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Automated Agricultural Pests Identification using Convolutional Neural Network-based Transfer Learning

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CONTENTS

CLassifying agricultural pests is a crucial task in precision agriculture, which employs technology to enhance farming techniques and increase crop productivity. Accurately identifying and categorizing pests is necessary for effective pest management because different pests require different control measures. This study conducts an exploration of Agricultural Pests Classification (APC), which will significantly benefit every Bangladeshi engaged in animal husbandry. The system can be practically implemented to aid farmers in pest management, resulting in increased crop yield and reduced pesticide usage. The proposed approach in this paper utilizes Convolutional Neural Network (CNN)-based pre-trained deep transfer learning classifiers (CNN-TLCs) to automatically categorize agricultural pests from the public Kaggle dataset "Agricultural Pests," which includes 5534 raw images of 12 different varieties of agricultural pests. Multiple image processing techniques such as image cropping, resizing, rotation, color conversion, filtering, and contrast enhancement were applied to obtain high-quality images to train the models and achieve maximum accuracy. By utilizing Inception-V3 and DenseNet-201 models on the preprocessed images, the system obtained an accuracy of 97.22% and 97.51%, respectively. The high accuracy of the proposed method indicates its effectiveness in recognizing agricultural pests from digital images and helping farmers prevent pest infestations, leading to increased crop production and positively impacting the national economy.

1.1 INTRODUCTION

The world is expected to face an increase in population by almost 2 billion people by 2050, which means that food safety is going to be a major issue in the future [1]. Agriculture is one of the most important industries in order to meet the rising demand for food, and increasing agricultural production is one solution to this issue. On the other hand, pose a serious threat to agricultural output, affecting crop yields and quality as well as increasing production costs and lowering revenues.

In countries like Bangladesh, where agriculture provides the primary source of income for a sizable majority of the population, the situation is particularly dire. The Food and Agriculture Organization of the United Nations (FAO) estimates that pests and diseases cause major economic losses in Bangladesh by affecting 20% to 40% of crop production [2]. The situation is further compounded by the fact that Bangladesh is not economically strong, which means that the impact of crop losses due to pests can be devastating for farmers and the economy as a whole. In developing countries, where many farmers lack access to effective pest control measures, crop losses due to pests can be particularly devastating, leading to food shortages and hunger. Agriculture in South Asia has been plagued by significant pest infestations. About 25%

of the food grains in fields and storage are lost due to their severe deterioration [3]. Rice is the main staple meal and the most important crop in Bangladesh, the brown plant hopper (BPH) and stem borer are two of the pests that cause the most damage to rice production [4]. Accurate identification and categorization of crop pests are necessary for the implementation of effective pest management measures that can reduce their impacts and protect crops. Farmers would be able to take prompt and efficient action to reduce the damage if they can know the pest from the system. The use of pesticides, the development of pest-resistant crops, and adjustments to irrigation and fertilization schedules are just a few examples of the quick reactions and actions that farmers may be able to take effectively.

We believe that our proposed method can significantly improve agricultural production and food security given the deep learning technologies' rapid progress and the growing availability of data. We propose an approach that uses convolutional neural networks (CNNs)-based transfer learning models (Inception-V3 and Densenet-201) to recognize and categorize pests from images, enabling farmers to take appropriate action and determine the best pesticides to apply. To increase the accuracy of pest classification, our suggested method combines the use of transfer learning, fine-tuning pre-trained models, and data augmentation techniques.

1.2 LITERATURE REVIEW

Numerous academics, researchers, and agriculture specialists investigated the potential techniques applied to various domains on pests classification that are pertinent to this study, and below we present a review summary of them.

