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Deep Learning-Based Crop Pest Detection and Classification using DenseNet Technique

Z. Ali[1], F. Ali[2], M. M. Iqbal[3], S. Ramzan[4], W. Ali[5], A. Tariq[6]

[1,2,3,5,6] *Department of Computer Science, University of Engineering and Technology, Taxila, Pakistan*
[4] *Department of Computer Science & IT, Govt. Sadiq College for Women University, Bahawalpur, Pakistan*

[3] munwar.iq@uettaxila.edu.pk

Abstract- A correct classification of species will help in choosing a proper strategy for crop management, but designing a self-operating solution is also problematic due to the high similarity among species. The agriculture field has immense potential for improvement of needs of food and provides healthy food. Yield loss is a major problem in the agriculture field due to the attack of various insect pests. Farmers often face challenges in the recognition of crop insects as a significant portion of the crop is damaged. Early information on pest attacks can help farmers to reduce damage and enhance the productivity of crops. The quality of crops is degraded due to pest attacks. This paper aims to detect insect pests in crops using a deep learning technique. The DenseNet model is used with respect to recognizing insect pests. The model neck creates feature pyramids for feature extraction to obtain a single-stage image randomly sized for input, and output with proportionate-size feature maps at various levels. IP102 dataset is utilized for the purpose of training, and testing of the model. The total images of 292 rice leaf caterpillars and 669 for rice leaf roller class were used for training and testing of testing respectively. Experiments were conducted on two classes namely rice leaf caterpillar and rice leaf roller. The highest classification accuracy of 87.90% was achieved. The classification results of the model are utilized to recognize insect pests in crops.

Keywords- Crops, Machine Learning Techniques, Densely Connected Network (DenseNet).

I. INTRODUCTION

The extremely important cash crops often devote broad quantities of production. Crop yields have to be improved because of the increasing need for crops in poor countries due to their continuous rise in population. The existence of variation within the world is biological diversity plays an important role in improving the quality of crops. Crop improvement depends on a broad base of degree genetic divergence. Wheat is the most important crop and food source for humans. It has a huge impact on humans. It is cultivated widely for cereal grain, a global staple food. It was first cultivated in Fertile Crescent around 9600 BCE. It is cultivated on land area more than any other crop. It contains a certain amount of major nutrients like fiber and protein. Wheat provides high essential nutrients in the United Kingdom; a prosperous country underlines its importance globally. The utilization of wheat is increasing in such countries where the climate does not suit its production. Increasing worldwide requirement of wheat to make healthy products and to increase utilization of these along industrialization. Insect attack is a major problem in the field of agriculture that degrades the quality of crops and also results in a low market for the final product. Pests attack also results in the degradation of the productivity of crops [1].

Generally, pest attacks cause a reduction in the production of crops. Various crop models have been designed for the estimation of agricultural production by considering weather conditions, soil conditions, and changes in climate. Only a few models considered the impact of insects, despite damage directly resulting from pest infections and indirectly from pesticides for the reduction of pest damage. Due to the change in climate resulting expansion of pests geographical distributions, reduction in their biological control, and increase in their generations is harmful to crops [2]. Special attention is required from decision-makers, researchers, and farmers to know how climate change can impact pests [3]. Proper checking is required to provide a solution, negligence can lead to a reduction in crop production and an increase in poverty, even in the death rate.

