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ARTIFICIAL INTELLIGENCE FOR CLASSIFICATION AND DETECTION OF MAJOR INSECT PESTS OF BRINJAL

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ABSTRACT

The present study was carried out during rabi 2020-21 at the College of Horticulture, Venkataramannagudem, West Godavari, Andhra Pradesh. Detection and monitoring of insect pests through Artificial intelligence (AI) were conducted using the Python software through Keras and Tensorflow frame works and for this purpose CNN VGG-16 model was used. A total of 204 insect images were loaded and included in four datasets. All the datasets were resized to 224 _ 224 pixels. CNN VGG-16 model codes developed for automatic pest classification and detection of pest images were run through python language to retrieve the predicted output. In the pursuit of detecting insect classification an accuracy of 95-98% for 4 insect classes viz., brinjal shoot and fruit borer larvae and adults, *Epilachna* beetle grub and adults were predicted with F1 score of 0.89 which shows that the CNN (VGG) model is consistent in detecting the type of insect.

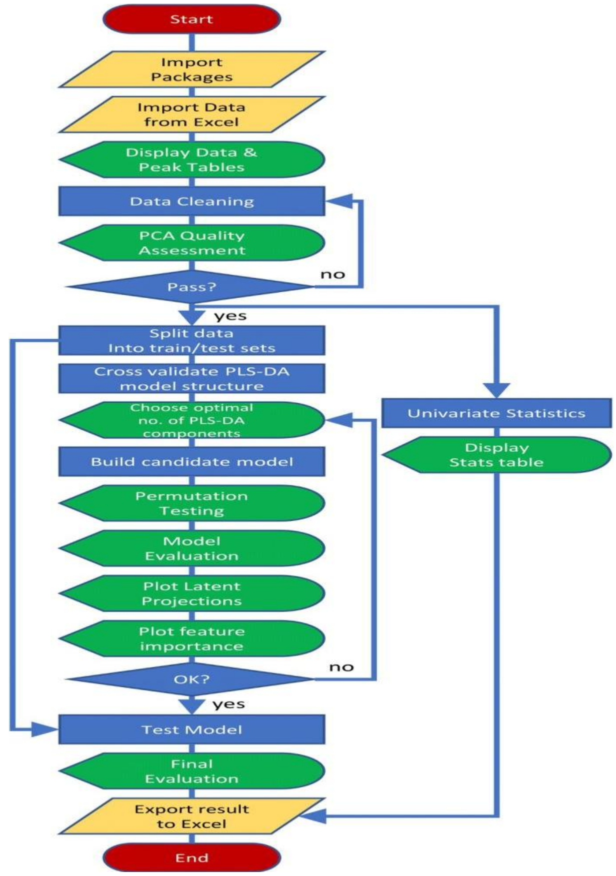
Key words: Machine learning (ML), Convolutional neural networks, python language, keras, tensor flow, insect pest, insect images, prediction models, insect boxing, insect monitoring

Artificial intelligence (AI) techniques provides the best possible solution for objective estimation of a large number of pest insects in a short time period through application of machine learning regression techniques at various stages of crop growth (Zhu et al., 2016) which can be an alternative to traditional way of pest monitoring and detection which requires long time for identification, classification, detection, counting and their damage assessment. In this paper we propose a new method to classify and detect insect pests based on Convolutional neural networks (CNN). The idea behind this method comes from the observation that the human eye does not focus on all its field of view, but accurately discriminates between its relevant and not relevant parts. Detection and monitoring of pests using AI is done through the Python software and other supporting frameworks such as Keras and Tensorflow by developing pest detection codes using VGG-16 model. The insect images in the pest datasets are subjected to bounding boxes (Kasinathan et al., 2020) to limit the size of the photo only to include the image of the insect. Further image augmentation techniques can be deployed to create new artificially generated image datasets for training and validation. The pre-trained model for pest classification and detection i.e., VGG Net (Garcia et al., 2020) can be used to extract the insect morphological features (feature extractor) which will distinguish the insect objects to classify unseen objects through codes / algorithm using python programming language. The training process of this VGG model will modify the input layer (Tuda et al., 2020) where the first few layers will be hidden in the dataset. The output layer will be dense and the fully connected layer with nodes where the output is visualized through Softmax activation function of the VGG model. The Artificial intelligence algorithm / codes that have been developed for insect pest classification and detection will predict accuracy to the original insect pest datasets. The invaluable information on early and quick detection of crop pests is currently being integrated into the pest management modules as a novel tool for pest identification, classification, monitoring, surveillance, prediction and timely interventions for pest suppression.

