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Pest Classification using Morphological Processing in Deep Learning

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Abstract

Agriculture relies heavily on the prompt detection of pests. There are numerous technologies for identifying pests, but almost all of them are susceptible to misclassification due to inadequate lighting, background distractions, a diversity of collection techniques. Thus, pests that are only partially visible or oriented differently. This misclassification could result in a significant yield loss. We presented an architecture that would use skeletonization together with neural networks as classifiers to give excellent classification accuracy under the aforementioned parameters in order to alleviate this problem. The paper compares the performance of CNN. CNN with VGG16 and the proposed system on accuracy metric. The results obtained are on disoriented images. From the findings it is observed that for data augmented dataset CNN gives 80% accuracy, CNN with VGG16 gives 95% accuracy, and CNN with feature extractor, skeletonization achieved good accuracy which is up to 98%. A web app and an android app is also developed to classify the pest which will help the farmers to identify the name of the pest without going into technical details. This framework will surely help farmers in identifying pest names instantly which will later help in identifying the name and quantity of pesticide.

Keywords: CNN; VGG16; Pests; Skeletonization; Feature extraction

Introduction

The national economy depends considerably on agriculture., it is very important that the crops, fruits, and vegetables are protected from insect attacks. The pests or insects hamper the quality of the crops, fruits, and vegetables and this affects the economy of the nation.

Crop losses from pests are substantial in terms of both quality and quantity of production. According to the "Indian Council of Agricultural Research (ICAR)", about 35-40% of annual crop yield gets wasted because of Pest and plant diseases. Around 60 million tons or 10-12% of crops get wasted due to pests and some nematodes (microscopic worms).

Therefore, reducing loss and increasing agricultural output depends on insect control. Thus, it is crucial to identify them in time and do treatment according to the identified insect. Nevertheless, there are numerous problems with the conventional pest identification technique. Firstly, the most commonly used method is the manual identification of insects which is done by an expert or entomologist [1].

Secondly, there are many insects that have similar phenotypes and different species of the same insects. Therefore, the traditional manual identification method is time-consuming, expensive, and tedious [1].

Intelligent agriculture is recently introduced which proposes an automated parallel processing framework developed using different algorithms and wireless communication techniques like IoT [2–5].

Several insect identification techniques use classifiers to find pests in the field. The machine learning classification techniques reduce time as well as produce prompt responses. The existing models are trained over a very small dataset, thus they get higher training and testing accuracy but for images of different orientations, their accuracy reduces.

To overcome the misclassification problem of differently oriented images, "Convolutional neural networks (CNNs)", which is a type of DL technique, have recently been used as a successful way for automatically classifying crop pests [6–8]. This paper compares the performances of the following three deep learning techniques. CNN, CNN with VGG16 architecture, and CNN with skeletonization. The paper proposes CNN with skeletonization which can identify armyworms, whiteflies, Stem borers, and Gall flies with 90% accuracy for the limited dataset. The result of classification can be seen on a web app or an Android app.

Literature review

DL algorithms have provided a great answer for image classification. Research on solving the classification problem progressed with the classification of pests using a deep-learning algorithm; CNN. Researchers started comparing traditional ML algorithms like "SVM", "DT", "KNN", and "Naïve Bayes" with the deep learning algorithm; CNN. Classification of a few insects depending on the morphology of insects and insect images with common orientation is carried out. In a traditional machine learning technique classifier performance depends upon the features extracted. The author has done pest identification using the morphology of insects, Edge detection using Canny, and skeletonization. Further, after feature extraction classifiers like "SVM" and "Naïve Bayes" are used. The author further applied CNN to improve accuracy and compared the performance of ML techniques with DL techniques. The author suggests working on more insects with the same morphological features and insects appearing in different orientations in images [9].

There are many pieces of research that have used different CNN architectures to check the performance of the model developed for classification. The paper collected insect images from Google Online and named the dataset as Mpest. It used VGG19 architecture to classify the pests. The paper also compared the performance of the proposed system (CNN with VGG19) with SSD and Fast RCNN considering parameters like mAP, inference time per image, and required training time. Due to limitations on the dataset, the algorithm did not perform as expected. Thus, image augmentation is needed. Also, to achieve good classification the insect growth period can be divided and classification can be done accordingly [10].

