Insect Pest Classification and Predictions in Different field of Cropsusing PC-CNN Model

[1]P. Deepan,[2]T.Kalai Selvi, [3] R Jeevitha , [4]R.Sivaranjani &[5]R.Hemalatha

1- Assistant Professor, Department of Computer Science and Engineering(AI&ML), St. Martin's Engineering College, Secunderabad, Telangana.
2- Assistant Professor(SLG-I) , Computer science and Engineering,Erode Sengunthar Engineering College,Thudupathi, Perundurai.
3- Assistant Professor, Computer science and Engineering, KPR Institute of Engineering and Technology, Coimbatore.
4- Assistant Professor, Computer science and Engineering,Tamilnadu college of Engineering, Coimbatore.
5- Assistant Professor, Electronics and Communication Engineering, Velalar College Of Engineering and Technology,

Abstract—India is one of the developing countries in the world, and its economy depends on the agricultural crops. Pest attack is a critical problem in the agriculture sector that results in degradation of quality and productivity of crops. So, farmers have to monitor and take care of the pest attack on crops regularly to ensure crop quality which is a challenging task. In recent decades, several models have been developed for automatic pest classification using Support Vector Machine (SVM),Artificial Neural Network (ANN), k-nearest neighbors (KNN), Naive Bayes (NB), and Random Forest (RF).However, such models are based on a hand-crafted feature extraction process and the accuracy has saturation as it is very difficult to classify and detect pests with similar feature types and different positions in the natural environment. So, in order to improve the accuracy, we have introduced PC-CNN (Pest Classification- Convolutional Neural Network) for classifying the pests.The architecture consist of three convolution layers of 32 filters with kernel size of 3x3, pooling size of 2x2 and fully connected layer 1024. For improving performance assessment, 1539insect pest images has been collected from Wang dataset and performed three k-fold validation(3-fold, 5-fold and 10-fold) process. Experimental results showed that10-fold cross validation model for the insect pest classification outperformed the other two k-fold cross validation by achieving 88.4% of accuracy.

Keywords:Insect, Pest, Convolutional Neural Network, Filed crop and traditional model.

1. Introduction

Crop pest identification and classification is one of the most difficult tasks in agriculture.An insect cause damage to crops and ismainly affect the productivity of crop yield.Because of their complicated structure and great degree of similarity in appearance between different species, classifying insects is a difficult endeavor.Early detection and classification of insects in crops is critical, especially in order to avoid the spread of insects that cause crop illnesses by using effective pesticides and biological control approaches.Manual insect identification is often time-consuming, labor-intensive, and inefficient.To address these issues in the agricultural research field, a vision-based computerised image processing system based on machine learning was developed for accurate classification and identification of insects.

In general, the features used in insect pest recognition and classification methods are split into three categories: handcrafted feature learning, unsupervised feature learning, and deep feature learning based methods [2].Previously, insect pest classification was done using an approach based on handcrafted feature learning.This method [3] was mostly employed to develop engineering features including colour, shape, texture, spatial, and spectral data.For plant leaf classification, the unsupervised feature learning approach [4] is an alternative to the handcrafted features method for learning unlabeled data.The goal of the unsupervised feature learning method is to find low-dimensional features that capture some of the high-dimensional input data.When feature learning is done in an unsupervised approach, it allows for a type of semi-supervised learning, in which features learnt from an unlabeled dataset are used to improve performance in a supervised context using labelled data.k-means clustering, principal component analysis (PCA), sparse coding, and auto encoder are just a few of the unsupervised feature learning approaches accessible.When compared to handcrafted-feature learning approaches, unsupervised feature learning methods have achieved great classification performance in real-time applications [5].However, due to the lack of semantic information provided by the category label, the optimal discrimination between classes cannot be guaranteed.To increase classification performance, we must improve classification performance and extract powerful discriminant features.

