# Pest Detection System for Rice Crop Using Pest-Net Model

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**Abstract.** This paper presents a model for automatic pests identification of rice crops using the CNN approach called the Pest-Net model. This model aims to classify six different major pests affecting rice crops. To establish the novelty and credibility of our work, we have also used the transfer learning approach of CNN i.e. AlexNet model for the classification of the same dataset. It is observed from the experimental results and performance measures that the Pest-Net model performed well and gave good recognition accuracy of 88.6% as compared to the AlexNet model.

**Keywords:** CNN · Pest-Net · AlexNet · Transfer learning · Pest · Rice crop

## 1 Introduction

The population in India mainly depends on agriculture for their economic income. To cultivate the crop requires adequate irrigation, sufficient sunlight, quality of the soil, and the construction of water dams and water wheels. Among the many crops grown in India, rice is majorly grown and consumed which is around one-fourth of the population of our country. Rice is one of the most significant human food crops, accounting for one-tenth of all arable land on the planet [1]. It is an edible cereal crop whose binomial name is Oryza Sativa (L) commonly known as Asian rice. Asia produces more than 90% of the world's rice, the main production is in China, India, Indonesia, and Bangladesh. Human beings consume 95 percent of the world's rice harvest.

Plant diseases and insect pests cause major yield loss in plants and crops. So, early diagnosis of pests must be very important to the food industry as these might affect the productivity of crops. The general observation method by farmers is time-consuming, costly, and incorrect at times. Due to this reason, we aim to tackle the issue of identification of the pests of rice crops, as rice is the most consumed crop worldwide.

A manual examination can be used to detect pests, but it is a time-consuming and costly procedure. As a result, professionals such as plant pathologists, agriculture experts, and farmers monitor the plants and crops frequently which is a tiresome procedure. Hence the need arises to use the technology in the agriculture sector. This is possible due to


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advancements in technologies such as computer vision, machine learning, and deep learning techniques.

In this work, our goal is to identify and classify pests that cause harm to the rice crop. A pest is an animal, which causes harmful and damaging impacts on the yield of the crops. Here we have collected the pest dataset from Kaggle. The dataset consists of hundred different class labels but we have considered only the pests which affect the rice crop. So a total of six different class labels are considered which include rice gall midge, rice leaf caterpillar, rice leaf roller, rice leafhopper, rice shell pest, and rice water weevil.

The remainder of the article is organized as Sect. 2 narrates the literature survey, Sect. 3 discusses the dataset, Sect. 4 discusses the methods used, Sect. 5 shows the experimental results, and the end conclusions are given in Sect. 6.

## 2 Literature Survey

T.Y. Kuo et al [2] discuss the recent advances in image processing techniques applied to many aspects of the agriculture industry. They used sparse-representation-based classification algorithms to find a variety of rice grains.

Eusebio L et al [3] identified and classified the rice affecting pests. The transfer learning approach of CNN is utilized, because of fewer data available. Inception v3 model is utilized and after training the model, they got a good recognition accuracy of 90.9% on the collected dataset.

Ebrahimi M. A et al [4] developed an automatic pest detection mechanism for identifying thrips found on strawberry plants. They used the machine learning classifier SVM using color index and choice of region of interest with less than a 2.5% error rate.

Thenmozhi, K et al [5] deployed an automatic crop insect detection system to identify the insect in its early stage. They used the shape detection method for extracting the shapes of the insects like oval, circle, cylindrical, etc. of the sugarcane crop. Using Sobel edge detection the system can identify the insects with good accuracy as compared to the manual methods.

V. Malathi et al [6] worked on the classification of pests present in the paddy crop. They used the transfer learning approach to classify the pest dataset. This pest dataset consists of ten different class labels with 3549 pest images. The ResNet 50 model is fine-tuned over different hyper parameters to obtain a good recognition accuracy of 95.02%.

Pattnaik et al [7] identified and classified 10 different pests present on the tomato plant. The pest dataset consists of 859 images of pests. They used the transfer learning approach to identify the pests. 15 different trained models were exhaustively used to classify the pests. After fine-tuning the models with correct parameters, it is observed that the DenseNet169 model has given an average recognition accuracy of 88.83%, which is the highest compared to the other 14 models.