"Convolutional neural network (CNN) with deep architectures" is being used in image classification applications where it does involuntary extraction of features is done and studies intricate features. This learning suggested an effective deep CNN model to categorize insect species. For the categorization of insects, the proposed model was assessed and compared with those that had already been trained, such as "AlexNet", "ResNet", "GoogLeNet", and "VGGNet". The pre-trained models are improved by the use of transfer learning [1].

The author states that the pest images to be classified can be collected online in real time environment and uninterruptedly train classifier models more accurately for multi-class insect identification. The images of sticky paper traps from different locations can be collected using wireless sensor nodes at a remote server at a fixed time. The author worked on pests like Fly, Gnat, Whitefly, Mothfly, and Thrips. As the images are received, they are used to train the model using unsupervised learning. The method is able to raise the classifier models' average F1 score from 0.88 to 0.926, which is nearly equal to the 0.94 F1 score attained with supervised learning. The suggested method eliminates the need for the manual collection of new images, which saves the effort needed to train new image classifier models [11].

A manually operated UAV for classifying insects on soybean crops is developed. The study aims to prove that CNN outperforms other conventional feature extraction methods. The manually controlled UAV uses an Nvidia GeForce GTX 1080 Ti Gaming Graphics Processing Unit (GPU) Card. It is possible to launch an autonomous UAV for identification. Additionally, attention must be paid to the height of UAVs for detection and a high-resolution camera is required to capture good-quality pictures [12].

The proposed solution involves utilizing CNN to find and identify insect pests in crops (CNN). Based on explainability methodologies, insects are located from the input data. Explainability emphasizes the hues and shapes captured by CNNs' visualization maps. The paper uses IP102 dataset and achieved an accuracy of upto 58.90% which still has to be improved [13].

The paper uses IoT and Deep Learning (DL) framework-based monitoring and detection of insects in real-time using remote insect traps. Through the use of yellow paper sticky traps, the images are captured. To track the status information, a web-based GUI for Android mobile devices has been built. A faster RCNN ResNet50 object detection framework is used which achieved 94% accuracy. The author suggests that the images collected from the yellow paper trap have insects of the same class. Yellow paper trap with multi-species and from different families is still a future scope. The paper aims to develop a drone to identify insects [(14)].

The author proposed insect detection and classification based on improved convolutional neural network. The proposed system uses Xie's dataset which consist of 24 insect classes consisting of 1 image each. The dataset is very small. The improved network architecture was implemented based on VGG19 and RPN (Regional Proposal Network). VGG19 consist on 16 convolutional layers, 1 roll pooling layer and 2 fully connected layers. Their model is trained on pre-trained model. Thus, their system gets accuracy up to 90% . The proposed system has VGG19 is faster and more accurate than the existing methods [(10)].

Methodology

CNN

An artificial neural network that has been successfully utilized to analyze visual pictures is CNN. It draws inspiration from biological processes, and the connections between the neurons are analogous to those in the animal visual cortex. There are 3 layers in CNN, include an input layer, a hidden layer, and an output layer. In general, an image is made up of a matrix of pixels, and these pixel values, along with weights and biases (for non-linearity), are fed to the input layer. The output layer will typically be a fully linked layer that classifies the image to the appropriate class. Convolutional, pooling, or fully linked may be the hidden layer. Before we train a CNN model we have to primarily build a Fully connected neural Network. Basic steps to build the neural network are:

1. Input image to be flattened to 1 dimensional (width pixels x height pixels
2. Normalizing the image pixel value (divide by 255
3. Apply One-Hot Encoding
4. Construct a model architecture (Sequential using Dense layers (Fully connected layers
5. There are many activation functions used out of which relu and softmax are used often.
6. Train the model and make predictions Mostly Accuracy is considered an evaluation metric

A CNN model can be further built by adding a Conv2D layer and max pooling layers. One can add any number of layers to achieve accuracy. However, overfitting and underfitting are both criteria that must be taken care of.

