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A NOVEL APPROACH FOR INSECT-PEST IDENTIFICATION USING MULTIPATH CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

For sustainable agriculture development and ensuring food security, there is an urgent need to improve the detection, monitoring, prediction, and identification of crop diseases and insects. Every year about 37% of rice crop gets damaged due to pests and insects. Without using any preventive measures, we could have lost about 70% of crops due to pests and insects. This study aims to identify the insects at the early stage using a multipath Convolution Neural Network. The main objective of this proposed work is to devise a model to efficiently identify the pest by images captured by mobile cameras. At the initial stage, it basically focuses on the classification of 6 classes of insects. The accuracy of classification for different classes of crop pests and insects achieved was 99%. The proposed method's accuracy is better than CNN, Faster CNN, DenseNet-121, and Deep Residual Learning.

Keywords: Classification, Image Processing, Insect-pest, Insect Identification, Multipath CNN

Insect catastrophes are one of the significant factors affecting crop production in terms of crop growth. The extent of crop loss due to insect-pests varies across countries and crops. Estimated losses due to insect-pests have ranged from 31.5% in Asia to 2% in Europe in the last two decades and every year, about 37% of rice crop gets damaged due to these (Savary *et al*., 2000). Though the use of pesticides increases the yield but affects the environment badly. At the same time, if we don't take any preventative step for our crops because of insect infestation(Poudel and Kafle, 2021).

Some insects are beneficial, while others can become pests when they cause harm. The distinction between the two terms lies in their context and the impact they have on the environment and human activities. The beneficial insects act as pollinators for crops and help in biological control, nutrient recycling, and soil rejuvenation. Therefore, the identification of pests and insects plays a crucial role in maintaining a healthy balance and maintaining biodiversity and in selecting appropriate preventive measures and their management. Traditionally, farmers have relied on entomologists and experts to identify pests and insects affecting their crops, leading to a cumbersome and time-consuming process. However, with the widespread availability of smartphones and the internet, there is an urgent need for a mobile-based solution that enables farmers to identify pests and insects early on by simply taking pictures with their mobile cameras.

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Pest and Insect identification has intrigued researchers for over two decades. Several Machine Learning (ML) models and Deep Learning models have been suggested for this purpose. CNN models, based on Deep Learning, differ from traditional ML algorithms like k-NN and Decision-Trees. Additionally, Deep Neural Network approaches outperform traditional ML methods by automatically extracting features from training data. Several CNN architectures like VGG16, VGG19, Inception V3, MobileNet, ResNet50 have been proposed by researchers for classifying the ImageNet dataset with 1000 classes. These Convolutional Neural Networks (CNNs) have demonstrated excellent performance in the ImageNet Large-Scale Visual Recognition Challenges (Traore *et al*., 2018).

This paper uses a multipath Convolutional Neural Network (M-CNN) to identify the pest and insects of field crops. The main objective of taking multi-paths is its ability to identify image information from all planes. To capture more detailed features, the MCNN utilizes three pathways that receive input with different filter sizes of the same image. The advantage of using a multipath CNN for insect identification lies in its ability to capture and integrate diverse features from images, enhancing the model's accuracy and robustness. By processing input through multiple pathways that focus on different visual aspects, such as texture, shape, and color, the multipath CNN can effectively learn intricate patterns inherent to various insect species. This results in improved classification performance and better generalization across a wide range of insect images, making it a potent tool for accurate insect identification. This model effectively improves image classification accuracy compared to conventional single-path models. The performance of the model is compared with CNN, Faster CNN, DenseNet-121, and Deep Residual Learning. The proposed model showed the highest accuracy of 99.47% and outperforms the compared models.

Image processing is revolutionizing everyday computer applications when combined with deep learning. It is used in many different fields, including as stock exchange prediction (Al-shamery, 2021), surveillance applications (Ullah *et al*., 2019) and numerous agricultural applications, including plant identification (Yaiprasert, 2021), fruit, leaf, and vegetable recognition (Zhang *et al*., 2016; Behera, 2020), and insect detection and identification (Maharlooei *et al.,* 2017), make extensive use of deep learning**.**

Various image processing techniques like SURF (Huang *et al*., 2009), SIFT (Larios *et al*., 2008), SVM (Ebrahimi *et al.*, 2017) etc. are being used by researchers across the globe not only for insect identification, but also for disease recognition. The preprocessing techniques, features selected to be extracted, classifier used, and the knowledge of suitability of the classifier plays an important role in modeling an efficient algorithm for the identification of insects. However, it is difficult to set a priori among different preprocessing techniques and different shallow classifiers (Ngugi *et al*., 2021).