MATERIALS AND METHODS

In the present study AI / ML algorithm was used for classification and detection of insect pests in brinjal crop at various stages of crop growth. The data was analysed on 2.3 GHz Intel corei5 processor with 8 GB of RAM using the Python software and other supporting frameworks such as Keras and Tensorflow. A laptop with the configuration was utilized for this research viz., RAM of 8 GB and System Type of 64-bit Operating System, x64-based processor. The research on detection and monitoring of insect pest classes of brinjal crop was executed on Anaconda platform of windows 10 along with Google drive for data storage. In the current analysis, the insect datasets were preprocessed, augmented, trained, tested and classified using Anaconda web-based platform applied by Google for implementing machine learning and deep learning models.. Tensor Flow and Keras are the primary libraries used herein and these packages were loaded onto the anaconda environment for model implementation. Total Power Unit (TPU) runtime available for free of cost in anaconda was utilized since the size of the data set used was around 8 GB. The insect pest data set acquired for this analysis was uploaded into google drive and then loaded into anaconda for further analysis. The primary reason for choosing google drive as a data repository for this analysis is that the size of the insect data set was around 4 GB. The CNN models for pest classification and detection was done through Python programming language where advanced importing packages such as Tensorflow and Keras were used for deep learning.

The various python libraries used for implementing CNN model to train the algorithm of insect datasets are NumPy, TensorFlow and Keras. Insect dataset for Insect classification and insect detection of brinjal crop was performed as suggested by Kasinathan et al. (2020). Insect Dataset had a total of 204 insect images of solanaceous and cruciferous crops. The total 204 insect images in the dataset were further grouped in to ten insect classes which were augmented for pest detection and monitoring. A total of 55 insect images were included per class, and they were divided into 80–20% train-test ratio. In dataset, the training set contained 163 insect images, and testing set contained 41 insect images. Image augmentation was applied for all the 204 insect images of brinjal crop mentioned in table 1. The insect images were rescaled to the size of 224_ 224 pixels. Image data augmentation techniques such as Horizontal and Vertical Shift Augmentation, Horizontal and Vertical Flip Augmentation, Random Rotation Augmentation and Random Zoom Augmentation were used to increase the training set for achieving improved accuracy and eliminate the problems of overtraining. Image augmentation was applied to insect dataset images to expand the training dataset. Later, shape features extracted from the insect images and ANN, SVM, KNN, and NB machine learning algorithms were applied to classify the insect classes. CNN based insect classification was adapted for comparison performance. The experiment was conducted with 9-fold cross-validation for insect dataset to evaluate the performance of the machine learning algorithms. The flow chart as given here for pest detection algorithm was done using VGG-16 model (Kasinathan et al., 2020). Classification accuracy was calculated to compare the observed and the predicted outcome of insect pest dataset classes which revealed that the number of correct and incorrect predictions categorized. The classification accuracy of the VGG-16 model used for pest classification and detection was calculated as suggested by Kasinathan et al. (2020).



Flow chart for insect pest detection algorithm (after Kasinatha et al., 2020)

RESULTS AND DISCUSSION

The present study was carried out to classify and detect the insect pests viz**.,** brinjal shoot and fruit borer larvae and adults, *Epilachna* beetle larvae and adults in brinjal crop using AI/ML at various stages of crop growth. The different insect pest stage features were used for insect classification by applying ANN, SVM, KNN, NB, and CNN models. The performances of machine algorithms for two datasets were compared to provide insect class information and detection of insects performed with datasets. The insect pest detection algorithm is simple and efficient in terms of computation time for detecting insects in agriculture fields. Image processing techniques were applied to segment the foreground of insect pests and locating the position of the insect in the image with a bounding box. Detection and monitoring of major pests of Brinjal crop through AI/ML were conducted on a 2.3 GHz Intel corei5 processor with 16 GB of RAM using the Python software and other supporting frameworks such as Keras and Tensorflow. The insect classification and detection were performed through image preprocessing, data augmentation, training and classification for various insect pests. The procedure for pest detection was done through AI / ML algorithm using VGG-16 model. A total of 204 insect images were loaded and resized to 224 _ 224 pixels. Open colour visualisation (CV) technique reads the color image in the order of BGR (Blue, Green, and Red) format.