A deep convolutional neural network algorithm is used by RuJing et al. [5] to analyze more than 30,000 pieces of data, including 82 different types of crop pest image data. Comparing their method to other models, the results are highly excellent. By employing a customized CNN approach, they were able to achieve 91% accuracy. An enhanced convolutional neural network model with an 89% mean average precision (mAP) was implemented by Denan Xia et al. [6] They used the VGG19 model as a starting point before extracting further features, re-shaping them all, and turning them into one-dimensional vector classification. They personally gather the data from public databases and web browsing, and the augmented dataset is extended. randomly choosing the 60 test photographs, where only 660 images are used as an actual dataset. The dataset had been expanded into 4800 photos after augmentation. And there are 24 classes of insects represented by this data. In this study [7], researchers focus on detecting greenhouse insects as part of an integrated pest management (IPM) strategy. They use CNN image classification models and techniques after utilizing an object detector method to identify the pest as an object in the first sector or step of their approach. Tiny YOLOv3 is used to detect objects. The output detection accuracy provided by algorithms is 91%. Total number of photos collected - 3,280 * 2,464. They divide the test dataset into two portions: the initial one is 6 months after the first year of data coverage, and the second is 8 months after that. In object detection, the model was improperly fitted for a variety of situations and classes, leading to many instances of overfitting problems. Somjit et al. [8] carry out a study to identify the species and sex of insects. applying 2646 pictures to a supervised machine-learning model. The prediction accuracy in this work is 100%. Machine learning models are trained using the Google Teachable Machine (GTM).

In this study, [9] utilized deep learning methodologies to improve models. The implementation of the improved AlexNet model resulted in very high accuracy and detection times of 96.6% and 312 ms, respectively. They employed four different leaf types as separate datasets, and each one achieved a success rate of above 91%. The classification of insects and leaf diseases is provided by the preprocessed data that were used for all trial results. Crop pest classification caught the attention of researchers who were utilizing artificial intelligence to investigate the agricultural sector. This issue was addressed by [10], who developed a deep convolutional neural network architecture to classify pests' images that were cropped using canny edge detection and then enhanced. This study examined three publicly accessible datasets of 40,24, and 40 classes and achieved accuracy rates of 96.75%, 97.47%, and 95.97%. Their future work was to include performing subclasses of different species. This research [11] concentrated on localization, counting the number of pests, as well as their identification and classification. With more than 80k labeled image data across 16 classes, they have gathered a large-scale dataset. Then, in order to create region proposals for feature maps that could differentiate between pest and non-pest areas, the Region Proposal Network (RPN) was adopted. The Position-Sensitive Score Map (PSSM) was then used to identify the pests and fine-tune the bounding boxes from the region proposals with 75.46% mean average precision. Here, the major difficulties were occlusion and dense pest dispersal under complicated circumstances. Computerized techniques, particularly seven pre-trained models—including VGG-16, VGG-19, ResNet-50, Inception-V3, Xception, MobileNet, and SqueezeNet—were trained with the necessary fine-tuning and evaluated for their performance to identify insect species in the early stage [12]. Later, to improve performance, the three top-performing CNN models, Inception-V3, Xception, and MobileNet, were combined using weighted voting determined by a genetic algorithm. They attained 98.81% accuracy on the 40-class D0 dataset, which is available to the public.

The authors of this article [13] used shape feature extraction with the Sobel operator to contour the insect from the foreground using two datasets, representing 9 and 24 insect classes. Then, using 9-fold cross-validation, machine learning methods including support vector machine (SVM), naive bayes (NB), artificial neural networks (ANN), k-nearest neighbors (KNN), and convolutional neural network (CNN) models were applied. These methods achieved an accuracy of 91.5% and 90% for the two datasets, respectively. This [14] study introduces a deep neural network model with 11 trainable layers, including 8 convolutional and 3 fully connected layers, to improve insect categorization accuracy. They used data augmentation to obtain more generic data with 10 classes and trained their model primarily on a public dataset, where they evaluated 100% accuracy. After that, they tested with 98.92% accuracy using a different public dataset with nine classes.

1.3 PROPOSED METHODOLOGY

This study employs a systematic method, where theoretical analysis of convolutional neural network (CNN)-based transfer learning classifiers to predict the agricultural pests from digital images. In this research, methodology typically includes the overall research design, data collection methods, data analysis techniques, and other statistical or mathematical models used to interpret the data. The systematic diagram of the proposed method is presented in Fig. 1.1.

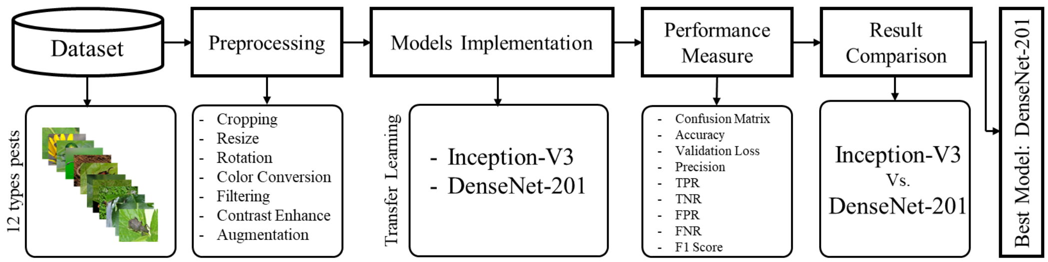


Figure 1.1 The working procedure includes data collection, data pre-processing for model training, and performance calculation to predict the agricultural pests from the images.