- **Convolution Layer:** Features from the input image are extracted by this layer. It kernelizes the input image. during a convolution process in order to recognize and extract particular features.
- **Pooling Layer:** The pooling layer reduces the spatial dimensionality of the convolutional layer's feature maps. To decrease the size of the feature maps and the computational complexity, it down-samples the data.
- **Activation Layer:** The output of the pooling layer is subjected to a non-linear activation function at the activation layer, such as the ReLU function. The model can learn more intricate representations of the input data.
- **Fully Connected Layer:** Based on the features, predicts the image's class that has already been extracted in earlier stages.
- **Dropout:** When all features are connected to a fully connected layer a problem of overfitting may occur. To deal with this problem When using a dropout layer, a few neurons from the neural network are removed during training, reducing the size of the model.
- **Activation Function:** These functions are used to learn the complex relationship between the variables of the network. These functions will decide which information can be passed forward in the network and which cannot be passed. This is the most important parameter of the CNN model.

CNN can be used in different applications like Speech signal processing [(15)], Bio-medical signal processing etc. There are various CNN Architectures used for image classification. Some of them are; "LeNet", "AlexNet", "ZFNet", "VGGNet", "ResNet", "GoogleLeNet", "MobileNets" [(16)]. Each architecture differs in performance. The metric used for performance evaluation is Accuracy which is calculated after plotting the confusion matrix.

Skeletonization

Skeletonization is the process of reducing background components in a binary image to skeleton remnants that preserve the extent and connectedness of the original region while eliminating the majority of the original foreground pixels. Skeletonization makes BLOB a very thin line. Skeletonization is used basically for object identification.

When only the basic shape of an object on the image is of importance, extreme morphological processing techniques like thinning and skeletonization are applied. Skeleton maintains the size of the input object, in contrast to the thinning procedure. The edges of the input object are reached by the end points of the skeleton.

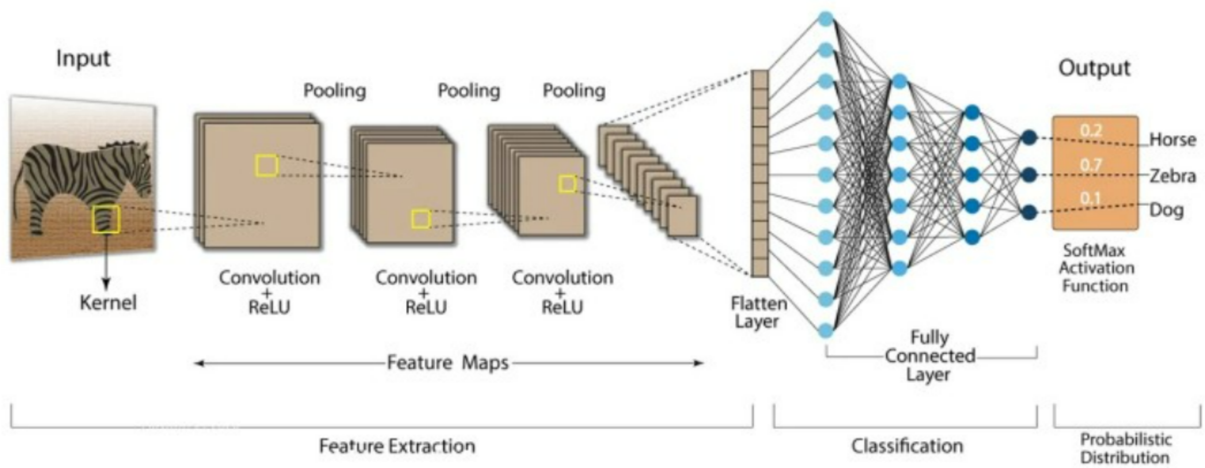

Fig 1. Convolutional Neural Network (CNN). (Source: https://www.linkedin.com/pulse/what-convolutional-neural-network-cnn-deep-learning-nafiz-shahriar/)

Thinning reduces binary picture objects to a collection of straightforward digital lines (or arcs), which roughly follow the medial axis (center line) of the original objects. The structure that is obtained is unaffected by minute inclines in the visual object. Recursively, the technique eliminates simple border sites with several neighbors. The thin arcs' endpoints are not lost when using this technique[9].