The economy of a nation is disrupted, especially in agroeconomic countries where most of the population is dependent on agricultural fields for living. Pests can result in famine and scarcity of food. There are several types of insect pests. These insects can affect the crop seeds during germination or affect the plant leaves. The insect pests are discussed here for diagnosis and detection of insects for effective treatment. These pests decrease the production of crops by affecting the plant leaves. For effective treatment of these plant diseases, understanding of few things like the appearance and symptoms of attack is necessary for effective treatment [4-5]. The main insect pests that harm the plant leaves are rice leaf caterpillars and rice leaf rollers. Pests often attack greenhouse crops, some are very small in size also soft-bodied. They are pear-shaped and delicate insects. They cause serious damage to many foods in most parts of the world. Their heavy infestation results in plant death [6-7]. Symptoms include growth stunting and malformations. They are sluggish pests. They affect the crop and degrades the quality. In the seed, the formation of discolored seeds happens, or empty seeds are formed. Their ability to exploit plants rapidly makes them serious pests to crops. They cause important losses to crop yield and the quality of most fruit crops. They can transmit even over long distances and it is a great concern in the agriculture context. They also create infections in plant populations. Pests affect the economy in a negative way. It also threatens food security. When an insect once occurs in crop fields, it is difficult to control it [8-9]. Insect pests attack crops in different regions of the country. Some insects emerge from the soil, they begin to search for potatoes, tomatoes, and aubergine to feed upon in fields. This begins with walking but after unsuccessful finding, they continue to search with flight [9-10]. Insect pest species cause severe damage to its host. Some pests have long antennae, especially in males we call them longhorns. Some pests have long antennae, especially in males we call them longhorns. They contribute to fungal infection of crops and direct damage to grains. The pests seriously affect the virtue of the product and the ability [11].

II. LITERATURE REVIEW

Traditional insect detection has the drawbacks of identifying insects on crops because it requires well-trained taxonomists to do this job. They conducted experiments on classification by selecting shape features by utilizing Wang, Xie dataset and the number of classes considered were 9 and 24 respectively and techniques were used based on ML namely Artificial Neural Network, Support Vector Machine, k-nearest neighbors, Naïve Bayes, and Convolutional Neural Networks [1]. Pest management is a difficult job because pest recognition requires much more attention than the see-and-spray approach. They used a multiple-classifier system approach for the identification of pests in crops. The system is innovative because it uses multiple classifiers and gives more classification accuracy of type of the pests. Thrips are harmful pests that threaten strawberry greenhouses. Support vector machine method used for identification of thrips. The choice of suitable region and color index was successful for the detection of thrips. Farmers use insecticides to control insect pests that can harm crops. While their other target is to enhance crop yield. They proposed optical sensors along with machine learning. They obtained 10,000 pieces of evidence of flying insects appearing in oil seed rape crops. The classification accuracy of the model is 80 percent [12].

Identification of insects using images is challenging and important research. A machine learning approach is proposed for correct species classification. They conducted experiments by separating classes into adult classes and early stages. They achieved 86.33 % accuracy for adult class [13]. Rapid pest identification is required for effectual crop protection. Experts are needed for the identification of insects. They proposed automated machine learning for pest identification. The accuracy can be increased with training images with the use of inverted images. Their model provides a starting point in the training of a machine learning model [14-15]. The production rate of crops is reduced with reason of the presence of whitefly pests. The technique used for the detection of whiteflies is image segmented. The k-means cluster algorithm can be to identify whiteflies pests. The chief objective of the model is to identify the location of whiteflies and it is successfully achieved. Insect pests cause severe loss to farmers and farmer communities. Insects are the reason behind the damage to crops.

They introduced histogram and contour identification for feature extraction and a Support Vector Machine for the classification of images. The proposed system helps farmers to save the environment [16]. Insect identification plays a vital role in food security and a stable agricultural economy. They proposed a Scale-Invariant-Feature-Transform (SIFT) integrated engaged with HMAX model for invariance rotational variations. They used a support vector machine to recognize pests. The proposed model achieved good results with a detection ability of 85.5%. The model provides the idea for rapid identification of pests [17]. Weather is a factor that affects badly in picking of times. They recognized pests on tea leaves using SVM. It then concluded that the SVM classifier had already been used in the identification of pests in tea leaves. The model achieved 74% accuracy [18]. Detection technology relies on artificial enumeration which requires large labor, feedback delay, low efficiency, and artificial faults. Rapid identification of pests can reduce the use of pesticides. They proposed a classification model based on Bag of Words and SVM. The Algorithm achieves ideal precision. The model can assist in precise spraying [19].