Rahman *et al*. (2020) proposed a small CNN model for detecting diseases and pests from rice plant images. The authors have suggested a small CNN architecture, which has only 2 stages. The devised model is compared with NasNet Mobile, MobileNet, and SqueezeNet CNN architecture. The model has achieved an accuracy of 93%. The size of this small CNN is 99% smaller than VGG16.

Early pest detection and management are crucial for ensuring food security, but grain storage must also be kept secure. A more effective ReFCN neural network model is suggested in another experiment (Shi *et al*., 2020) to recognize and detect the stored-grain pest. Eight groups of stored grain insects were examined. The model's accuracy was obtained at 88.06%.

A low-cost, long-lasting automatic pest identification system has been developed as a result of the investigations reported by Xia *et al.* (2015). In order to determine the characteristics of the insects' colours, the Mahalanobis distance was determined. The correlations of determination between the proposed work and the manual identification method were determined to be extremely strong. The correlations of determination were discovered to differ for various insects, even for low-resolution photos. i.e., for aphids, thrips, and whiteflies.

Kasinathan *et al*. (2021) employed a modern machine learning technique to classify and detect the insect pests of field crops. In the IP102, Wang, Xie, Deng datasets, after extracting the foreground and identification of contour, 9-fold cross-validation was applied. Wang dataset has nine insect classes, and the Xie dataset has 24 insect classes. The classification rate was found to be 91.5% and 90% for 9 and 24 classes of insects.

A hybrid strategy that incorporates digital image processing methods and neural networks was used by Espinoza *et al*. (2016) to classify two species of pests that impact tomato crops: *Bemisia tabaci,* also known as whitefly, and *Frankliniella occidentalis*, also known as thrips.

To identify the insects, methods such as segmentation, morphological operations, and color property estimation were applied. A feed-forward artificial neural network was then used to categorize the insects. For the identification of whiteflies, the researchers obtained high precision (0.96), recall (0.95), and F-measure (0.95) values. For the thrips identification, however, precision of 0.92, recall of 0.96, and F-measure of 0.94 were attained. Gupta *et al.* (2023) compared various machine learning and deep learning techniques for insect and pest identification and found that deep learning models give better results than machine learning models.

MATERIALS AND METHODS

Insect dataset

This study includes dataset of insects of 6 classes namely Green Horned Caterpillar, Acronicta Tridens Caterpillar, Rice Stink Bug, Helicoverpa, Thistle Caterpillars, Dysdercus Cingulatus. For this purpose, images were collected from field of Durg and Raipur Districts of Chhattisgarh with the help of Indira Gandhi Krishi Vishawa Vidyalaya in the months of January,2020 to December, 2020 using 5 types of mobile camera. The utilization of five different types of mobile cameras in collecting insect data for training and testing the Multi-path CNN in the methodology enhances the model's robustness and generalization. By incorporating diverse sources of image data captured through various mobile cameras, Multi-path CNN becomes more adaptable to different imaging conditions, resolutions, and color representations. This approach ensures that the trained model can effectively identify and classify insects across a broader spectrum of real-world scenarios, thus improving its accuracy and practical applicability.

Sample image of each class of insect is shown in Fig. 1 and the number of images after augmentation is shown in Table 1.

Fig.1. Sample images of each class of insects

Collected images were augmented by simple augmentation methods. Image augmentation methods are techniques used to artificially increase the size of a training dataset by applying various transformations to the images in the dataset. These transformations can include rotation, scaling, flipping, and adding noise to the images. The goal of image augmentation is to expose the machine learning model to a wider variety of images during training, which can improve its performance on unseen data. Common image augmentation methods include random cropping, color jittering, and mix-up.