Pests and dataset

This paper focuses on pests belonging to four classes namely; armyworms, whiteflies, Stem borers, and Gall flies. With the support of data augmentation the pests dataset was expanded to around 4000 images. Out of total dataset 70% dataset was used for training the model and 30% of dataset is used for testing the model validity. Figure 2 shows the sample pest images collected from farm field.

Fig 2. Sample images of pests collected from crop field

Proposed work

The paper mainly focuses on pest image classification in a given diagram. Figure 3 shows the proposed methodology. The images obtained from farm fields are of different pests. Initially, the pest images are labeled and organized in their respective classes. This paper uses 4 classes of pests. Later all the images are resized and the data Augmentation is performed. In order to extract features the image is converted to binary and then skeletonization is done. The skeletonized image is input to the deep learning model. The classification result can be seen on a Web app and an Android app.

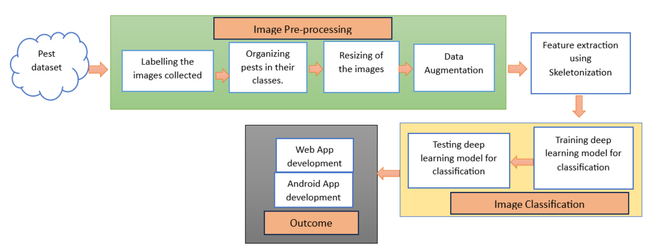

Fig 3. Proposed Architecture for **Pest Classification**

- **Algorithm 1: CNN used for classification**

1. Obtain pest images
2. Perform pest annotation
3. Preprocessing of the images collected
4. Data Augmentation
5. Train the CNN model for classification
6. Test the CNN model for validation
7. Perform performance analysis in terms of Accuracy

- **Algorithm 2: CNN with VGG16 used for classification**

1. Obtain pest images
2. Apply Data Augmentation
3. Load pre-trained VGG16 model
4. Add a flattened layer and 2 dense layers
5. Compile model over accuracy Matrix
6. Plot loss and accuracy graphs
7. Test the CNN VGG16 model for validation
8. Perform performance analysis in terms of Accuracy
9. Build an android app

- **Algorithm 3: Skeletonization for feature extraction and CNN for classification**

1. Obtain pest images
2. Apply Data Augmentation
3. Convert images to binary
4. Apply skeletonization for feature extraction
5. Train the CNN model for classification
6. Test the CNN model for validation
7. Plot the confusion matrix
8. Test Performance with Accuracy as the evaluation parameter
9. Build an Web app

Result and Discussion

CNN being a layered network does not require a feature descriptor or a feature extractor. Considering this a CNN model was trained with the expanded dataset and was tested for validity. The accuracy achieved was 80%. Later to improve the accuracy few more layers were added to the CNN model. Thus, CNN with VGG16 was built. The model resulted in accuracy between 95% to 98%. The model built using CNN showed up with 80% accuracy in classifying the pest. The paper proposed a framework built using skeletonization for feature extraction and a CNN model used for pest classification. This framework resulted in 90% accuracy.

The training and testing with the proposed system are performed on slightly disoriented images. If the images provided are clean then the accuracy may reach up to 98%. Figures 4 and 5 showcase the loss and accuracy achieved over 20 epocs. Figure 6 is a web app developed for classification of pest. This web app will first upload the test image. The image will be converted to binary. Later feature extraction is done using skeletonization. The web app will display the name of the pest.

Android app developed for pest classification is seen in Figure 7. Also Figure 8 shows a comparison between deep learning techniques like CNN, CNN with VGG16 architecture, and CNN with feature extractor; skeletonization which is the proposed framework.