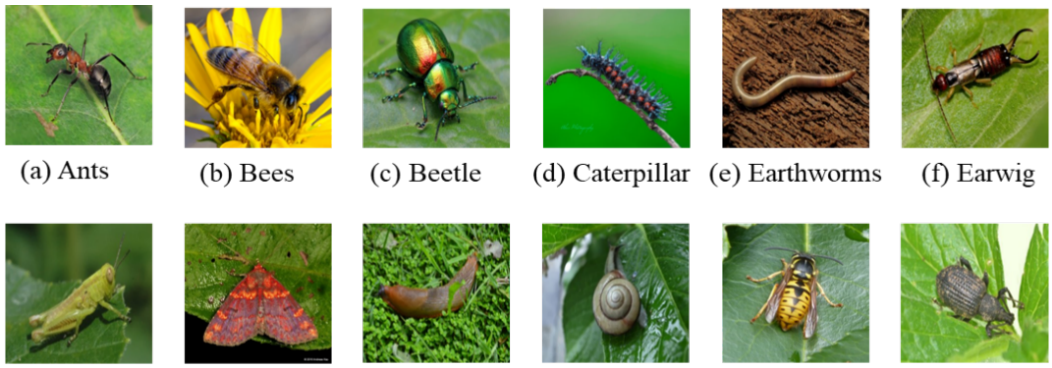
1.3.1 Data Collection

In this experiment, the “Agricultural Pests Dataset” from Kaggle [15], a publicly available dataset that contains images of 12 different insect species, including ants, bees, beetles, caterpillars, earthworms, earwigs, grasshoppers, moths, slugs, snails, wasps, and weevils is used. These are the pests that farmers must contend with because they are frequently present in agricultural fields. These pictures of agricultural pests include a wide range of real-world scenarios, forms, colors, and sizes and are gathered from Flickr using the API. The sample dataset is presented in Fig. 1.2

1.3.2 Image Processing

An essential stage in research applications of computer vision and image processing is image processing. Preprocessing can assist to improve picture quality, lower noise levels, correct for distortion, and get images ready for additional analysis [16]. Following are some typical strategies employed in this study with explanations: Cropping Image: Selecting a portion of the original image and removing the remainder is known as cropping. This is a typical image processing technique used to extract an image’s region of interest or delete undesirable elements.

Resize Image: Resizing an image entails altering its proportions, either by making it smaller or larger. This may be helpful for a number of things, including scaling photographs to match a particular output format, lowering the size of huge images to conserve disk space, and standardizing image sizes for analysis. Image Rotation: An image’s orientation is modified by a specific amount when it is rotated. This can



(a) Ants (b) Bees (c) Beetle (d) Caterpillar (e) Earthworms (f) Earwig

(g) Grasshopper (h) Moth (i) Slug (j) Snail (k) Wasp (l) Weevil

Figure 1.2 Sample image of each pest (a) Ants, (b) Bees, (c) Beetle, (d) Caterpillar, (e) Earthworms, (f) Earwig, (g) Grasshopper, (h) Moth, (i) Slug, (j) Snail, (k) Wasp and (l) Weevil.

be helpful for aligning photographs for analysis or processing, or for adjusting the orientation of an image that was taken at an angle.

Color Conversion: The process of color conversion includes converting an image's color space from one representation to another. This may be helpful for a number of things, such as transferring photos between formats or altering them for processing or analysis.

Image Filtering: Using a convolution operation and a filter kernel, image filtering is a technique for enhancing or changing a picture. A tiny matrix called the filter kernel is slid across the picture, and for each pixel, the values of the pixels in a certain neighborhood are multiplied by the corresponding values in the filter kernel, and then the output pixel value is produced by adding the resulting values. The picture may be smoothed, certain characteristics can be enhanced or sharpened, and noise can be eliminated by using filters.