The watershed approach was employed by Xia et al [8] to segment the insects, and then the Mahalanobis distance was used to extract color information from the YCrCb color space. The closest distance between the retrieved feature vector and the reference vectors associated with each class was used to classify each item as whitefly, aphid, or thrip.

In pictures taken under controlled circumstances, Wen et al. [9] employed the SIFT descriptor to extract features for the characterization of 5 pest species. SVM produced the greatest accuracy results out of the six classifiers examined.

Huang et al [10] worked on classifying the tomato pests. Eight different pests affecting the tomato were taken into consideration. They utilized the hybrid approach of DL to extract the features and classify them using ML methods. For classification, they also utilized the VGG 16 model which gave a good recognition accuracy of 94.95%.

Based on the above analysis of the literature a major gap is noticed that no researcher addressed pests identification that harms the rice crops, though rice is the major crop across the globe. To increase the yield of rice crops, detection of pests and other disease-affecting agents is need to be taken care of at an early stage, so that the spread of the disease is stopped. Hence our main goal of this research is to present a new system for identifying the pests of rice crops in a real-time environment. This may help increase rice yield and help the farmers in the productive production of rice.

## 3 Dataset Description

The dataset is collected from Kaggle, it contains hundreds of pests that affect different crops and plants. We have collected only the rice affecting pests. These include six different categories which are shown below in Fig. 1.

Table 1 shows the summary of the pest database used.

**Fig. 1.** Rice Gall Midge, Rice Leaf Caterpillar, Rice Leaf Roller, Rice leaf Hopper, Rice Shell Pest, Rice Water Weevil.

**Table 1.** Summary of pest database

| Category | Training | Testing | Total |
|---|---|---|---|
| **Rice Gall Midge** | 295 | 74 | 369 |
| **Rice Leaf Caterpillar** | 209 | 52 | 261 |
| **Rice Leaf Roller** | 390 | 97 | 487 |
| **Rice Leaf Hopper** | 138 | 35 | 173 |
| **Rice Shell Pest** | 688 | 172 | 860 |
| **Rice Water Weevil** | 323 | 81 | 404 |
| **Total** | 2043 | 511 | 2554 |

## 4 Proposed Model

Here, we describe the method used for the classification of pests. We introduce a deep learning-based CNN model. Several layers are placed on top of one another, with each layer using the preceding layer as input to the model. CNN requires extremely little pre-processing and excels at picture analysis. To detect pests, we employ the convolution neural network (CNN) architecture, which provides the state of the art results. And to establish the novelty we have created our own deep Convolutional Neural Network, which we call as Pest-Net. Table 2 shows the layer used for creating the Pest-Net model.

**Table 2.** Pest-Net layers

| CNN Layers | Type | Output Size |
|---|---|---|
| Conv 1 | Convolution | 64 × 64 × 32 |
| Pool 1 | Max Pooling | 64 × 64 × 32 |
| Conv 2 | Convolution | 63 × 63 × 64 |
| Pool 2 | Max Pooling | 63 × 63 × 64 |
| Conv 3 | Convolution | 62 × 62 × 128 |
| Pool 3 | Max Pooling | 62 × 62 × 128 |
| Conv 4 | Convolution | 61 × 61 × 256 |
| Pool 4 | Max Pooling | 61x61x256 |
| Conv 5 | Convolution | 61 × 61 × 384 |
| Pool 5 | Max Pooling | 61 × 61 × 384 |
| FC | Fully Connected | 4 |
| Probability | Softmax | 4 |

The complete step-by-step process of the Pest-Net model is discussed extensively below.