The deep learning model is made up of several processing layers that can learn more powerful feature representations of data at different degrees of abstraction [6].When compared to handmade and unsupervised features, deep feature learning was discovered to automatically learn from data using deep neural networks.The following is a summary of the structure of this research article.The review and related efforts for the insect pest classification are described in Section II.The proposed work for an insect pest disease recognition system in various field crops is discussed in Section III.The benchmark dataset is described in full in Section IV.The results and analysis of the experiments are described in Section V.Finally, in section VI, the conclusions are presented.

2. Related Work

Agricultural yield production is falling day by day as a result of a variety of natural and human-caused factors. The pest's problem is one of the primary reasons for the lower production rate.As a result, experts place more value on computerised pesticide prediction and classification in order to quickly detect pests before they harm crops. When farmers observe a disease, they fertilise it without knowing if it is beneficial or harmful, and the whole thing is destroyed. In order to tackle this issue, researchers are attempting to develop models to identify pests as beneficial or detrimental.

Vijai et al. [7] introduced a genetic system for image segmentation techniques to identify and classify plant leaf disease in 2015.Ding et al. [8] discovered a deep learning-based pipeline for automatically identifying pests from images taken during a field trip in 2016. They didn't exploit any pest-specific engineering, which means they can adopt any species with less human effort, and the results were promising. Monzurul et al. [9] published a paper in 2017 describing an integrated method to image processing and machine learning for diagnosing leaf disease from images. The use of a segmentation approach and a support vector machine led in 95% accuracy in disease classification over 300 images.Using six machine learning methods, Wen et al. [10] suggested a local feature-based insect categorization for orchard insects. Similarly, Wang et al. [11]introduced an automatic insect identification system by specifying seven geometrical criteria, and the classification results of ANN and SVM only obtain good results for a limited number of insect classes.

For the classification of Tomato leaf diseases, Zhang et al. [12] used genetic algorithm support vector machines (SVMs).Alehegn [13] established a technique based on colour, texture, and morphological aspects for classifying plant disease as affected leaf and healthy leaf in order to distinguish and classify tomato leaf diseases and healthy leaf.CNN has been applied in a variety of agricultural applications in recent years, including disease leaf object classification, leaf disease prediction, and disease detection.Plant leaf disease identification using deep learning, on the other hand, has received little attention in the literature.As a result, novel approaches are necessary in this area. Deep CNNs were used by the authors in [14] to solve disease identification tasks for various plant leaf diseases using different datasets and varying numbers of layers.

3. Proposed Work

In this section, we have to develop Pest Classification Convolutional Neural Network (PC-CNN) model for classification of insect pest images.There are many deep learning methods exist, but the CNN is common method for classification as it produce the excellent result for different kind of input. The LeCun et al. introduced the first CNN model.The CNN is a type of neural network whose design is based on the notion of a biological neuron defined as the receptive field, which is used to mimic the connectivity pattern of neurons in the human brain. The CNN model is a feed forward neural network that consists of a stack of filters (convolutional layer) and sub-sampling layers (pooling layer) that alternately repeat themselves, with one or more fully connected neurons (fully connected layer/dense) at the end.