Contrast Enhance: In order to make the details of a picture more visible or to enhance the image's overall visual appeal, a method called contrast enhancement is employed to increase the difference in brightness or color between the various portions of the image. Many techniques, including histogram equalization, adaptive histogram equalization, and contrast stretching, can be used to achieve this. Image Augmentation: Image augmentation is a technique used to increase the size and diversity of a training image for transfer learning models. It involves applying a variety of transformations to the original data, such as rotation, scaling, flipping, cropping, and color shifting, in order to generate new samples that are similar to the original data, but with small variations that can help improve the model's performance.

After rigorous image processing, the raw image processes to enhance the contract are present in Fig. 1.3. With over 5,534 images from 12 different classes, this multi-class dataset can be considered to be nearly balanced. Following an 80:20 split into the training and test sets, this dataset contains 4,371 images in the training set and

1,163 images in the test set. The following Table 1.1 provides a clear distribution of the data samples:

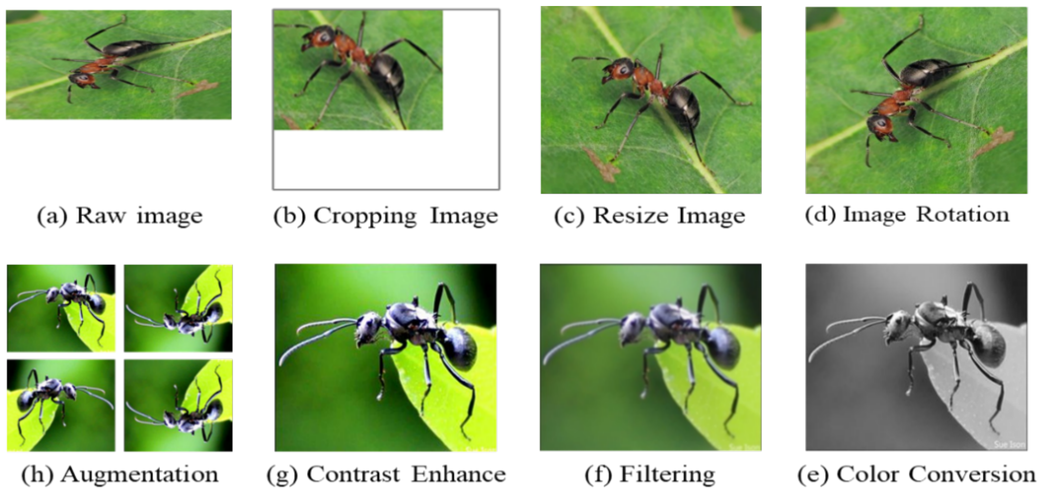


Figure 1.3 Several image processing applied into (a) raw image and getting (b) cropping image, (c) resize image, (d) image rotation, (e) color conversion, (f) image filtering, (g) contrasts enhance and augmented image to increase the size of the dataset.

1.3.3 Model Implementation

After concluding the preprocessing operations, we must employ our processed images to train the required models. To achieve good accuracy, we have tested two transfer learning models for this purpose. Transfer learning, which employs previously trained models on new problems, is a powerful strategy for achieving notable outcomes in classification tasks with constrained sample sizes that reuse pre-trained models on a new problem. Deep transfer learning models (DTL) can also be hyper-tuned to further enhance the outcomes. In this paper, a DTL model with Inception-V3 and DenseNet-201 is proposed.

Inception-V3: Inception-V3 [17] is a 48-layer deep convolutional neural network used for image classification [17][18][19]. This is a pre-trained version of the network that has been trained on over a million pictures from the ImageNet collection. This model is more efficient than the previous one, and it employs multiple strategies for improving the network with optimized model adaptability to reduce error rates. Fig. 1.4 shows the architecture and Table 1.2 depicts the layer of the Inception-V3 model that has been used in this paper.

Densenet-201: A well-known type of CNN called Dense Convolutional Network (DenseNet) employs transfer learning, making it trainable and sustainably deeper, more accurate, and more effective. This network contains N(N+1)/2 direct connections because of the architecture's dense feed-forward connections between each input layer and every subsequent layer. All previous layers' feature maps are utilized as in-

Table 1.1 Dataset distribution for each of class.