Table 1. Details of insects used for classification

Sr. No.	Category/Class name	No of images after augmentation
1	Green Horned Caterpillar	3135
2	Acronicta Tridens caterpillars	3270
3	Rice Stink Bug	3000
4	Helicoverpa	3561
5	Thistle Caterpillars	3019
6	Dysdercus Cingulatus	3061

Software tools used

- **Anaconda,** a distribution of Python (De Smedt and Daelemans, 2012; Shukla and Shukla, 1985) is used, which is widely used for voluminous data processing and data analytics. In the study, anaconda Navigator IDE with Spyder is used for implementation of model.
- **Keras**, a high-level, deep learning API is used for implementing neural networks. It is written in Python and is programmer friendly API.
- **Kivy,** a graphical user interface opensource **Python** library is used for making Graphical User Interface.

Multi-path CNN for insect identification

In the paper, a Multipath Convolution Neural Network is used for accurate identification of field crops insects. So far published results of performances of different architecture of CNN demonstrate the overall performance without any consideration of why some images do not get good results and how that could be improved (Sori *et al*., 2019;Gayathri *et al*., 2021).

A Multipath Convolutional Neural Network is used for global and local feature extraction from images, followed by a machine learning classifier to categorize the input according to the severity. The multipath convolution layer enables many global structures to be generated with a large filter kernel. In the proposed Crop insect identification model, a Multipath CNN with six convolutional layers is used and the SoftMax function is used as the classifier. The proposed insect identification model is shown in Fig. 2.

Multi-path CNN architecture design is a CNN Network having multiple path convolutional layers, the path considering smaller, medium, and larger receptive field sizes. In the proposed model three pathways are used to better approximate local dependencies at the first and second paths and global dependencies of the neighboring pixels at the third path.

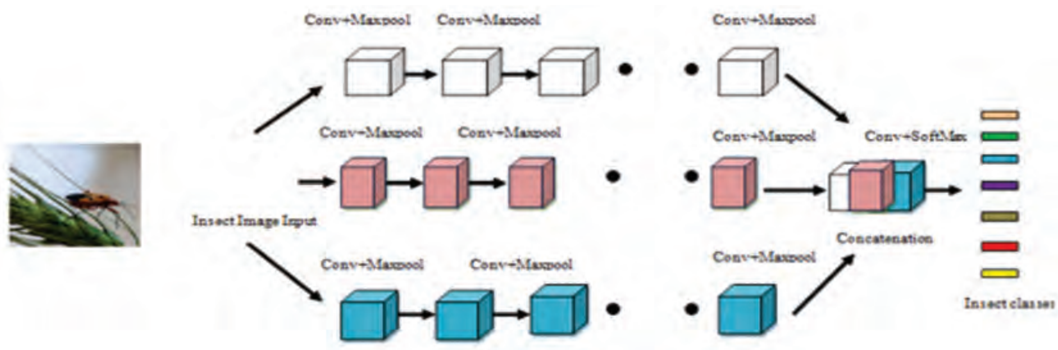

Fig. 2. Insect Identification Model

To each of these paths images with different field size is given as input. To find the impact of an average of field size of images, a concatenation function is used and it concatenates the output of the last convolution layer of each path followed by a SoftMax function to predict the final class of the insect.

Evaluation metrics

For model evaluation, the metrics selected are Precision, Recall, Specificity, and Accuracy The classification accuracy of the model is calculated by the following Eq. (1),

$$\text{Classification accuracy} = \frac{TP+TN}{TN+FN+FP} \qquad (1)$$

$$\text{Recall} = \frac{TP}{TP + FN} \qquad (2)$$

$$\text{Precision} = \frac{TP}{TP + FP} \qquad (3)$$

$$\text{Specificity} = \frac{TP}{FP + TN} \qquad (4)$$

The TP, FP, FN, and TN represent the true positive, false positive, false negative, and true negative. The insect that appears in the image is considered as TP if it is classified correctly; otherwise, it is regarded as FN. The insect which is not present in the image is considered as TN if the classification is done incorrectly; otherwise, it is referred as FP.

RESULTS AND DISCUSSION

In this work, the model is trained and tested on six classes of insects. Each class is divided into test, train, and validate datasets. Below is the summary of the training of the model which tells the loss and accuracy with each epoch for the training dataset as well as the validation dataset. As shown in Fig. 3, the accuracy was found to be 99.34% in Epoch 10^{th} and was increased to 99.47% in 100^{th} Epoch.

For comparing the accuracy of model CNN, Faster CNN Deep Residual Networks and DenseNet-121 are chosen. The Multipath CNN based proposed Insect Identification model outperforms the above models. Comparative analysis of the proposed insect identification model with other methods is shown in the Table 2. Graphically the comparison of model with other state of art model is given in Fig. 4.