They presented a transfer learning framework to classify pests present in tomato plants. They utilized online sources to obtain a dataset that consists of 859 images of 10 classes [20]. The dataset is collected in real-life scenarios, which consists of 1426 images and covers eight classes of pests. Inception v3 and VGG16 were adopted and fine-tuned for pests recognition [21]. They proposed a lightweight deep network CPAFNet for the recognition of pests. Feature extraction process completed using class-activation-map-algorithm [22]. They proposed ResNet34 for the detection of pests. Images were collected from entomology researchers, some images were collected from the field, and some were collected from the internet. The proposed model achieves better accuracy [23]. They proposed Deep-Convolutional-Neural-Network for the detection of pests. The model is built using different DCNN, interpretation was made based on on accuracy value and performance [24]. Insect monitoring provides a decision-making tool and contributes to the optimization of crops. It also improves the yield of production. The aim of the research is to review of evolution insect pest recognition in terms of the method used [25]. A robust DL method can be used for pest recognition and comparison with already work done in the same field. A deep learning model can be trained and evaluated to obtain performance according to its detection quality [26]. The data acquisition process plays an important role in correct recognition of insect pests because model will be trained on features of that data [27]. Pre-processing of model performs major contribution in training of model [28]. Performance metrices guarantee the capability of model that can be used for further research in the same field .

Table 1. Literature Survey using ML, DL Methods

Sr. #	References & Year	Dataset used	Technique used	Results
1	2021 [12]	Insects collected in oilseed rape (OSR) from Rothamsted farm (N 51.806146, E0.359080), England	Optical sensors with machine learning	Classification accuracy is 80 %
2	2022[13]	IP102	Machine learning including maturity stages classification	Accuracy of 86.33% for adults
3	2019 [16]	Captured images	Machine learning, SVM	It helps farmer to save environment, Effective outcome and clear results
4	2018 [17]	McGill color image dataset (Olmos & Kingdom, 2004)	SIFT, SVM	Accuracy 85.5%, Rapid recognition of pests
5	2021 [18]	Images taken at PTPN IV Bah Butong Plantation using Xiaomi Note 5 Pro Camera	Support Vector Machine (SVM)	Model achieved 74% accuracy
6	2020 [21]	Images collected in real life scenario	VGG16 and Inception v3 fine tuned for detection	Fine tuning by pre-trained ImageNet always provides best results
7	2020 [23]	Images collected from different sources i.e., online, from field, from researchers	Deep residual model RESNet34	The model recognizes pests in a better way with good accuracy

III. Materials and Methods

Insect recognition is a multi-step process where various operations are carried out for the detection of the multiple stages as given in Figure-1. Pest recognition is comprised of some major steps like obtaining dataset images, model training, and model evaluation. Eventually, the presence of insects in the crop leaf can be detected using the trained model.

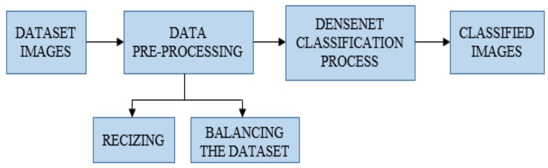

Figure 1. Insect Detection Process

3.1 Dataset

The dataset IP102 has over seventy-five thousand images of 102 categories. IP 102 has a larger scale, which benefits a method that is based on deep learning. It involves many features like the image that belongs to a similar category can capture dissimilar growth forms of similar types of insect pests. This unique diversity of the IP102 dataset is ignored in previous datasets. The pet face dataset was downloaded from the Kaggle website. The balanced dataset contains 292 images of class rice leaf caterpillar and 669 images of class rice leaf roller. This dataset is open-source and is publicly available for research purposes. 961 images were used for experimentation purposes. Insect pests exist in various categories, and the two of them are presented.

- *Rice Leaf Caterpillar*

It endangers the crop, especially in the summer season. The caterpillar is a pests to maize crops crop, and it is the caterpillar life stage of moth. It tends to cause infection to plants in a field until the crop is exhausted. Caterpillar is a threat to maize crops and their production. The maize crop is a staple diet for rural people. Caterpillar negatively affects the economy. It also threatens food security. When a caterpillar once occurs in crop fields, it is difficult to control it [8]. It was initially found in maize crops in Pakistan and the year was 2019, and now affects maize, millet, and sorghum crops in different regions of the country.

Figure 2. Rice Leaf Caterpillar Image

- *Rice Leaf Roller*

Rice leaf roller is a pest to rice crop in Asia. A most significant pest that causes destruction to grains and degrades grains weight [29]. It has caused huge losses to rice crops in various Asian countries. Rice leaf folder is a notorious pest, its infestation could result in significant loss to the economy. It along with other insects is known to adopt the multi-stop migration in which they land for some time to infest a crop and fly in search of another crop.