Class	**Training Samples**	**Testing Samples**	**Total**
Ants	399	100	499
Bees	408	102	510
Beetles	312	104	416
Caterpillars	360	94	454
Earthworms	252	71	323
Earwigs	372	94	466
Grasshoppers	384	101	485
Moths	396	101	497
Slugs	300	91	391
Snails	396	104	500
Wasps	396	102	498
Weevils	396	99	495
Total	4371	1163	5534

Table 1.2 Detailed Specification of Inception-v3 Model.

Layer	**Filter (number/size)**	**Input size**	**Output size**
Conv1	2/(7×7)	224×224×3	111×111×64
Maxpool1	2/(3×3)	111×111×64	54×54×64
Conv. 1×1	1/(1×1)	54×54×64	54×54×64
Conv2-1	1/(3×3)	54×54v64	54×54×192
Maxpool2	2/(3×3)	54×54×192	25×25×192
Conv1×1a	1/(1×1)	25×25×192	25×25×96
Conv1×1b	1/(1×1)	25×25×96	25×25×16
Maxpool-a	1/(3×3)	25×25×192	25×25×192
Conv1×1c	1/(1×1)	25×25×192	25×25×64
Conv3-3	1/(3×3)	25×25×96	25×25×128
Conv5×5	1/(5×5)	25×25×16	25×25×32
Conv1×1d	1/(1×1)	25×25×192	25×25×32
Conv1×1a	1/(1×1)	12×12×480	12×12×96
Conv1×1b	1/(1×1)	12×12×480	12×12×16
Maxpool-a	1/(3×3)	12×12×480	12×12×480
Conv1×1c	1/(1×1)	12×12×480	12×12×192
Conv3×3	1/(3×3)	12×12×96	12×12×208
Conv5×5	1/(5×5)	12×12×16	12×12×48
Conv1×1d	1/(1×1)	12×12×192	12×12×64

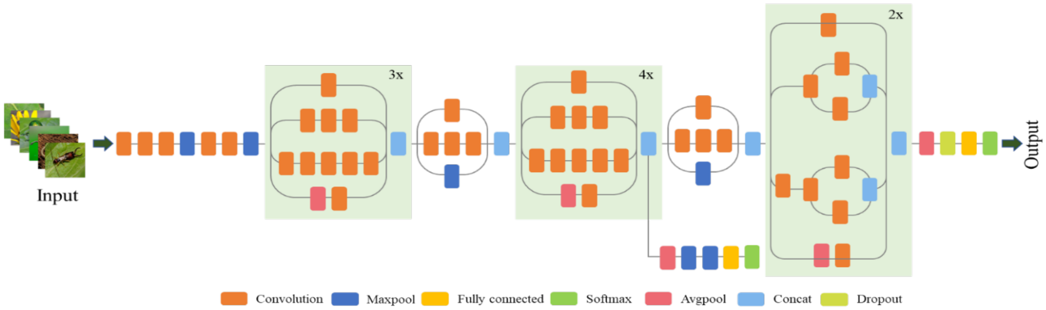


Figure 1.4 System architecture diagram of proposed Inception-V3 model.

puts for each layer, and the feature maps of that layer are used as inputs for all succeeding levels. Traditional convolutional networks with N layers have N connections, one between each layer and the layer after it [20], as opposed to these networks. In addition to performing brilliantly, the vanishing gradient problem is greatly mitigated, feature reuse is encouraged, feature propagation is strengthened, and the number of parameters is significantly reduced in this architecture. Utilizing a convolutional neural network and its own learned weights on the ImageNet dataset, the proposed model is used to extract features [21][22][23]. Fig. 1.5 shows the architecture and Table 1.3 depicts the DenseNet201 model that has been developed for classifying agricultural pests.

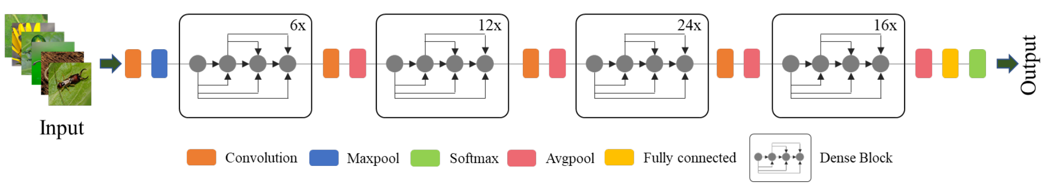


Figure 1.5 System architecture diagram of proposed Densenet-201 model.