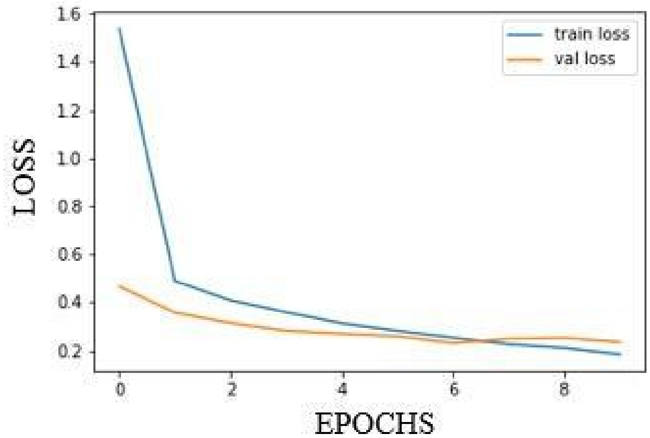

Fig 4. Loss parameter graph over epochs

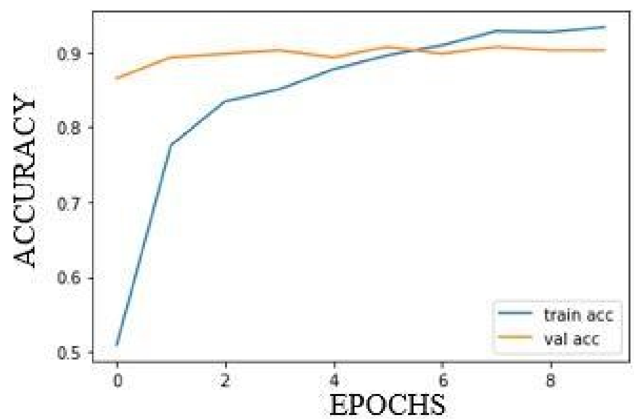

Fig 5. Accuracy over epochs

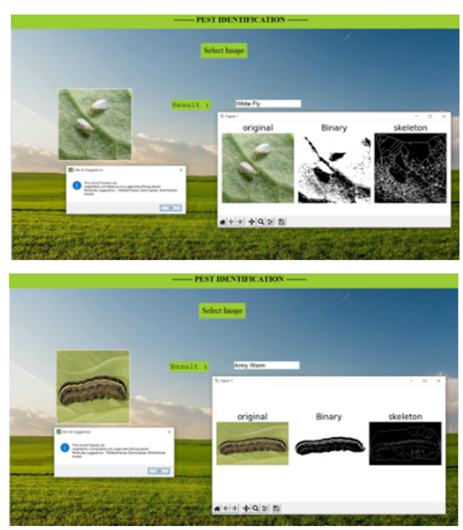

Fig 6. Web app for pest classification using skeletonization

Fig 7. Android app for pest classification

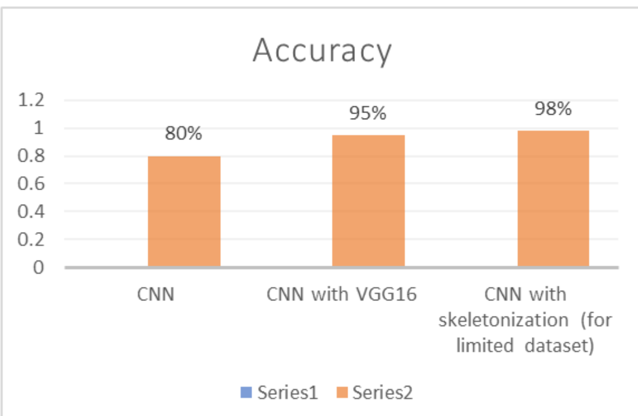

Fig 8. Comparison of pest classification deep learning techniques

Conclusion

The paper proposed an insect identification and classification technique by using feature extraction using skeletonization and classification using CNN for accurate identification and classification. This framework achieves accuracy with a dataset with disoriented images. However, the dataset used is still limited. The accuracy can be improved by expanding the dataset. As compared to CNN and its different architectures in terms of accuracy the proposed system gives better results.

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