early detection of infestations can be achieved through the use of this system. Images and computer vision are key to automating the identification and counting of insects in plants, not only reducing labour-intensive manual measurements, but the technology is also capable of increasing productivity.

The use of thermal images allows the differentiation of the foreground from the background, but it can only be applied to objects that emit infrared light. Despite their current resolution, thermal cameras do not seem sufficient for object detection, but further advances can be expected as sensor technology advances. Viewing an object from a different angle can give it a completely different appearance. Detectors are challenging to recognize different objects from different viewpoints since most models are tested under ideal conditions. It has been quite a challenge to detect objects because of these challenges.

References

[1] Liu, Jun, and Xuewei Wang, "Plant Diseases and Pests Detection Based on Deep Learning: A Review," *Plant Methods*, vol. 17, no. 1, pp. 1-18, 2021. *Crossref*, https://doi.org/10.1186/S13007-021-00722-9

[2] Fouqiya Badar, and Ayesha Naaz, "Detection of Fruit Diseases using Image Processing Techniques: A Review," *SSRG International Journal of Electronics and Communication Engineering*, vol. 9, no. 4, pp. 10-14, 2022. *Crossref*, https://doi.org/10.14445/23488549/IJECE-V9I4P102

[3] Mohamed Esmail Karar et al., "A New Mobile Application of Agricultural Pests Recognition Using Deep Learning in Cloud Computing System," *Alexandria Engineering Journal*, vol. 60, no. 5, pp. 4423-4432, 2021. *Crossref*, https://doi.org/10.1016/j.aej.2021.03.009

[4] Deepali M Bongulwar, Vijay Prakash Singh, and S. N. Talbar, "Evaluation of CNN based on Hyperparameters to Detect the Quality of Apples," *International Journal of Engineering Trends and Technology*, vol. 70, no. 10, pp. 232-246, 2022. *Crossref*, https://doi.org/10.14445/22315381/IJETT-V70I10P222

[5] Naeem Ullah et al., "An Efficient Approach for Crops Pests Recognition and Classification Based on Novel DeeppestNet Deep Learning Model," *IEEE Access*, vol. 10, pp. 73019-73032, 2022. *Crossref*, https://doi.org/10.1109/ACCESS.2022.3189676

[6] O. Nagaraja, and M. Krishnappa, "Leaf blight of Castor caused by Alternaria ricini: Detection and Pathogenicity in Castor (Ricinus Communis L) Seed," *SSRG International Journal of Agriculture & Environmental Science*, vol. 3, no. 4, pp. 6-10, 2016. *Crossref*, https://doi.org/10.14445/23942568/IJAES-V3I4P102

[7] Dan Jeric Arcega Rustia et al., "Automatic Greenhouse Insect Pest Detection and Recognition Based on a Cascaded Deep Learning Classification Method," *Journal of Applied Entomology*, vol. 145, no. 3, pp. 206-222, 2021. *Crossref*, https://doi.org/10.1111/jen.12834

[8] D. Sheema et al., "An Algorithm for Detection and Identification of Infestation Density of Pest-Fall Armyworm in Maize Plants using Deep Learning based on IoT," *International Journal of Engineering Trends and Technology*, vol. 70, no. 9, pp. 240-251, 2022. *Crossref*, https://doi.org/10.14445/22315381/IJETT-V70I9P224

[9] Li, Wei, et al., "Recommending Advanced Deep Learning Models for Efficient Insect Pest Detection," *Agriculture*, vol. 12, no. 7, pp. 1065, 2022. *Crossref*, https://doi.org/10.3390/agriculture12071065

[10] T.Nagarathinam, and Dr. K. Rameshkumar, "A Survey on Cluster Analysis Techniques for Plant Disease Diagnosis," *SSRG International Journal of Computer Science and Engineering*, vol. 3, no. 6, pp. 11-17, 2016. *Crossref*, https://doi.org/10.14445/23488387/IJCSE-V3I6P103