A 201-layered convolutional neural network has the acronym DenseNet-201. It contains four robust blocks, each with varying amount of growth rates. The blocks are made up of 6, 12, 24, and 16 levels in order. There is a transition layer between each dense block that performs feature map-down sampling and reduces the number of channels to reduce the network's computational cost. A batch normalization layer is followed by a convolutional layer and an average pooling layer in the transition layers [24]. The convolutional layer reduces the number of channels, whereas the average pooling layer decreases the spatial resolution of the feature maps. The features are then classified using a Fully-Connected layer with Softmax as the activation function. This layer returns the categorization probabilities for each class. Our model has 96,351,244 trainable parameters out of a total of 114,673,228 parameters.

Table 1.3 Detailed Specification of DenseNet-201 Model.

Layer	**Filter (number/size)**	**Input size**	**Output size**
Input Layer		224×224×3	224×224×3
Conv. Layer (stride 2)	96/7×7	224×22×3	112×112×96
Max pool (stride 2)	96/2×2	112×112×96	57×57×96
1st Dense block	6/((1×1)/(3×3) 4k/k)	57×57×96	57×57×384
Transition layer	1/((1×1)/(2×2) 192/192)	57×57×384	29×29×192
2nd Dense block	12/((1×1)/(3×3) 4k/k)	29×29×192	29×29×768
Transition layer	1/((1×1)/(2×2) 384/384)	29×29×768	15×15×384
3rd Dense block	24/((1×1)/(3×3) 4k/k)	15×15×384	15×15×2112
Transition layer	1/((1×1)/(2×2) 1056/1056)	15×15×2112	8×8×1056
4th Dense block	16/((1×1)/(3×3) 4k/k)	8×8×1056	8×8×2208
Average pooling	2208/8×8	8×8×2208	1×1×2208
FCL with Softmax		1×1×2208	12

1.3.4 Performance Calculation

Transfer learning classifiers model development must include a process called performance evaluation, which lets us gauge how well the model predicts agricultural pests. The effectiveness of transfer learning algorithms may be assessed using a variety of metrics and methods, such as:

Accuracy = ((TP+TN)/(TP+FN+FP+TN)) × 100%
True Positive Rate (TPR) =((TP)/(TP+FN)) × 100%
True Negative Rate (TNR) = ((TN)/(FP+TN)) × 100%
False Positive Rate (FPR) = (FP/(FP+TN)) × 100%
False Negative Rate (FNR) = (FN/(FN+TP)) × 100%
Precision = (TP/(TP+FP)) × 100%
F1 Score = (2 × (Precision ×Recall)/(Precision+Recall)) × 100%
Error Rate = (FN+FP)/(Total No. Observation) × 100%

1.4 RESULTS AND DISCUSSIONS

The experimental approach involved classifying agricultural insects using two pre-trained CNN models. The dropout rate, optimization algorithm, learning rate, and epochs were some of the combinations of layers that were determined via trial and error, along with the number of frozen convolutional layers, fully connected layers, and epochs [25][26]. The number of fully connected layers was maintained as uniformly as feasible across the models in order to evaluate the feature extraction performance of the models. The cost function utilized during the model training was categorical cross-entropy, and it was minimized using the Adam optimization technique. In the output layer of the models, the SoftMax activation function was used. Several rounds of picture pre-processing were carried out, including image scaling, filtering, and quality improvement, to get the image ready for model training. The experiment employed 5534 images in total, divided 80:20 across the two data sets. 1163 of these were saved for evaluating the model's capacity to recognize and classify agricultural pests, while 4371 of these were utilized to fit the algorithms. We assessed the confusion matrix for each class as a performance measure for the three deep-transfer learning methods utilized in order to identify the best efficient model for the classification challenge. The dataset had been employed to train each model 40 times. Common classification criteria including accuracy, error rate, true-positive-rate (TPR), false-negative-rate (FNR), false-positive-rate (FPR), true-negative-rate (TNR), precision, and F1-score are utilized to assess the proposed method's classification performance [19]. Fig 1.6 and Fig. 1.7 visualizes the confusion matrix for the 12 class and Table 1.4 and Table 1.5 also present the tabulated format of the confusion matrix in 2×2 values for Inception-V3 and DenseNet-201, respectively.

Table 1.4 Tabulate format of confusion matrix for Inecption-V3 model (Converted 2×2).