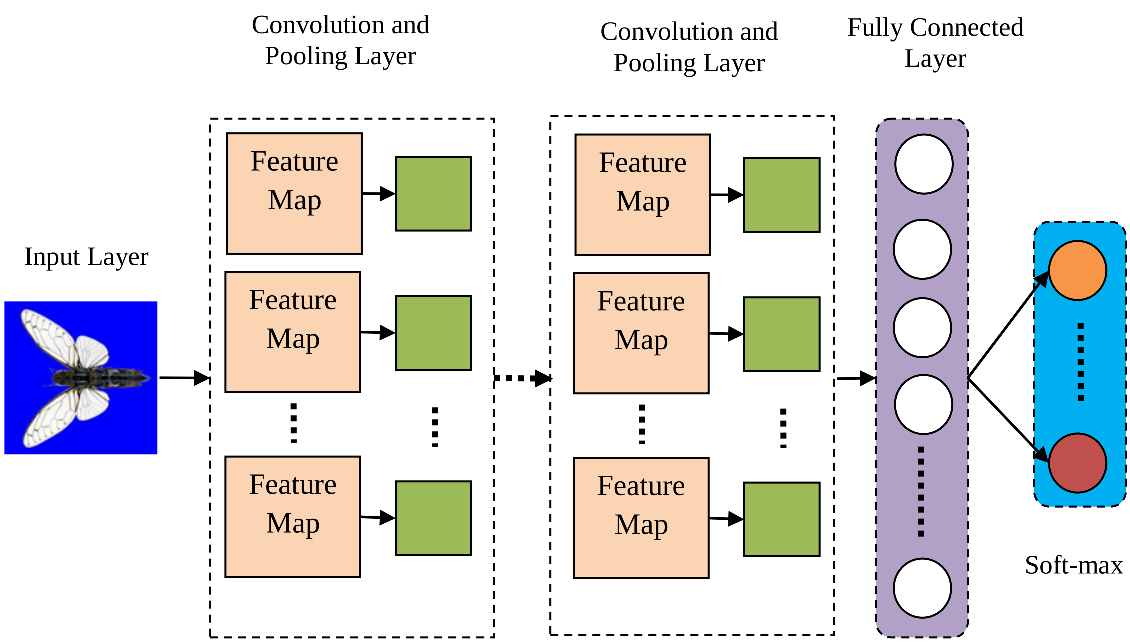

Fig. 1 Architecture of Insect Pest Classification and Prediction Model

Despite the fact that this model can be used in a variety of domains, it works perfectly in image processing.Individual blocks or layers are concatenated together to form the CNN.These layers are being assembled in order to complete a set of tasks.The classic convolutional neural network overall architecture, which includes the following layers, is depicted in Figure 1.

- Convolutional Layer
- Pooling Layer (Down-Sampling/ Up-Sampling)
- Fully Connected Layer (one dimensional data)
- Output Layer (Classification)

Convolution layer (Feature Extraction)

The convolution layer is one of the fundamental building blocks of a CNN, and it is from this layer that the term "Convolutional Neural Network" is derived. The goal of the convolution layer is to learn feature representations from the inputs by using a sequence of filters or kernels whose parameters must be learned. It uses linear multiplication as a convolution operational activity to extract high-level properties from the input image, such as lines, edges, and interior shape.

This layer is a 3D matrix with the dimensions of h×w×c and associated weights for each point, where h indicates the height of the inputs, w indicates the width of the inputs, and c indicates the channel depth. The input shapes are convolved with the kernel size of k×k.As shown in Figure 2, each kernel is moved from left to right, one element at a time, starting from the top-left corner of the input.When the top-right corner is reached, the kernel is moved one element below, and then the kernel is moved from left to right again, one element at a time. Repeat this process until the kernel reaches the bottom-right corner.

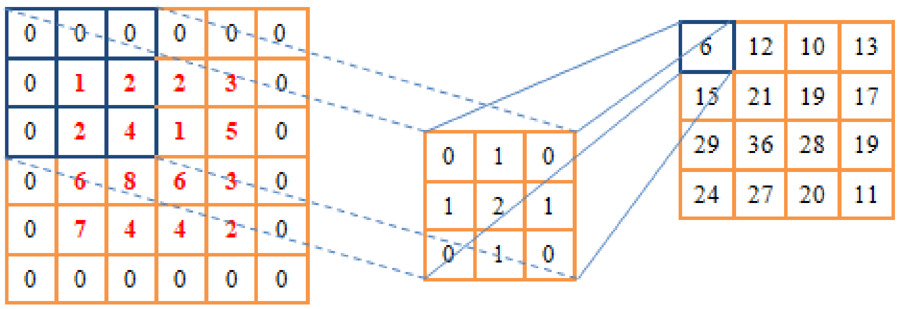

Fig. 2 Convolution Process

Activation function

The Rectified Linear Unit is the activation function that is used (ReLu). The kernel or filter size utilised for each convolution layer is 3×3 in order to speed up the training process and improve identification accuracy. The activation function of the ReLU is defined as follow:

$$b_{i,j,k} = \max(a_{i,j,k}, 0) \quad (1)$$

where, $a_{i,j,k}$ is the activation functions input at the k-th channel location (i, j). Every negative value in the filtered images is removed and replaced with zeros in this layer. The procedure of ReLU activation function is depicted in Figure 3.

