Insect and Pest Detection in Stored Grains: Analysis of Environmental Factors and Comparison of Deep Learning Methods

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Abstract: Majority of the world's population depends on agro-based economy for their income and survival. In developing and under-developed countries, due to reasons like basic farming techniques, less educational and technological exposure, lack of technological advancements and recent agricultural knowledge, yield of the crops is very low and moreover there is a huge loss during storage also. Insects, pests and diseases more often affect the stored grains and cause heavy damage to the quantity and quality of the grains. Insecticides and pesticides cannot provide better solution all the times and hence there is an acute need for computer vision based techniques capable of monitoring the spread of insects in the initial stages of storage and protecting the stored grains from further damages and losses. Hence, this paper provides analysis of various factors which can cause damage to the stored grains natural ways to protect crops. It provides the comparison results of various standard deep learning methods that are used to detect the insects and pests in stored grains.

Keywords: Insects and pests, stored grains, CNN, environmental factors, YOLOv5 algorithm.

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1 Introduction

Agriculture serves as the main occupation for people all over the world since it is the main source of livelihood. In most of the developing countries, around 70% of the population depend on agriculture for their source of income. Agricultural productivity and consumption is affected by various environmental and other human factors [1,2,3]. Even though, globally steady improvement can be seen in grain production due to advancements in technology, post harvest loss is estimated at around 25 % each year [4]. Out of the total loss faced, 6% of the loss is due to loss of grains during storage after harvesting. Grain storage is a critical phase in order to get maximum profit in agricultural domain in which loss may occur due to invasion of insects, pests, pathogens and rodents. The insects and pests still reduce the quality of remaining stored grains. Out of the total loss during grain storage, technical inefficiency accounts to 50% of the loss approximately.

The common grain pests namely lesser grain borer, rice weevil and rust red flour beetle increase loss of grains and their management difficulty in two important ways: i). Directly impact the management cost for the farmers through the expense of pest control in the farms and ii). Increase the cost for pest management for grain storage authorities in bulk storage areas. Grain insect pests can be classified into primary and secondary pests. The primary grain insects affect only the fresh and whole unbroken grains whereas the secondary pests feed on already damaged grain, dust and milled products during storage.

Different losses that are faced commonly while storing grains are given below:

i. *Quantitative loss*: If the insects feed directly into the grains, it can cause heavy loss in weight of the grains. For example, common pest namely rice weevil consumes about 14g from 20 mg rice for its development. The total weight of the grains is lost to a maximum extent and cause heavy loss to the farmers.
ii. *Qualitative loss:* Most of the grain pests consume grain embryos which in turn lower the protein content of the grains and also the quality of seeds capable of germination. The chemical components

of the grain will get affected and the contaminated grain with infected skin and body parts further attract the spread of pathogenic microorganisms.

iii. *Loss of seed viability:* The viability of the seeds will be severely affected and cannot be used for sowing and further plantation. The capability of seeds to develop into plants will get degraded.

iv. *Damage of storage containers:* The grains are usually stored in wooden containers, polythene, lined bags, sacks, etc. Some pests like lesser grain borer can damage these containers and hence the grains will be lost and wasted to a great extent. If the storage container is damaged, people will have the tendency to avoid buying those products out of fear about its quality.

Small farmers use to store their grains in small amount in their house itself whereas large amount of grains like rice, wheat, turmeric, millets are stored in warehouses for use in the required time period. In spite of the artificial pesticides and insecticides to protect them, considerable amount of loss cannot be avoided. In order to achieve maximum yield, the agricultural processes need to be integrated with modern technological interventions equipped with artificial intelligence techniques like machine learning and deep learning methods. It can help in eliminating the harmful insects that damage grains and hence improve the productivity of crops.

2 Literature Review

The methods which are commonly used for insect and pest detection and controlling of environmental parameters to avoid invasion of insects and pests in the stored grains are discussed below.

During the earlier days, people have used trap types for catching pests and insects. Different types of traps were placed near the location where grains are stored. If any insects come near this location, they will be stick and caught in the trap. But, that will be manual procedure and is very inefficient. Traditional methods of pest management like near infrared, acoustic methods and electrical conductivity create lot of difficulties in sampling, reduction in speed and lot of manual workload. Initially, machine learning based image recognition methods are commonly used by researchers for a long time. Deep learning methods are gaining popularity in the recent days by successful implementation and better classification results in different applications [5].