Figure 3. Rice Leaf Roller Images

3.2 Image Pre-processing

Images are collected randomly, and these can vary in size. So, these images are preprocessed and transformed in uniform size. The dataset images are resized to 128, 128, and 3 for the DenseNet model to improve accuracy. This is the default input size of the models, then dataset balancing is performed to fix overfitting.

3.3 Use of Deep Learning Method for Insect Recognition

We have used DenseNet for the recognition of pests. DenseNet performs better in the detection of insects. A detailed description of the model is provided below.

3.4 DenseNet

A densely connected neural network is a type of Convolutional neural network. In DenseNet, every layer is connected to all layers in front of it directly and the model is built from transition layers and dense blocks. There are three operations in a dense block such as batch normalization, ReLu, and Convolution. The transition layers between two contiguous blocks are Convolution and average pooling. The network becomes thinner because each layer accepts feature maps from preceding layers. Steady feature map size is required To guarantee that feature maps are connected which also indicates the size of input and output convolution layers is the same, steady feature map size is needed.

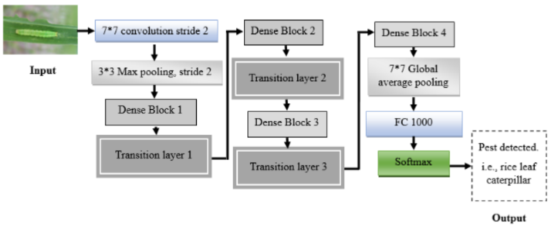

Figure 4. DenseNet Architecture

3.5 Model Training and Process of Model Learning

The dataset often plays a tremendous role in achieving high accuracy for deep learning models. The model can be trained and tested on the dataset.

3.6 Disease Prediction

After training the model, the classifier will predict insects on given images as fractured or normal, based on model training.

IV. RESULTS AND DISCUSSION

The DenseNet model is used to recognize whether insect pests like rice caterpillars or rice leaf roller exist or crop is healthy. The total images used for training were 961, 292 of rice leaf caterpillar class and the rest of the images were of rice leaf roller. DenseNet model was used to obtain high accuracy with respect to pest identification. For pests recognition, training instances in the batch were 32 for the model, and the number of epochs was set to 45. An input size of 128 x 128 x 3 is used for DenseNet.

4.1 Accuracy

Training accuracy refers to the accuracy obtained in the training process of the model and validation accuracy refers to the accuracy obtained in the testing process respectively. Similarly, the accuracy that has been obtained on the test dataset is validation accuracy. Accuracy can be explained as given through equation (01).

$$Accuracy = (TP + TN) / (TP + FP + TN + FN) \quad (1)$$

Here
True negative (TN) = Correctly predicted true outcome
True Positive (TP) = Correctly predicted true outcome
False Negative (FN) = Incorrectly predicted negative outcomes False Positive (FP)= Incorrectly predicted Positive outcomes
The proposed DenseNet model has obtained 87.90% training accuracy.

Accuracy Curve and Learning Curve

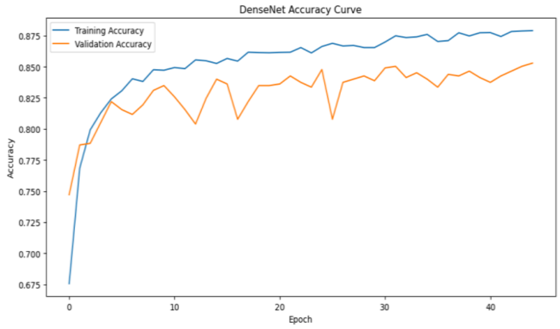

Figure 5. Accuracy Graph of DenseNet Model

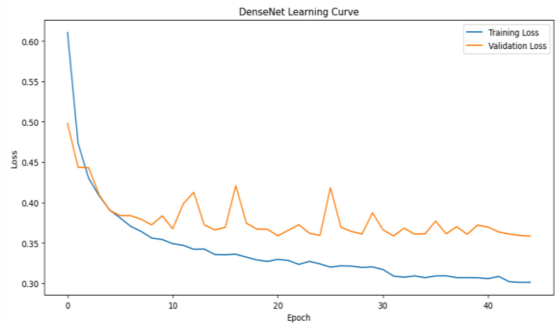

Figure 6. DenseNet Learning curve

4.2 Precision

Precision does not measure the number of positive entities rather it determines the capability of the model for classifying positive entities. Both positive as well as negative values are considered in precision. So it is dependent on both positive and negative entities. All positive entities are considered either they are positively classified or negatively classified. Precision can be explained as given through equation (02).