[11] Juan Guo, "ODRP: A Deep Learning Framework for Odour Descriptor Rating Prediction Using Electronic Nose," *IEEE Sensors Journal*, vol. 21, no. 13, pp. 15012-15021, 2021. *Crossref*, https://doi.org/10.1109/JSEN.2021.3074173

[12] S. Bhuvaneswari et al., "Disease Detection in Plant Leaf using LNet Based on Deep Learning," *International Journal of Engineering Trends and Technology*, vol. 70, no. 9, pp. 64-75, 2022. *Crossref*, https://doi.org/10.14445/22315381/IJETT-V70I9P207

[13] Wang, Zhenyu, Duokun Yin, and Senrong Ji, "Real-Time Factory Smoke Detection Based on Two-Stage Relation-Guided Algorithm," *Scientific Reports*, vol. 12, no. 1, pp. 1-15, 2022. *Crossref*, https://doi.org/10.1038/s41598-022-05523-1

[14] Nitin Kumar Vishwakarma, Dr.Ragini Shukla, and Dr. Ravi Mishra, "A Review of Different Methods for Implementing Smart Agriculture on an IoT Platform," *SSRG International Journal of Computer Science and Engineering*, vol. 7, no. 12, pp. 5-8, 2020. *Crossref*, https://doi.org/10.14445/23488387/IJCSE-V7I12P102

[15] Susovan Jana, Ranjan Parekh, and Bijan Sarkar, "Detection of Rotten Fruits and Vegetables Using Deep Learning," *Computer Vision and Machine Learning in Agriculture*, pp. 31-49, 2022.

[16] P. Sindhu, and G. Indirani, "Equilibrium Optimizer with Deep Convolutional Neural Network-based SqueezeNet Model for Grape Leaf Disease Classification in IoT Environment," *International Journal of Engineering Trends and Technology*, vol. 70, no. 5, pp. 94-102, 2022. *Crossref*, https://doi.org/10.14445/22315381/IJETT-V70I5P212

[17] Yizhou Xiong et al., "An Odour Recognition Algorithm of Electronic Noses Based on Convolutional Spiking Neural Network for Spoiled Food Identification," *Journal of the Electrochemical Society*, vol. 168, no. 7, p. 077519, 2021. *Crossref*, https://doi.org/10.1149/1945-7111/ac1699

[18] Ashay Rokade, and Manwinder Singh, "Analysis of Precise Green House Management System Using Machine Learning Based Internet of Things (IoT) for Smart Farming," *2021 2nd International Conference on Smart Electronics and Communication (ICOSEC), IEEE*, 2021. *Crossref*, https://doi.org/10.1109/ICOSEC51865.2021.9591962

[19] Jun LI, and Shang XIANG, "Intelligent Control of Urban Fresh Agricultural Products Supply Chain using Big Data and Internet of Things," *SSRG International Journal of Computer Science and Engineering*, vol. 7, no. 9, pp. 1-6, 2020. *Crossref*, https://doi.org/10.14445/23488387/IJCSE-V7I9P101

[20] Sharma, Anjuet al., "Smiles to Smell: Decoding the Structure–Odor Relationship of Chemical Compounds Using the Deep Neural Network Approach," *Journal of Chemical Information and Modeling*, vol. 61, no. 2, pp. 676-688, 2021. *Crossref*, https://doi.org/10.1021/acs.jcim.0c01288

[21] Nitin Kumar Vishwakarma, Dr.Ragini Shukla, and Dr. Ravi Mishra, "A Review of Different Methods for Implementing Smart Agriculture on an IoT Platform," *SSRG International Journal of Computer Science and Engineering*, vol. 7, no. 12, pp. 5-8, 2020. *Crossref*, https://doi.org/10.14445/23488387/IJCSE-V7I12P102

[22] Sheema, D et al., "Fall Armyworm Detection on Maize Plants Using Gas Sensors, Image Classification, and Neural Network Based on IoT," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 10, no. 2s, pp. 165-173, 2022.