1. **Pre-processing:** This is the first step in any image processing method, where the given dataset is adjusted according to the need of the problem. Before we train and test the model the dataset needs to be in uniform size and format. Hence we pre-process the dataset to a fixed size of 256 x 256.
2. **Input layer:** This layer accepts the images which are in M x M x N format. Where M x M are dimensions and N is the number of channels. For gray images N = 2 and color images it is N = 3. Here we are using color images which will be N = 3. This layer accepts input as 256 x 256 x 3.
3. **Convolution layer:** This is the layer where actual mathematical operations are performed. In the case of convolution, a bigger convolution filter can extract key information from an input picture, assisting in the more accurate identification of pests. We experimented with different filter sizes for our model like $4 \times 4$ and $5 \times 5$, which resulted in the time and space complexity of the model as the framework utilized is CPU. Hence, our introduced approach has five convolution layers with a $3 \times 3$ filter size. The first convolution layer has a filter size of $32 \times 3 \times 3$, the second has $64 \times 3 \times 3$, the third has $128 \times 3 \times 3$ the fourth has a filter size of $256 \times 3 \times 3$ and the last convolution layer has a filter size of $384 \times 3 \times 3$. These convolution layers help to boost the extraction efficiency. The convolution procedure, which yields Eq. 1, determines the whole feature map. Where $P_{\mathrm{i}}$ is a feature map and * the convolution operators, the $\mathrm{n}^{\mathrm{th}}$ input channel is designated by $\mathrm{X}_{\mathrm{n}}$, the kernels are defined by $\mathrm{Z}_{\mathrm{in}}$, and the bias value is defined by $\mathrm{B}_{\mathrm{i}}$.

$$p_i = B_i + \Sigma Z_{in} * X_n \tag{1}$$

The activation function used is ReLu as it is good at learning nonlinearity. This activation function is used mainly to solve the problem of over-fitting.

4. **Pooling Layer:** Pooling decreases various convolution layer parameters and isolates the important characteristics of these layers. This layer reduces the number of parameters in all areas, boosts computing performance, and calculates significant attributes to reflect all of the qualities of the selected region. We have different types of pooling functions like Max pooling and Average pooling. For our proposed model we have used the Max pooling operation. This function keeps the maximum value from a given sub-window.
5. **Fully Connected Layer (FC):** The proposed model uses FC layers. Before employing the FC layer, the last level, flatten, is where convolution layers and pooling layers' whole output is sent and reshaped into a single linear array of a matrix. The layers use the softmax activation function to learn important characteristics that may be used to recognize and categorize relevant input data. The softmax function is given by Eq. (2)

$$\mathrm{O}_x = S(\gamma)_x = \frac{e^{\gamma x}}{\sum_{n=1}^{N} e\gamma n} \tag{2}$$

In Eq. 2, S is the softmax function, which takes an N-dimensional vector and returns a set of real numbers between 0 and 1. O$x$ is the name of the output vector.

For comparison analysis, we have utilized the transfer learning approach of deep learning, where a pre-trained AlexNet model is used. This model is already trained on thousands of different categories. The Pest-Net and AlexNet model are trained extensively on pest datasets and the observed outputs are discussed in the consequent Section.

## 5 Experimental Results

In this part, we examine the experimental findings of our research. Pest-Net and the pre-trained deep learning model AlexNet are used for training and testing purposes. We divide the collected dataset into the training and testing part. 80% we utilize for training purposes and the rest 20% we utilize for testing. Hyper-parameter tuning of the models is kept the same so that we can compare both the models with standard parameters, which is shown in Table 3.

We have experimented with different batch sizes, learning rates, and solver types for both models. It is observed from the experiments that the low batch size, learning rate, and solver type as SGDM, both the models have underperformed and have required lot of hours to train the models. Whereas, in the above said table 3 both the models have performed better.

Table 4 and Table 5 show the species-wise recognition accuracy for Pest-Net and AlexNet.

Table 6 and Table 7 shows the Confusion matrix for Pest-Net and AlexNet model respectively.

The below graph Fig. 2 and Fig. 3 shows the accuracy obtained for training and testing datasets by utilizing Pest-Net and AlexNet models respectively.

Below Fig. 4 shows the results obtained using the Pest-Net model and Fig. 5 manifests the relative study of the Pest-Net and AlexNet model.

We have calculated the performance measures for the Pest-Net and AlexNet models which are the required measures to know how well the models perform on the given dataset. Table 8 shows the performance measures of the models.