In [6], authors have insisted that many researchers were using image analysis techniques that automatically scan X-ray images to detect insect infestations. The major problems in X-ray and NIR spectroscopy methods are that they are very costly and needs complex operating mechanisms which are very difficult for a farmer with low technical expertise. In [7], spatial association maps are used which have positive value if there are insects and mites inside the bin in which grains are stored and negative value if not. The association patterns between two adjacent samplings are analyzed and if there are no insects and mites, the association will be higher. If there are some trapped insects and mites, the association value might become low. Various statistical methodologies that are being used for in-storage sampling and surveillance in the grains warehouse are discussed in [8].

[9] has assessed, evaluated and critically analyzed the techniques used for judicious pest management in food storage. It presents and analyzes a variety of methods in real world applications. [10] has discussed about Integrated pest management (IPM) and the recent methods that are used for IPM are briefly reviewed. [11] made decisions on controlling pests using population dynamics and threshold insect densities. They insist that better sampling methods are very much essential for securing postharvest food with the sharp increase in human population. [12] has used radio-frequency grain bin imaging system to monitor and control stored grains. The dielectric properties of the grain are monitored to check moisture content, temperature, insect invasion and other abnormal changes. The captured values in images are processed to serve the purpose.

In [13], Multispectral Imaging (MSI) technology is combined with chemometrics to identify the variations between intact and insect-infested almonds. Principal Component Analysis (PCA) and Support Vector Machines (SVM) are used to classify them with better prediction results of 97%. [14] has researched on occurrence of stored grain pests in the underground pit grain storages of Eastern Ethiopia and found that around 70% of the grains were infected with mean germination in at least 7-8 months period. [15] has developed a method for detecting and classifying six different insects in the stored grain. RGB images of the live insects were used and Faster R-CNN based improved inception network is used to extract feature maps.

Deep learning methods have gained significance in recent years in food sensory and consuming researches. [16] has provided a detailed review of different deep neural network algorithms in food industry for ensuring food quality and safety inspection measures. They have found that deep learning algorithms outperform other machine learning algorithms for feature selection and further data analysis. [17] has proposed implementing acoustic technology with visual surveys and pitfall traps to identify and detect insects in Kenyan data warehouses to prevent wastage in postharvest maintenance. The measures are also taken to identify background noise. It is very much essential to reduce the losses incurred in postharvest maintenance phase.

[18] has used state-of-the-art IoT enabled system to monitor temperature, relative humidity and carbon dioxide and predict the type of insect activity in stored grains. DHT22 and CDM7160 sensors were used for this purpose. Only the abstract details of whether it is infected or not can be identified using this method and detailed analysis of the level of infection and controlling mechanisms are not possible in this approach. [19] has devised a portable postharvest insect detection system where electret microphones are used to record insect sounds. The sounds of insects captured are analyzed by custom written software which compares them with sounds of known pets. The sounds of 5 to 50 insects are differentiated by aggregation pheromones or other active semio chemicals.

[20] has categorized pesticides into four different forms namely gas, liquid, gel/foam and solid. Conventional strategies include usage of insecticide baits, aerosols, sprays, fumigants and inert gases. Food protection under postharvest condition may improve if these methods are improved or hybridized with other methods. Electrostatic dusts or sprays, nanoparticles, hydrogels, inert baits with artificial attractants, biodegradable cyanogenic protective grain coating are some of the advanced technologies. In [21], acoustic detection of immature insects hidden within the stored grains is proposed. The immature insects are large in number and are often present without adult insects inside the grains. Modern acoustic tools can effectively detect insects based on their images.

3 Environmental Factors Affecting Insects and Pests Management

Rather than implementing various machine learning and deep learning methods for detecting the insects and pests in the stored grains, it is always better to prevent the invasion of insects and pests in the beginning itself. This section discusses about various environmental factors which influence the attack of insects and pests and highlights natural ways to protect the grains without being attacked.