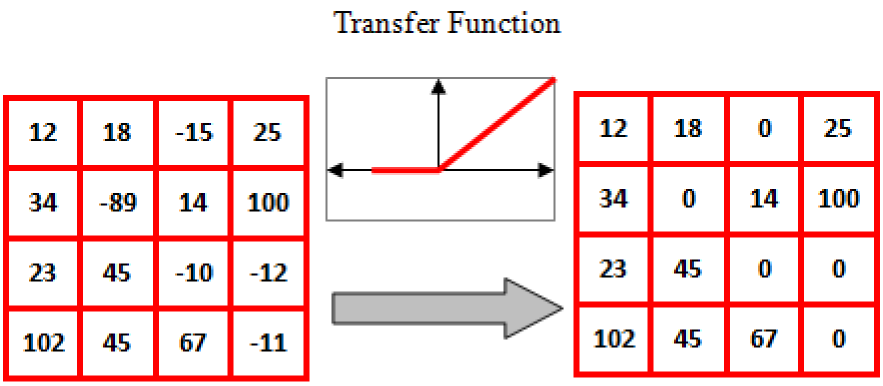

Fig. 3 Pictorial representation of activation function

Pooling or Sub-sampling layer

After the convolutional layer and activation function, the pooling layer is inserted as a sub-sampling process. The basic goal of a pooling layer is to reduce the number of feature maps while keeping the most important data. As a result, the number of parameters to learn and computations to conduct in the network is reduced. It also aids in avoiding the problem of overfitting. We can represent the output size of the matching matrix as O = (x, y) in equations 2 and 3 when we select the images as an input matrix I with dimensions I = (Ix, Iy)

$$x = \frac{I_x - (W_x - S_x) + 2 \cdot P_x}{S_x} \quad (2)$$

$$y = \frac{I_y - (W_y - S_y) + 2 \cdot P_y}{S_y} \quad (3)$$

The maximum value for each patch of the feature map is determined by the max-pooling method. On the other hand, Min-pooling determines the minimal value for each feature map patch. The pooling window size W = (2, 2) and stride length size S =(2,2) are both same in this scenario. This implies that the size will be reducing in half. Figure 4 shows the output of the pooling values when the input matrix for the pooling layer is a 4×4 matrix.

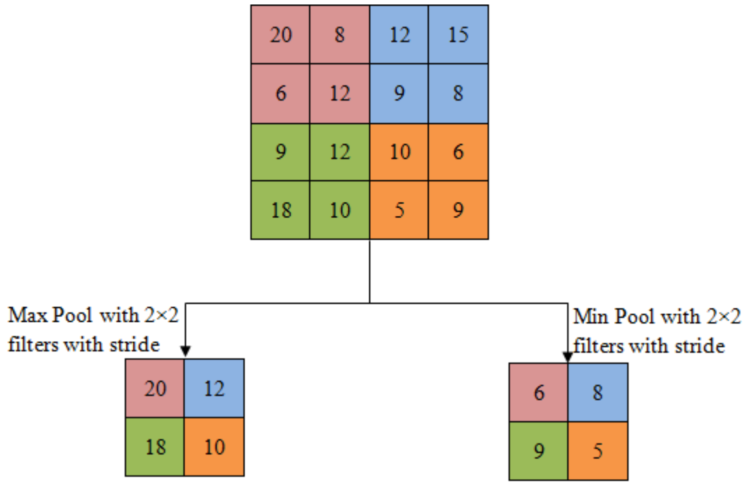

Fig.4 Working principles of max and min pooling layer

Flatten layer or Fully connected layer

A fully connected layer aim is to use the results of the convolution/pooling process to classify the image into a label. At the end of the model, CNN usually includes at least one fully connected layer. A stack of feature maps is the result of all of the convolution and pooling layers. Flattening a stack of feature maps into a one-dimensional feature space is done using a fully connected layer. Then it connects all of the flattened neurons together to summarise the feature maps.To determine the most accurate weights, this layer does its own backpropagation procedure.Weights are assigned to each neuron, and the most relevant label is given top priority. Finally, it calculates a score for each class based on the neuron's vote on each of the labels, with the winner being regarded the classification choice. In Figure 5, a 3×3 feature map is translated into one-dimensional data, and 9 neurons are entirely coupled to three neurons. A soft-max layer is connected to the last fully connected layer in the classification process to output the probability of each class.