**Table 3.** Tuning of Hyperparameters

| | Sl. No. | Name of the parameter | Parameter |
|---|---|---|---|
| | 1 | Solver type | Adam Optimizer |
| | 2 | Base learning rate | 0.0001 |
| | 3 | Batch size | 128 |
| | 4 | Epochs | 30 |
| | 5 | Training | 80% |
| | 6 | Validation | 20% |

**Table 4.** Species-wise recognition accuracy for Pest-Net

| Sl. No. | Species | Accuracy in % |
|---|---|---|
| 1 | Rice Gall Midge | 83.1% |
| 2 | Rice Leaf Caterpillar | 50.3% |
| 3 | Rice Leaf Roller | 77.6% |
| 4 | Rice Leaf Hopper | 79.4% |
| 5 | Rice Shell Pest | 95.8% |
| 6 | Rice Water Weevil | 82.9% |

**Table 5.** Species-wise recognition accuracy for AlexNet

| Sl. No. | Species | Accuracy in % |
|---|---|---|
| 1 | Rice Gall Midge | 71.6% |
| 2 | Rice Leaf Caterpillar | 48.1% |
| 3 | Rice Leaf Roller | 73.2% |
| 4 | Rice Leaf Hopper | 74.3% |
| 5 | Rice Shell Pest | 98.8% |
| 6 | Rice Water Weevil | 80.2% |

**Table 6.** Confusion Matrix of Pest-Net

| | GM | LC | LR | LH | SP | WW |
|---|---|---|---|---|---|---|
| **GM** | **59** | 4 | 5 | 0 | 1 | 2 |
| **LC** | 10 | **30** | 6 | 0 | 0 | 5 |
| **LR** | 2 | 1 | **79** | 0 | 5 | 9 |
| **LH** | 2 | 4 | 2 | **28** | 0 | 1 |
| **SP** | 1 | 1 | 0 | 1 | **171** | 0 |
| **WW** | 2 | 1 | 7 | 0 | 0 | **72** |
| **Accuracy in %** | | | | | **88.6%** | |

Experiment findings of this section show that the approach we presented provides effective results that can help with correct pest detection. And the results of the experiments reveal that the presented method's performance is significantly compatible with pest recognition.

**Table 7.** Confusion Matrix of AlexNet

| | GM | LC | LR | LH | SP | WW |
|---|---|---|---|---|---|---|
| **GM** | **53** | 7 | 5 | 1 | 3 | 5 |
| **LC** | 12 | **25** | 9 | 0 | 0 | 6 |
| **LR** | 5 | **0** | **71** | 0 | 9 | 12 |
| **LH** | **2** | **4** | **2** | **26** | 0 | 1 |
| **SP** | 0 | 2 | 0 | 0 | **170** | 0 |
| **WW** | 3 | 2 | 9 | 1 | 1 | **65** |
| **Accuracy in %** | | | | | **80.2%** | |

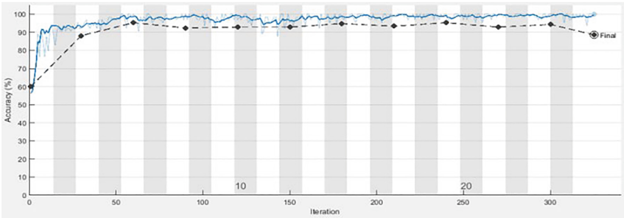


**Fig. 2.** Graph for accuracy obtained for training (blue) & testing (black) for Pest-Net.

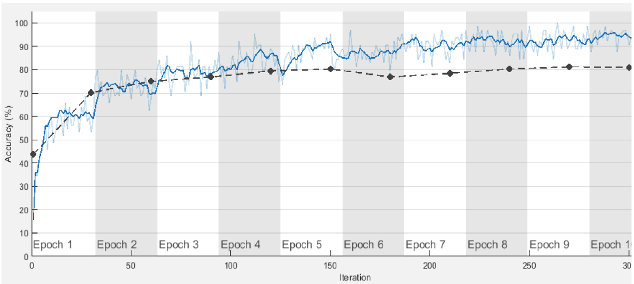


**Fig. 3.** Graph for accuracy obtained for training (blue) & testing (black) for AlexNet.

### 5.1 Discussions

The architecture of both the models is different. Many of the parameters like dropout layer, filter size and number of filters used in the model plays an important role in classification task. As the dropout layer is used to focus on the prominent features of the class and drops the not-so significant features. This layer we have avoided in our architecture. The number of filters in our architectures is increasing as we go deep down in the network. This implies we are extracting more number of features as we go down in the network. More number of features implies more accurate results to classify the given class. The Pest-Net model is trained from scratch, and has achieved a final accuracy of