3.1 Environmental Parameters

Insects and pests living in the stored grains rely on their food (grain) for the water required for its survival and hence there is no necessity of external water source. In general, if the moisture content of the grain is low (less than 10%), insects either tend to break the stored grains or utilize its own water energy stored with fatty tissues. By doing so, some of the insects survive and the remaining insects will not be able to survive and increase its population. In general, when the moisture content of the grains and the storage containers is above 15%, there is a chance for rapid increase in population of the insects. Studies have shown that some species of insects like foreign grain beetle and the larger black four beetle populate at a high speed in high moisture when compared with low moisture regions.

Most of the stored grain insects develop within short period of time at room temperature itself with high reproduction rate where some female insects can lay down 100-400 eggs. The life span of adult insects also ranges from weeks to years. Two primary environmental factors which impact the growth of insects are temperature and moisture level. The insects usually require temperature of around 15-20˚C for survival and reproduction and at around 25˚C, its population start damaging the crops. When the temperature is increased beyond 35˚C, the insect pests cannot survive and stop laying eggs and hence they will vanish soon. But, the challenging factor is that grain is an excellent insulator and hence the required air supply is provided to the insects during severe cold or winter seasons. Sometimes, when the temperature is too low for dyeing, some species still survive but they cannot feed and die out of starvation. Molds may grow in stored grains when the moisture content is greater than 14.5%. In some cases of species, the molds can produce mycotoxins which are harmful for health factors and seriously affect agrofood industries. More suitable temperature for grain molds is 25-30°C. Some species like Aspergillus spp grow well even at high temperature above 35°C. Spores of storage fungi usually occur during the period of harvesting, transporting and handling procedures. While storing, when the temperature and moisture levels are suitable, fungi start germinating and its growth is unstoppable.

3.2 Environmental Solutions to Control Invasion of Insects and Pests in Stored Grains

In order to avoid insect pest invasion into the stored grains, ventilator facility for required air exhaust is recommended. This can be done artificially by either positive pressure or negative pressure. The storage structures need to be equipped with provision of sucking the moisture or air out of the stored grains. In some environments, the temperature may not be sufficient to cool the grain. Refrigerated air may be supplied sometimes to meet the requirements. But, this method may look so expensive to implement for all the cases. However, this method can be used for some expensive grains. The refrigeration unit will be connected by an insulating pipe for protecting the grains from insect pests by grain chilling. In sub-tropical countries, partial dried grains are processed with dryeration and batch drying. In regions with warm climate, the grains are immediately stored in order to preserve the germination capability of the grains.

Artificial pesticides are often found to be effective in controlling the pests but cannot be used continuously by all categories of farmers due to its non-biodegradability, high cost and the negative impacts on human and also soil health. Hence, most of the agricultural practitioners are seeking alternative powerful and eco-friendly natural ways of pest control with low cost. Plant volatile organic compounds are being increasingly used to protect the grains against insects and pests. A broad review of plant volatile organic compounds commonly used to protect grains is given in [22].

4 Comparison of Deep Learning Methods for Detection

The deep learning methods namely Convolution Neural Network (CNN), Fast Region-based CNN (Fast R-CNN), Faster Region-based CNN (Faster R- CNN) and You Look Only Once v5 (YOLOv5) which are used to detect the presence of insects and pests in the stored grains are briefly described below.

4.1 CNN

The Convolutional neural network is a standard deep learning algorithm used for image processing which contains convolution, pooling and fully connected layers as given in fig.1. Multiple stacks of these layers can be constructed in order to achieve better learning and classification. The image is convolved with filters also known as kernel. If the input image is given by X and filter by f, the output of convolution operation (*) represented by Z is given as

$$Z = X * f \tag{1}$$

In the convolution layers, significant feature maps are extracted which contains Rectified Linear Unit (ReLu) as the activation function. For the input x, RELU function is calculated as

$$RELU\,(x) = \begin{cases} 0, if\ x < 0 \\ x, if\ x \geq 0 \end{cases} \tag{2}$$

If the dimension of input is (n, n) and that of filter is (f, f), then

$$Dimension\ of\ output = ((n\text{-}f+1), (n\text{-}f+1)) \tag{3}$$

Flatten layer then flattens the features maps obtained from convolution layer and passes them to fully connected layers. Fully connected layer implements linear and non-linear transformation operations. The execution on linear transformation is given by

$$Z = W^T.X + b \tag{4}$$

where W is the weight and b is the bias (constant). For multiple class labels, softmax activation function can be used which classifies the input and outputs the resultant class label for the corresponding input whose formula is given below.