[23] M. H. Nayeem et al., "Application of Image Processing for Plant Disease Identification Based on SVM Technique," *International Journal of Engineering Trends and Technology*, vol. 68, no. 1, pp. 83-90, 2020. *Crossref*, https://doi.org/10.14445/22315381/IJETT-V68I1P213

[24] Jhatial, Muhammad Juman et al., “Deep Learning-Based Rice Leaf Diseases Detection Using Yolov5,” *Sukkur IBA Journal of Computing and Mathematical Sciences*, vol. 6, no.1, pp. 49-61, 2022. *Crossref*, http://dx.doi.org/10.30537/sjcms.v6i1.1009

[25] Rajendra Akhil Kuma et al., "Crop Monitoring using Visual Sensors and IoT," *SSRG International Journal of Electronics and Communication Engineering*, vol. 4, no. 4, pp. 42-47, 2017. *Crossref*, https://doi.org/10.14445/23488549/IJECE-V4I4P109

[26] Johannes Full et al., “Systematic Derivation of New Fields of Application for Innovative Bio-Based Odour Sensors with Transfected Cells and Analysis of Economic Potentials,” *In Proceedings of the 1st International Electronic Conference on Biosensors*, *MDPI*, 2020. *Crossref*, https://doi.org/10.3390/IECB2020-07029

[27] Geetha D et al., "Human and Animal Movement Detection in Agricultural Fields," *SSRG International Journal of Computer Science and Engineering*, vol. 6, no. 1, pp. 15-18, 2019. *Crossref*, https://doi.org/10.14445/23488387/IJCSE-V6I1P103

[28] Rinu Chacko et al., “Data Based Predictive Models for Odour Perception,” *Scientific Reports*, vol. 10, no. 1, pp. 1-13, 2020. *Crossref*, https://doi.org/10.1038/s41598-020-73978-1

[29] Rina Mahakud, Binod Kumar Pattanayak, and Bibudhendu Pati, "A Hybrid Multi-class Classification Model for the Detection of Leaf Disease using XGBoost and SVM," *International Journal of Engineering Trends and Technology*, vol. 70, no. 10, pp. 298-306, 2022. *Crossref*, https://doi.org/10.14445/22315381/IJETT-V70I10P229

[30] Rana Muhammad Saleem et al., “Iot-Based Cotton Whitefly Prediction Using Deep Learning,” *Scientific Programming*, vol. 2021, 2021. *Crossref*, https://doi.org/10.1155/2021/8824601

[31] Aniket Ravindra Jambukar, and Prof. N A Dawande, "IoT based Smart Monitoring and Controlling System for Sericulture," *SSRG International Journal of Electronics and Communication Engineering*, vol. 7, no. 8, pp. 1-4, 2020. *Crossref*, https://doi.org/10.14445/23488549/IJECE-V7I8P101

[32] DingJu Zhu et al., “Knowledge Graph and Deep Learning Based Pest Detection and Identification System for Fruit Quality,” *Internet of Things*, p. 100649, 2020. *Crossref*, https://doi.org/10.1016/j.iot.2022.100649

[33] Geetha Lekshmy. V, P. A. Vishnu, and P. S. Harikrishnan, “Adaptive IoT System for Precision Agriculture,” *Inventive Computation and Information Technologies*, pp. 39-49, 2022. *Crossref*, http://dx.doi.org/10.1007/978-981-16-6723-7_4

[34] G. Murugesan, and B. Radha, "Crop Rotation based Crop Recommendation System with Soil Deficiency Analysis through Extreme Learning Machine," *International Journal of Engineering Trends and Technology*, vol. 70, no. 4, pp. 122-134, 2022. *Crossref*, https://doi.org/10.14445/22315381/IJETT-V70I4P210

[35] JiachenYang et al., “Data Quality Assessment and Analysis for Pest Identification in Smart Agriculture,” *Computers and Electrical Engineering*, vol. 103, p. 108322, 2022. *Crossref*, https://doi.org/10.1016/j.compeleceng.2022.108322