Precision = TP (True Positive)/ TP (True Positive) +FP (False Positive) *(2)*
Here
(TP) = True outcome
(FP)= False outcomes

The proposed DenseNet model achieved a precision value of 0.81%.

4.3 F1 Score

F1 produces a number by combining both precision and recall values. Whenever the values of precision, and recall are greater, then the F1 value is also greater. The greater value of the F1 score shows that the model is performing very well. So it sweetly adds up the predictive performance of the model. F1 score can be explained as given through equation (03).

F1 Score = 2 (Precision*Recall)/ (Precision +Recall)* *(3)*

The proposed DenseNet model achieved an F1 score value of 0.83%.

4.4 Confusion Matrix

A more accurate way to present the accuracy of the model is to use a confusion matrix. It determines the classification performance of the test data. It includes predictive values as well as actual values. Predictive values are obtained by the predictive outcome of the model and actual values are the true values of the samples. It not only identifies the error but also gives knowledge about the type of error. The confusion matrix for the DenseNet model is presented in Figure 7.

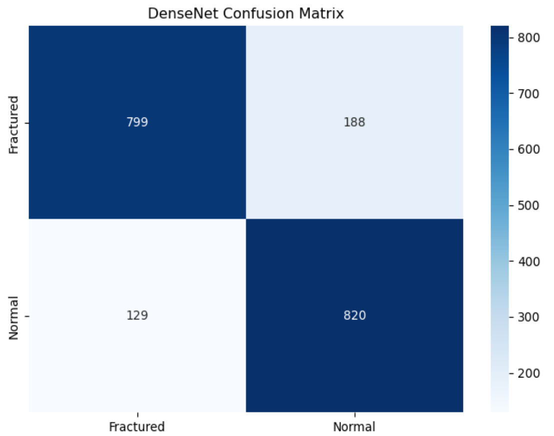

Figure 7. Confusion Matrix

Comparison with Existing Work

The comparison between the proposed DenseNet model and the existing one is presented in Table 2. The metric considered for comparison is accuracy that how accurately a model recognizes pests on crops with respect to techniques used in papers of pest insect classification.

Table 2. Comparison with Existing Work

References	Author	Technique Used	Accuracy
[12]	Kirkeby, C.,	Optical sensors with machine learning	80%
[17]	Deng, L.,	Support-Vector-Machine (SVM)	85.5%
[18]	Steven, S.J.I,	Support-Vector-Machine (SVM)	74%
Proposed Model		Densely connected neural network (DenseNet)	87.90%

The DenseNet model outperformed all the techniques because it is trained efficiently. As it can be observed from the training accuracy of the model. Results can be seen as higher than all other techniques, confusion matrix is also presented that highlights model performance.

V. Conclusion and Future Directions

In this research, a DenseNet model was applied to detect insect pests, specifically focusing on two classes: rice caterpillar and rice leaf roller. The model demonstrated high accuracy, achieving 87.90%. Precision and F1-score were calculated, resulting in values of 0.81% and 0.83%, respectively. The confusion matrix and evaluation metrics were used to verify the model's performance. The success in accuracy and detection rate showcases the model's effectiveness in insect pest recognition. For real-time applications, integrating this model with drone cameras for capturing images of insect pests in fields is proposed. In the future, drones equipped with cameras can capture field images, which will then be processed by the classifier for disease identification. This classification model can play a crucial role in promptly identifying diseases, enabling targeted treatment for infected plants based on the identified disease. The comparison also presented comprising accuracy of different other models with the proposed DenseNet model. In the future, this technique can be utilized with another dataset to improve accuracy and segmentation.

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