$$\sigma(\vec{Z})_i = \frac{e^{Z_i}}{\sum_{j=1}^{K} e^{Z_j}} \tag{5}$$

where σ - softmax function, $\vec{Z}$ - input vector, e^{Z_i} – standard exponential function for $\vec{Z}$ and e^{Z_j} - standard exponential function for output

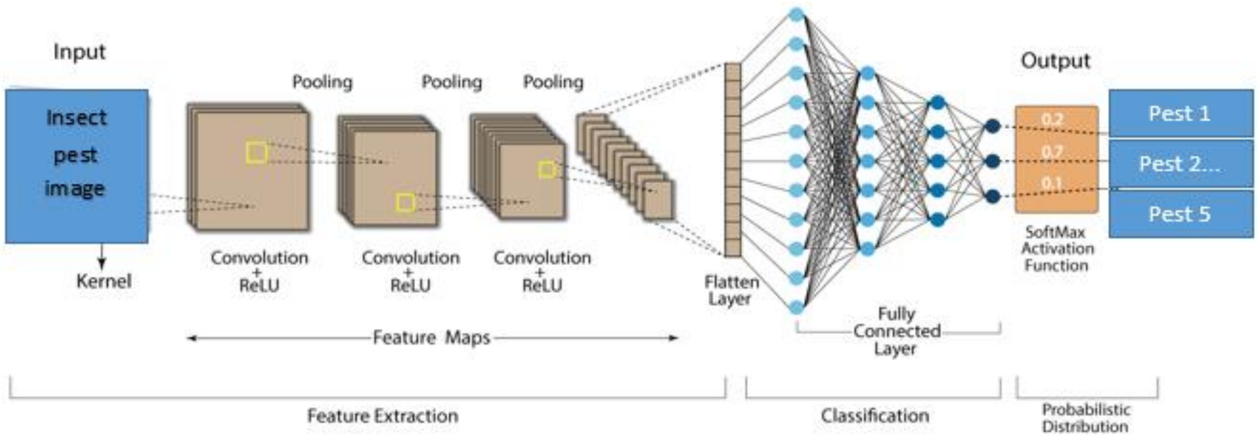

Fig. 1: CNN Architecture

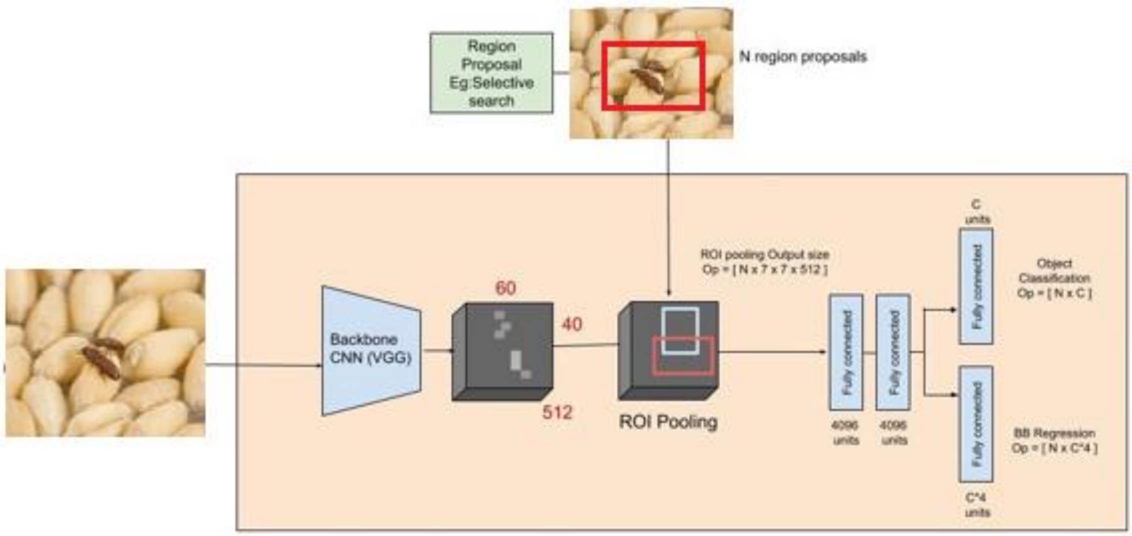

Fig. 2: Fast R-CNN

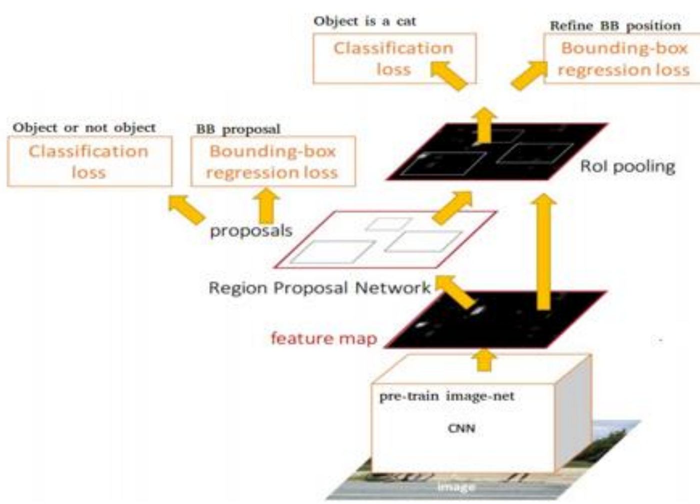

Fig. 3: Faster R- CNN

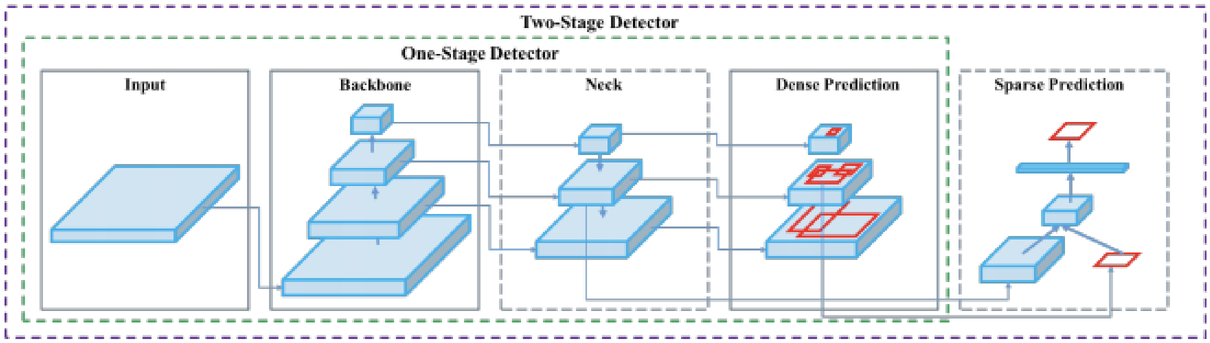

Fig. 4: YOLO v5 algorithm

vector. It gives probabilities for every ROI over (K+1) class labels p = p_0, p_1, p_2,.. p_k. The classification loss

$$L_{cls}(p,u) = -\log(p_u) \quad (6)$$

4.2 Fast R-CNN

In Fast R-CNN, the operation is fast since the convolution operation is done only once per image and the feature map is generated from the output of convolution operation. Region based ROI pooling is done and the architecture is given in fig.2. R-CNN process 2000 region proposals per image and that overburden is avoided in Fast R-CNN and hence faster execution can be observed.

4.3 Faster R-CNN

In Faster R-CNN, the image is first provided as input to the backbone network that generates the convolution feature map which is then passed to the Region Proposal Network (RPN). As given in fig.3, for each sliding window, a maximum of k anchor boxes are generated and for mini-batches are generated from them. It receives the feature map and generates anchors which are given into the classification layer for classifying the objects with the resulting bounding box. The training loss for RPN for multiple classes is given by

$$L(\{p_i\},\{p_i^*\}) = \frac{1}{N_{cls}}\sum_i L_{cls}(p_i,p_i^*) + \lambda\frac{1}{N_{reg}}\, p_i^* L_{reg}((t_i,t_i^*) \quad (7)$$

where p_i – predicted probability that anchors has object or not, p_i^* - ground truth value of anchors has object or not, t_i and t_i^* - coordinates of anchors predicted and ground truth coordinate of bounding boxes respectively, L_{cls} - classifier loss, L_{reg} – regression loss, N_{cls} and N_{reg} – normalization parameters of mini batch size and regression respectively and λ – constant.