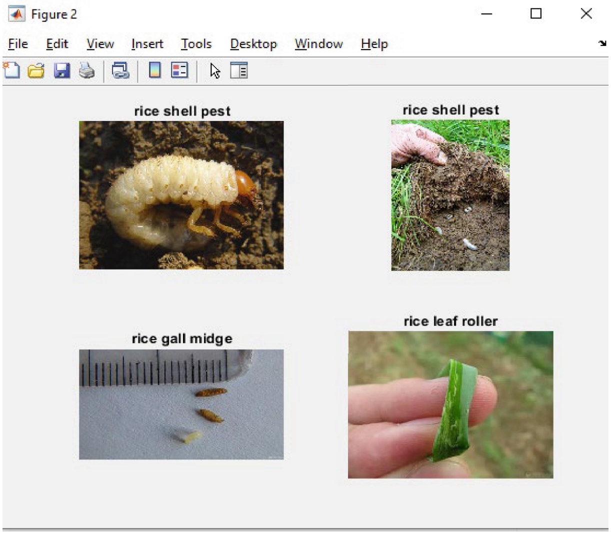


**Fig. 4.** Obtained result using Pest-Net model

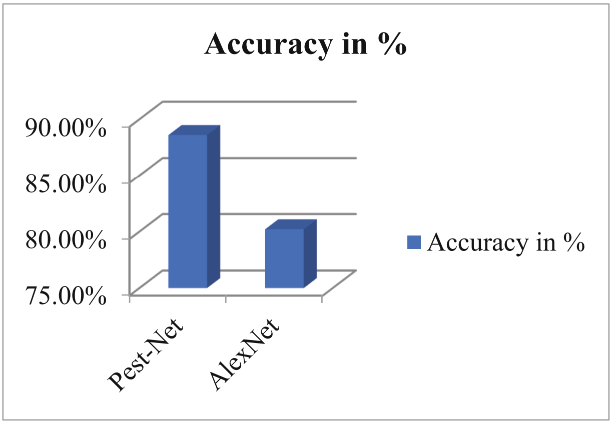


**Fig. 5.** Comparative analysis of Pest-net and AlexNet model

88.6% with a low error rate to classify the Pest dataset. Hence, the model can be used to predict the rice pests with good accuracy.

The only draw-back of our network is that, it requires more time to train the model, as we are training the model from scratch. The table 9 shows the time elapsed to train both the models.

The main advantages of our work signify as:

1. Our paper aims to work on the most consumed crop in the world i.e., rice. We have worked on the identification of pests present on the rice crop.

**Table 8.** Performance measures: Precision, Recall, F1 score using Pest-Net and AlexNet

| **Pest-Net (Own Network)** | | | | |
|---|---|---|---|---|
| | **Precision** | **Recall** | **F1score** | **Accuracy** |
| **Pest-Net** | 0.8924 | 0.7986 | 0.7889 | 88.6% |
| **Transfer Learning** | | | | |
| **AlexNet** | 0.7438 | 0.7765 | 0.7598 | 80.2% |

**Table 9.** Comparison based on Time required to train the model.

| **Sl. No.** | **Model** | **Accuracy** | **Time required to train the model** |
|---|---|---|---|
| 1 | Pest-Net | 88.6% | 302 min 47 s |
| 2 | AlexNet | 80.2% | 235 min 44 s |

2. To the best of our knowledge, we are the first kind to work on six different major pests affecting the rice crop.
3. An exhaustive comparison of transfer learning and own proposed approach is presented. The presented approach is experimented with different hyper parameters to obtain optimized accuracy.
4. Comparison analysis of Pest-Net and AlexNet is made on some standard parameters, to justify the fact that the Pest-Net model has got good accuracy. This is presented in Table 8.

## 6 Conclusions

In this work, we aim to identify and classify the pests found on rice crops. The dataset is collected from Kaggle. Using the CNN approach, the Pest-Net model is developed from scratch and trained on the pest dataset. For comparison analysis transfer learning approach of CNN is also utilized i.e., a pre-trained AlexNet model is used. It is observed from the experimental results that the developed Pest-Net model performed well and gave promising results compared to the already trained AlexNet model. This is because the Pest-Net model is developed and trained on the pest dataset from scratch. Farmers with smart-phones can use these generated models to help them control rice insect infestations. Once pests have been detected and reported to the Department of Agriculture, these will assist personnel in providing support to farmers.