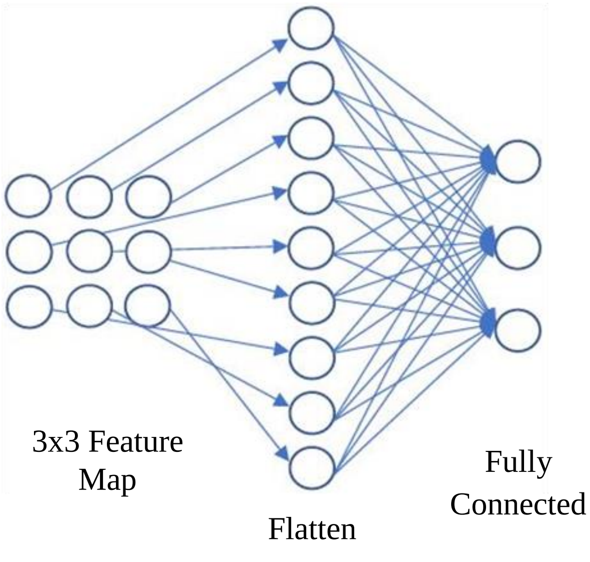

Fig. 5 Working principles of Flatten and fully connected layers

4. Dataset Description

For evaluating our proposed approach, we havechosennine classes such as Auchenorrhyncha, Coleoptera,Heteroptera, Hymenoptera,Lepidoptera, Megalptera, Neuroptera, Odonata and Orthoptera from Wang dataset. The Wang dataset is a small scale high-resolution image that contains 1359 images which consist of 9 classes. Each class contains 151 images of size of 64x64 pixels with three spectral bands red, green, blue.As shown in Table 1, number of training and validation images fork-fold validation process(3-fold validation, 5-fold validation and 10-fold validation) is used for analysing the performance of the proposed model.The sample images of insect pest images have been shown in Figure 6.