CNN VGG-16 model Codes developed for automatic detection of 204 insect pest images given in four classes of data sets were run through python language. In the initial stage of study, images were acquired using the digital camera as suggested by Kasinathan et al. (2020). The size of the image was of the standard 1920 x 1080 and in SRGB color format. The pictures taken by digital camera contained a lot of noise in the form of fingers, leaves or the insects in the midst of other insects. We used bounding boxes method to limit the size of the photo only to include the image of the insect. We used image segmentation techniques using state of the art deep learning algorithms according to the procedure laid out by Liu et al. (2019) such as VGG to approximately isolate the shape of insect using the basis of a common insect. To improve the performance of the deep learning model, we have reduced the resolution to 50 x 50 to shorten the computational and training time and which also helpful to the farmers who usually use low-resolution cameras. Edge detection was used to mark out the edges of the insect since some of the insects were having same color such as the beetle adults and grubs. Initial results showed that edges detection gave erroneous results i.e., 2 or more insects were having similar shape but varied distinctly. Image processing techniques were applied to segment the foreground of insects and locating the position of all the insect images with a bounding box. Further image processing was done but it was time consuming and sometimes resulted in less accuracy than the model with no image processing applied, while it extracted feature in insects appearing visually distinct, in insects which were visually similar such as the adult beetle and the beetle grub, extraction of features made the images of both insects looksimilar, visually.

To increase the data sets for more accuracy, precision and F1 score, various image augmentation techniques were used viz., Horizontal and Vertical Shift Augmentation, Horizontal and Vertical Flip Augmentation, Random Rotation Augmentation and Random Zoom Augmentation. Using these processes, nine new artificially generated image datasets of the original insect pest dataset which was loaded for training were obtained. Further through this process of data augmentation, a total of 892 new images were produced with nearly 200 for each class. Out of the 892 new images produced by augmentation**,** The entire new dataset was divided in to 80:20 split ratio where 80% of the new augmented datasets were used for training and 10% was used for testing and the other 10% for validation of datasets. VGG model is the pre-trained convolutional neural network (CNN) invented by Simonyan and Zisserman from Visual Geometry Group (VGG) at University of Oxford in 2014 which is able to be the 1st runner-up of the ILSVRC (ImageNet Large Scale Visual Recognition Competition) 2014 in the classification task. VGG Net has been trained on ImageNet ILSVRC data sets which included images of 1000 classes split into three sets of 1.3 million training images, 100,000 testing images and 50,000 validation images. The model obtained 92.7% test accuracy in ImageNet. VGG Net has been successful in many real-world applications such as estimating the heart rate based on the body motion, and pavement distress detection.

VGG model was used with the purpose of enhancing classification accuracy by increasing the depth of the CNNs. VGG 16 and VGG 19, having 16 and 19 weight layers, respectively, was used for object recognition. VGG Net took input of 224 _224 RGB images and passed them through a stack of convolutional layers with the fixed filter size of 3×3 and the stride of 1. There were five max pooling filters embedded between convolutional layers in order to down-sample the input representation (image, hidden-layer output matrix, etc.). The stacks of convolutional layers were followed by 3 fully connected layers, having 4096, 4096 and 1000 channels, respectively. The pre trained model for insect pest classification and detection i.e,. VGG Net had extracted the insect morphological features (feature extractor) that can distinguish the objects and was used to classify unseen objects through codes / algorithm developed by using python programming language. In the pursuit of detecting insect classification accuracy, CNN (VGG) model algorithm analysed through python software had an accuracy of 95-98% using 4 insect classes and 92-95% using 10 insect class datasets. The average accuracy metric showed that the present model accurately detect the type of insect across the dataset and F1 score shows perfect precision. The investigated model had an F1 score of 0.89 which signifies that the model is consistent in detecting the type of insect. The VGG model with multiple Convolutional Layers has the required power to identify patterns on the backs of insects. Regular Dropout layers will give us the way to train the model on unseen data using regular bitmasks. However, there was a subtle misclassification in the output pertaining to detection of beetle subclass viz., "epilachna beetle adults" and "epilachna beetle grubs" since all of these insect pests were grouped in single class by the VGG algorithm under the same feature. Overall, our CNN (VGG) model developed for pest classification and detection performed well with 95% accuracy to the original insect pest data.

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AUTHOR CONTRIBUTION STSTEMENT

NSK carried out the experiment, acquisition of images and analysed the data, and wrote the manuscript. NE supervised the experiments, provided technical support, and critically revised the manuscript. CH and KUK susbstantively revised it. All authors read and approved the final manuscript.

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COFLICT OF INTEREST

No conflict of interest.

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