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## References


1. Thorburn, C. 2015. "The rise and demise of integrated pest management in rice in Indonesia," Insects(April 2015), 381–408.
2. T.Y. Kuo , C. L. Chung, S.Y. Chen, H.A. Lin, Y.F. Kuo, "Identifying rice grains using image analysis and sparse-representation-based classification", Computers and Electronics in Agriculture, vol. 127, pp. 716–725, September 2016.
3. Mique Jr, Eusebio L., and Thelma D. Palaoag. "Rice pest and disease detection using convolutional neural network." In Proceedings of the 2018 international conference on information science and system, pp. 147–151. 2018.
4. Ebrahimi, M. A., Mohammad-Hadi Khoshtaghaza, Saeid Minaei, and Bahareh Jamshidi. "Vision-based pest detection based on SVM classification method." *Computers and Electronics in Agriculture* 137 (2017): 52–58.
5. Thenmozhi, K., and U. Srinivasulu Reddy. "Image processing techniques for insect shape detection in field crops." In *2017 International Conference on Inventive Computing and Informatics (ICICI)*, pp. 699–704. IEEE, 2017.
6. Malathi, V., and M. P. Gopinath. "Classification of pest detection in paddy crop based on transfer learning approach." *Acta Agriculturae Scandinavica, Section B—Soil & Plant Science* 71, no. 7 (2021): 552–559.
7. Pattnaik, Gayatri, Vimal K. Shrivastava, and K. Parvathi. "Transfer learning-based framework for classification of pest in tomato plants." *Applied Artificial Intelligence* 34, no. 13 (2020): 981–993.
8. Xia, Chunlei, Tae-Soo Chon, Zongming Ren, and Jang-Myung Lee. "Automatic identification and counting of small size pests in greenhouse conditions with low computational cost." *Ecological informatics* 29 (2015): 139-146.
9. Wen, Chenglu, and Daniel Guyer. "Image-based orchard insect automated identification and classification method." *Computers and electronics in agriculture* 89 (2012): 110-115.
10. Huang, Mei-Ling, Tzu-Chin Chuang, and Yu- Chieh Liao. "Application of transfer learning and image augmentation technology for tomato pest identification." *Sustainable Computing: Informatics and Systems* 33 (2022): 100646.
11. Garcia, J and Barbedo, A.2013. "Digital image processing techniques for detecting, quantifying and classifying plant diseases," Springer Plus, 2 (2013) 660.
12. Alam, M. Z., Crump,A. R., Haque, M. M., Islam, M. S., Hossain, E., Hasan S. B., Hasan ,S. B. and Hossain, M. S. 2016. "Effects of integrated pest management on pest damage and yield components in a rice agro-ecosystem in the Barisal Region of Bangladesh," Environmental Science (March 2016).
13. Patil, J. K. and Kumar,R. 2011. "Advances in image processing for detection of plant diseases," Journal of Advanced Bioinformatics Applications and Research, 2(2)(2011) 135–141.
14. Hong-xing ,X., Ya-jun Y., Yan-hui ,L., Xu-song, Z., Junce ,T. and Feng-xiang, L.2017. "Sustainable management of rice insect pests by non-chemical-insecticide technologies in China," Rice Science, 24(2)(2017) 61–72.
15. Bajwa ,W. I. and Kogan, M. 2017. "Internet-based IPM informatics and decision Support," Integrated Plant Protection Center (IPPC), Retrieved September 2017 from ipmworld: https://ipmworld.umn.edu/bajwa .
16. Azfar,S., Nadeem ,A., and Basit ,A. 2015. "Pest detection and control techniques using wireless sensor network", Journal of Entomology and Zoology Studies, 3(2)(2015) 92- 99.
17. Agnihotri, Vivek. "Machine Learning-based Pest Identification in Paddy Plants." In *2019 3rd International Conference on Electronics, Communication and Aerospace Technology (ICECA)*, pp. 246–250. IEEE, 2019.