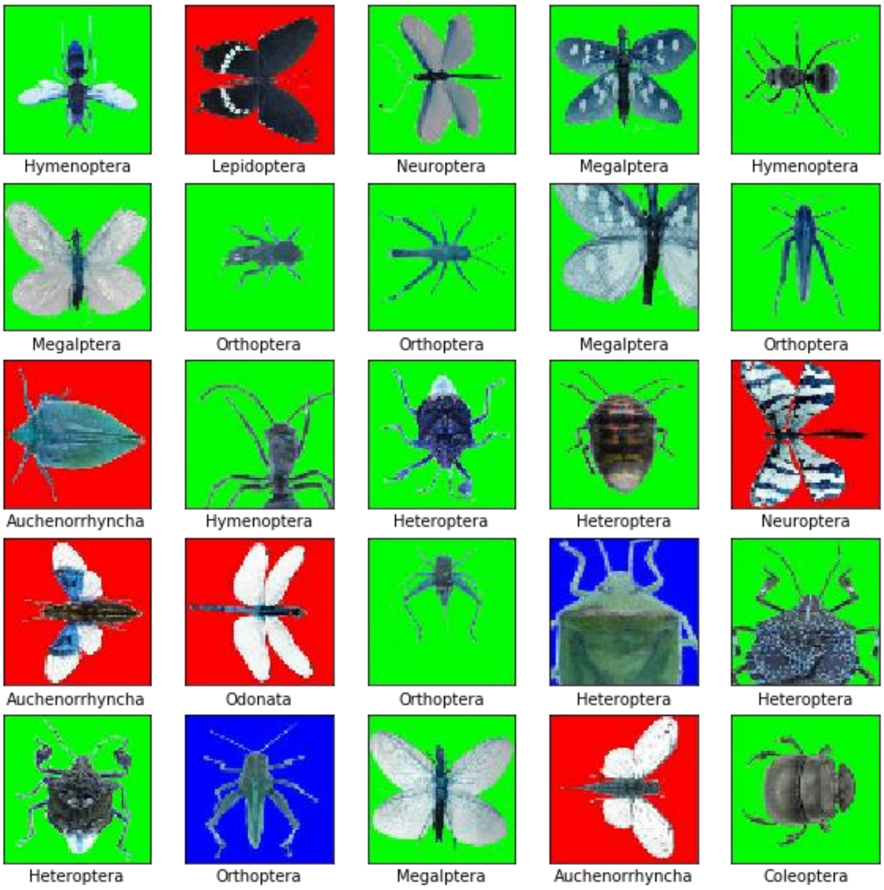

Fig 6. Some example insect pest images fromWang Dataset

Table 1. Train and Validation split based on K-Fold cross validation

S. No.	K-Fold Split	Total No. of Training Images	Total Number of Validation Images
1.	3-Fold Validation	906	453
2.	5-Fold Validation	1087	272
3.	10-Fold Validation	1223	136

4.1 Performance Evaluation Metrics

Evaluation metrics plays an important role for accessing the classification performance and improving model selection. We have used confusion matrices, accuracy, precision, recall and F1-score for evaluating the effectiveness of the proposed approach.TP, FP, TN, and FN class values are shown in Figure 7 for an insect pest classification and prediction system.If the classifier correctly predicts the class response at each instance, it is considered a "success," but if it does not, it is considered an "error." The error rate, which is a proportion of the errors made over the entire set of samples, is used to determine the classifier's overall performance.

Table 2. Confusion matrix process

	Positive	Negative
Positive	True Positive (TP)	False Positive (FP)
Negative	False Negative (FN)	True Negative (TN)

It is possible to find statistical metrics like as Precision, Recall, and F-measure for measuring the performance of classification algorithms from the confusion matrix, which are defined as follows:Precision (P), also known as detection rate, is the ratio of successfully labelled to total labelled instances.It is the percentage of correct positive predictions in a certain class.It is defined as follows:

$$\text{Precision(P)} = \frac{TP}{TP + FP} \tag{4}$$

where TP denotes the number of true positives and FN is the number of false negatives for a given class. TP + FP is the total number of test samples for a certain class. The ratio of correctly labeled images to total instances in a class is called recall (R) or sensitivity. It is also known as true positive rate and has the capability to measure the prediction model. It is defined as follows:

$$\text{Recall(R)} = \frac{TP}{TP + FN} \tag{5}$$

where TP denotes the number of true positives and FN is the number of false negatives for a given class. TP + FP is the total number of test samples for a certain class. The F1-measure tries to provide a single measure of performance by taking the harmonic mean of precision and recall. Both recall and precision can be high with a classification algorithm. The F1-measure is described as follows:

$$F1 = 2.\frac{P.R}{P + R} \tag{6}$$

The Accuracy can be defined as below:

$$\text{Accuracy} = \frac{\text{TP+FP}}{\text{TP+FP+FN+TN}} \tag{7}$$

K-Fold Validation

The goal of K-Fold validation is to be able to train and validate all of the images in the model at the same time. K-fold cross-validation is a type of cross-validation that involves iterating a collection of data k times. For each round, we divide the dataset into k parts: one is used for validation, and the remaining k-1 parts are merged into a training subset for model evaluation, as shown in Figure 7.