4.4 YOLO v5 Algorithm

Fig. 4 shows the architecture of YOLOv5 algorithm. It is an efficient algorithm which is quicker in process and there is no need of looking at the training set every time the algorithm iterates. It is looked up only once and the entire feature maps are studied. The backbone network can be used with neck and then followed by dense prediction and exact sparse prediction following it.

5 Experimental Results and Discussion

In order to validate the efficiency of various deep learning methods to detect insects and pests in stored grains, methods like CNN, Fast R-CNN, Faster R-CNN and YOLOv5 algorithms are compared. The experiments are conducted on the pest images of public IP102 dataset. It contains 75,000

Table 1. Classification accuracy of deep learning algorithms with different models

	Backbone architecture	CNN	Fast R-CNN	Faster R-CNN	YOLOv5
Aphids Cicadellidae	Inception V3	87.21	88.14	87.45	92.32
	Xception	88.60	89.48	90.27	93.14
	VGG19	89.0	90.16	91.35	92.76

	ResNet 50	89.23	90.74	92.41	93.65
Flea beetles	Inception V3	83.91	85.58	87.04	89.37
	Xception	84.20	85.39	87.37	88.31
	VGG19	84.91	84.63	88.34	89.67
	ResNet 50	85.67	86.52	88.36	90.50
Cicadellidae	Inception V3	86.74	86.71	87.94	93.41
	Xception	87.15	88.47	92.05	93.30
	VGG19	88.09	88.52	89.46	93.97
	ResNet 50	88.31	89.45	90.11	94.28
Flax budworm	Inception V3	77.01	78.94	80.61	85.30
	Xception	78.20	79.65	83.28	87.19
	VGG19	78.22	81.17	81.29	88.97
	ResNet 50	79.09	82.37	81.63	89.13
Red spider mite	Inception V3	79.14	83.63	86.09	89.34
	Xception	80.43	81.25	85.47	89.91
	VGG19	81.26	84.79	85.03	90.25
	ResNet 50	81.24	86.94	83.72	90.80

images of 102 types of insect species. Due to practical difficulties in implementing all these species identification, only 5 species namely aphids, flea beetles, Cicadellidae, flax budworm and red spider mite are taken for experimental analysis. Whenever classification is performed, there are more chances that samples taken for training and testing may go imbalanced. If the imbalanced samples are chosen for experiments, it may create overfitting or underfitting and classification may go biased [23]. In order to avoid that, equal number of samples (500 images) are taken from each class label and the experiments are conducted. The performance of algorithms like CNN, Fast R-CNN, Faster R-CNN and YOLOv5 algorithms are compared in terms of classification accuracy, precision and recall measures which are calculated as follows:

$$Classification\ Accuracy = \frac{Number\ of\ images\ correctly\ classified}{Total\ number\ of\ images} \tag{8}$$

$$Precision = \frac{\sum_{c\ in\ C} TP_c}{\sum_{c\ in\ C}(TP_c + FP_c)} \tag{9}$$

$$Recall = \frac{\sum_{c\ in\ C} TP_c}{\sum_{c\ in\ C}(TP_c + FN_c)} \tag{10}$$

All the algorithms are allowed to run for 25 epochs each and the average results of 30 runs are reported below. Table 1 reports the comparison of classification accuracy of deep learning methods with various underlying backbone architectures like Inception V3, Xception, VGG19 and ResNet models.

It is found that standard CNN implementation shows low accuracy whereas other CNN variations like Fast R-CNN and Faster R-CNN report comparatively better accuracy. Among all the methods which are compared, YOLOv5 reports better results. ResNet serves as the efficient backbone architecture model for all deep learning implementations and hence it is used in further experiments.

Tables 2 and 3 also demonstrate superior performance of YOLOv5 algorithm than that of other CNN variations. YOLOv5 algorithm is simple and efficient and includes augmentation and hence the required number of samples are introduced for training.