Table 2. Performance comparison of proposed MCNN model with other models

Model	Number of Insect classes	Accuracy
Faster CNN (Karar *et al*., 2021)	5	98.9%
CNN (Thenmozhi and Srinivasulu Reddy, 2019)	10	95%
Deep residual learning (Cheng *et al*., 2017)	10	98.67%
Dense Net-121(Shi *et al*., 2020)	8	88.06%
Proposed MCNN Model	6	99.47%

Performance evaluation of MCNN for different Train–Test Split

In this section proposed MCNN is analyzed empirically to evaluate the proposed model's performance. Table 3 shows the difference in accuracy for different splits of the same dataset. For a split of 80-20, it gives 99.47 % accuracy; for a 70-30 split, it gives 96.15% accuracy; for a 60-40 split, it gives 93.22% accuracy. As shown in Fig. 5, it is observed that an 80-20% split of train and test data achieves the highest accuracy.

Table 3. Accuracy Comparison of Model with different split of the datasets

Training-Test Split of Data	Accuracy (in %)
80-20	99.47
70-30	96.15
60-40	93.22

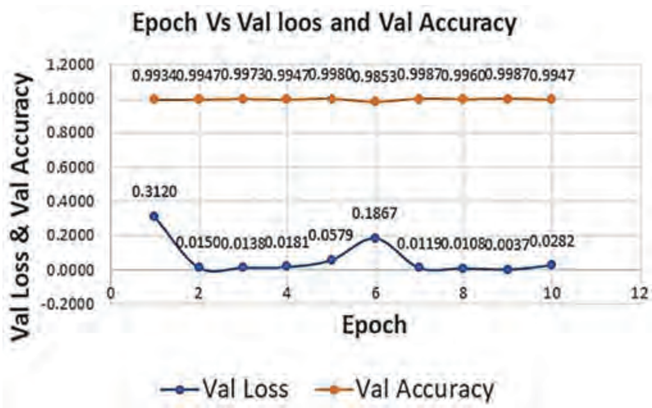

Fig. 3. Performance of proposed Insect Identification Model (1Unit=10 Epoch)

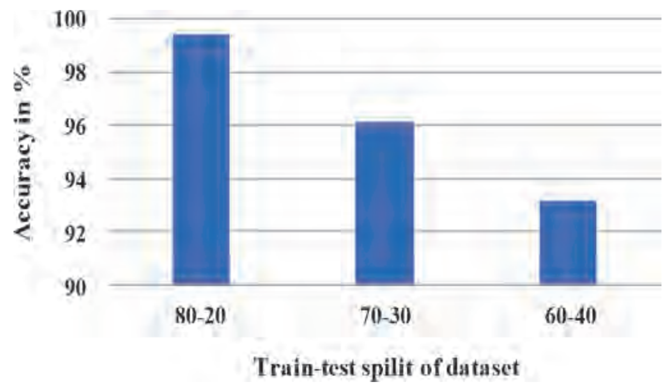

Fig. 4. Empirical Analysis of proposed model

This paper proposes an efficient Multipath CNN based insect identification model, which uses three pathways to better approximate local dependencies at the first two paths and global dependencies of the neighboring pixels at the third path. The accuracy is found to be 99.47%. The model outperforms many models of insect identification.

The pest and insect identification model MCNN has been developed so that it is future-ready. However, this work may be extended in the following ways. It can indeed be extended to other insect pests and insects for early identification in various crops. Additionally, the same approach can be applied to analyze leaf, stem, and fruit images of plants for disease identification, enabling faster and cost-effective detection of plant diseases. In future work, it would be valuable to explore more MCNN by compressing other popular pre-trained models like Inception-V3 and MobileNet, while maintaining high-performance evaluation metrics. This would provide additional options for implementing MCNN-based solutions in different contexts. All the images are taken on sunny days, so expected to fail abysmally. In the future, the model will be trained for multiple classes of insects with more data and to cover images of insects taking in all weather conditions.

Authors' contribution

Conceptualization of research work and designing of experiments (VAG, MVP); Execution of field/lab experiments and data collection (VAG, RRS); Analysis of data and interpretation (RRS, VAG); Preparation of manuscript (VAG)

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