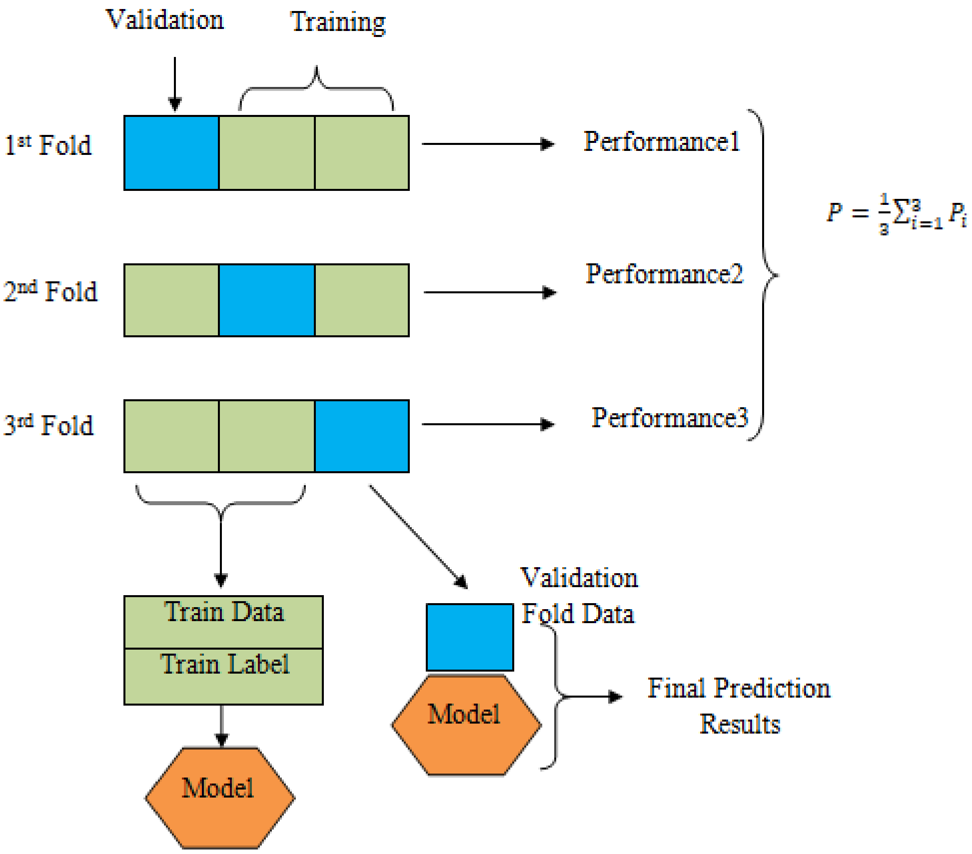

Fig. 7 The concepts of K-Fold cross validation

5. Experimental Results and Analysis

In this experiment, the proposed CNN model was trained and tested using tensor flow in Core i7 CPU 2.6GHz, 1 TB of Hard Disk and 8 GB of RAM.The training process is a process to make the system learn the features that exist in the image and classify these features. Dropout and Adam optimizers were employed to avoid the problem of overfitting concepts.In this study 1359 images of belonging to 9 classesinsect pestsnamely Auchenorrhyncha, Coleoptera, Heteroptera, Hymenoptera, Lepidoptera, Megalptera, Neuroptera, Odonata and Orthoptera are used.

Table 2. Performance evaluation of K-Fold crosses validation

S. No.	K-Fold Split	Accuracy	Precision	Recall	F1-Score
1.	3-Fold Validation	82	81.7	81.6	81.9
2.	5-Fold Validation	83.2	82.4	82.7	82.8
3.	10-Fold Validation	88.4	88.1	88.3	88

We analyzed the performance of 3-fold, 5-fold, and 10-fold validation in this study. Table 2 shows the number of images utilised for training and validation for the various k-fold validations. The performance of the proposed three k-fold cross validation of insect pest recognition system is shown in Figure 8 and Table 2. Figure 9 depicts the object classification confusion matrix. Miss predicted data items are placed above and below the diagonal of the matrix, whereas correctly classified data items are placed in the diagonal.