Table 2. Precision of pest detection algorithms

	CNN	Fast R-CNN	Faster R-CNN	YOLOv5
Aphids	0.88	0.89	0.91	0.93
Flea beetles	0.87	0.84	0.88	0.91
Cicadellidae	0.82	0.87	0.80	0.88
Flax budworm	0.84	0.81	0.82	0.88
Red spider mite	0.78	0.81	0.83	0.91

Table 3. Recall of pest detection algorithms

	CNN	Fast R-CNN	Faster R-CNN	YOLOv5
Aphids	0.84	0.79	0.81	0.84

Flea beetles	0.77	0.79	0.80	0.77
Cicadellidae	0.81	0.82	0.83	0.81
Flax budworm	0.82	0.84	0.86	0.82
Red spider mite	0.83	0.85	0.88	0.83

Table 4. Execution time of algorithms for pest detection (in seconds)

	CNN	Fast R-CNN	Faster R-CNN	YOLOv5
Aphids	120	102	89	78
Flea beetles	136	113	104	99
Cicadellidae	147	134	117	102
Flax budworm	138	126	119	97
Red spider mite	129	103	97	88

Table 4 also reports that in classifying 5 species of insects, YOLOv5 algorithm completes the classification process quicker than other methods since YOLOv5 looks at the training set only once and does not spend much time in repeated scanning of the training set.

6 Statistical Results

The experimental results obtained are validated by using t-test statistic. The performance of YOLOv5 algorithm which shows better results when compared with other algorithms are compared pairwise using t test. The t statistic is calculated using the formula

$$t = \frac{X_1 - X_2}{\sqrt{\frac{(n_1-1)S_1^2 + \left((n_2-1)S_2^2\right)}{n_1+n_2-2}\left(\frac{1}{n_1}+\frac{1}{n_2}\right)}} \quad (11)$$

where X_1 and X_2 are the mean classification accuracy of algorithms 1 and 2 which are compared, S_1 and S_2 represent standard deviation of the algorithms 1 and 2, n_1 and n_2 indicate the number of observations in algorithms 1 and 2 respectively. The number of observations taken from each pair of algorithm is 15. Only, the top 15 observations with high classification accuracy are taken into consideration. The alpha value is taken as 0.01.

Degrees of freedom $n_1 + n_2 - 2$ is 15+15-2 = 28.

The corresponding t value at the given significance level in the t table is 2.467. From table 5, it is inferred that the t value obtained by comparing YOLOv5 with each other algorithm is comparatively greater than the t table statistic 2.467. Hence, it is understood that there is a significant difference between YOLOv5 and other algorithms. Also, among the compared algorithms, YOLOv5 is close in performance to Faster R-CNN and hence its t value is less than that of other algorithms. Higher the t value obtained, higher the significant difference between the algorithms that are compared.

Table 5. Comparison of YOLOv5 with other algorithms using t test

Algorithms compared	Estimated t statistic
YOLOv5 Vs CNN	5.34
YOLOv5 Vs Fast R- CNN	4.97
YOLOv5 Vs Faster R-CNN	4.02

7 Conclusion

This paper has thus provided a brief overview of various environmental factors which influence the growth and spread of insects and pests in the stored grains and also various natural measures which can be followed by farmers to control them. In order to avoid the damages caused due to artificial pesticides and insecticides, natural and simple method of implementing image processing algorithm like deep learning models can be very beneficial. It does not cause any harm to the nutrient levels of the stored grains and very cost effective in identification of insects in the stored grains in the initial stages itself. It can be very effectively used by small scale and also large scale farmers and in warehouses to prevent the invasion of insects into the grains and damages and in turn economical losses caused by them. Organic compounds can also be used to protect the grains from the insects, but it needs extra cost and effort in implementing them. The better solution can be to maintain proper environmental parameters like temperature and moisture contents of the grains, storage containers and the storage rooms. When comparing the deep learning methods, YOLOv5 algorithm performs better and that is also validated by statistical t test results.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Devi Priya R has monitored the project progress and written the draft of paper

Anitha N and Devisurya V have completed the paper and performed revisions

Vidhyaa has done analysis of the existing methods for the chosen problem

Shobiya has designed the experimental setup

Suguna has implemented the algorithms and performed test analysis

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