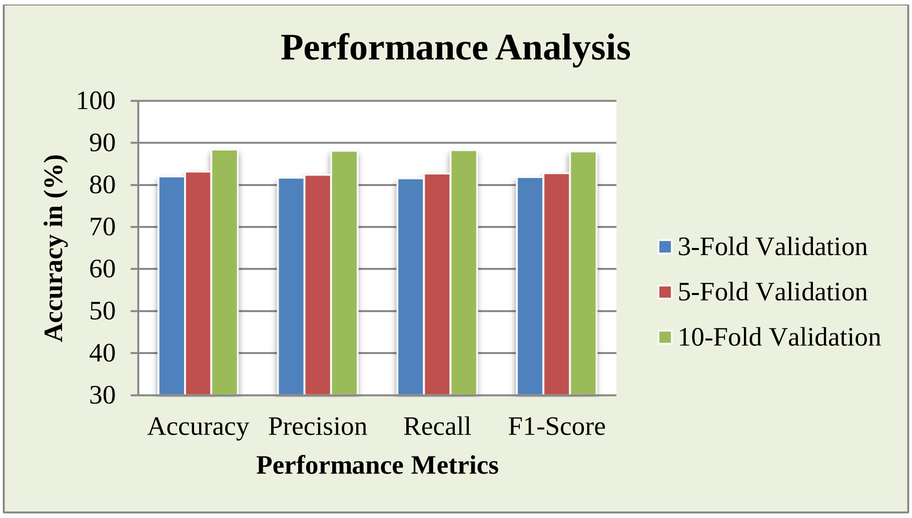

Fig 8. Performance Analysis of Wang Dataset for three K-fold validation

The accuracy of proposed model for 3-fold, 5-fold and 10-fold validation is 82%, 83.4% and 88.4% respectively. Based on experimental results, it is showed that, the proposed PC- CNN model with 10 Fold cross validation has higher accuracy than 5-fold and 3-fold cross validation. The overall performance analysis of three proposed model with three k-fold validation is shown in Figure 13.

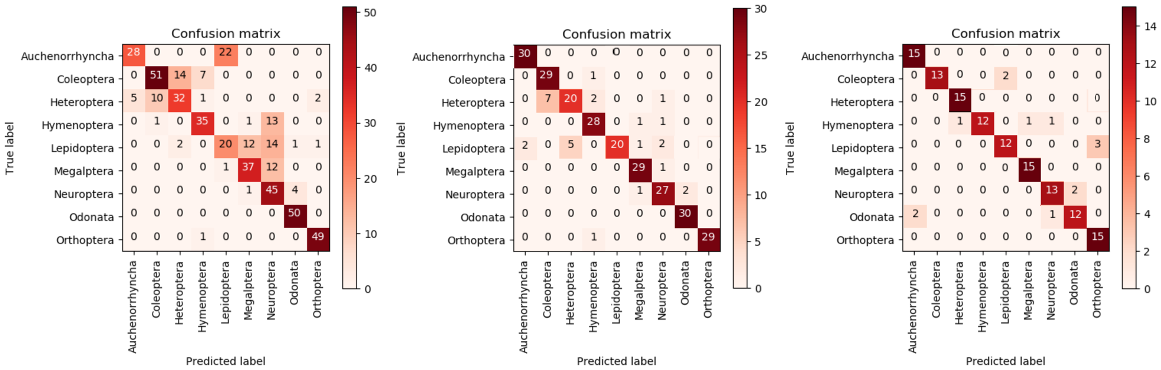

Fig 9. Confusion matrix of Insect Pest Classification System

6. Conclusion

In this paper, we have proposed an approach for insect pest classification and prediction model using Convolutional Neural Networks. The CNN model act as a feature extractor and classifier for the given training images as well as validation images. We have achieved 88.4% of accuracy for nine insect pestssuch as Auchenorrhyncha, Coleoptera, Heteroptera, Hymenoptera, Lepidoptera, Megalptera, Neuroptera, Odonata and Orthoptera for 10-fold cross validation process. In future, we have planned to develop the new automatic insect pest recommender system for agricultural field.

In order to demonstrate the efficiency of proposed models, experiments are conducted using K-Fold validation (3-fold, 5-fold and 10-fold cross validation) from Wang dataset. We have observed that all the three proposed CNN models with 10-fold cross validation have given better accuracy than 3-fold and 5-fold cross validation. The accuracy of the pest-identification system will be improved in the future by developing a more accurate and robust model. In the future, a smartphone application to detect pests and provide pest information to farmers will be developed. The application will play a significant role in early pest detection and crop damage prevention due to harmful pesticides and toxic pesticides for useful pests.

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