Model	Class	TP	FN	FP	TN
Inception-V3	Ants	93	7	8	1048
	Bees	89	13	5	1049
	Beetle	67	37	20	1032
	Caterpillar	69	25	42	1020
	Earthworms	43	28	12	1073
	Earwig	73	21	32	1030
	Grasshopper	81	20	39	1016
	Moth	95	5	1	1055
	Slug	68	23	7	1058
	Snail	97	1	3	1055
	Wasp	90	12	11	1043
	Weevil	97	2	12	1045

After computing the confusion matrix, class-wise performance is computed to benchmark these models and determine which is most effective for classifying and predicting agricultural pests. Class-wise performance is given below for each model.

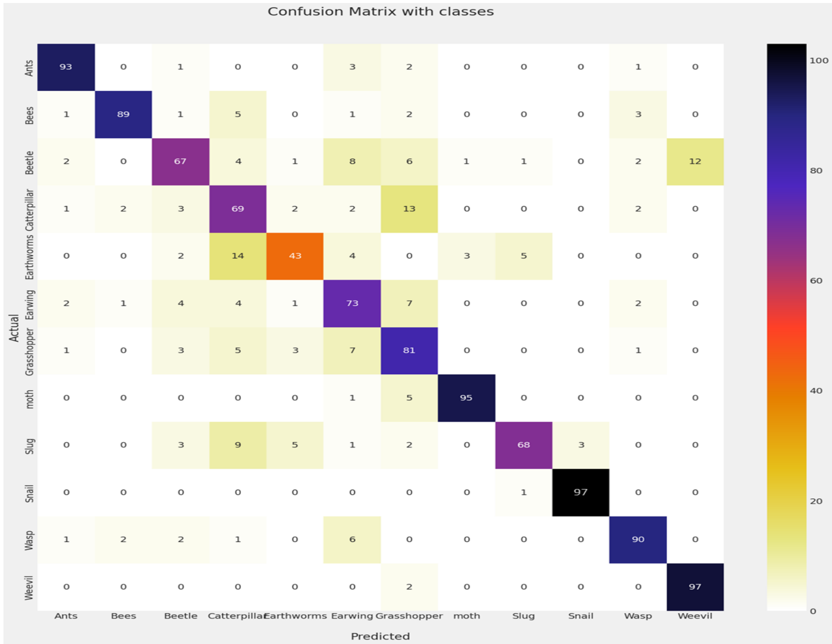


Figure 1.6 Confusion matrix for the Inception-V3 model (Multiclass).

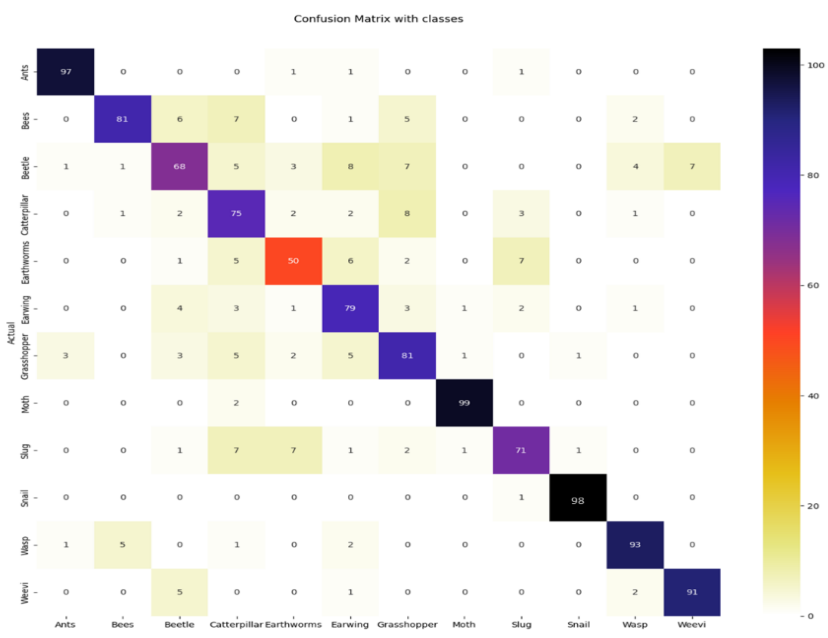


Figure 1.7 Confusion matrix for the Densenet-201 model (Multiclass).

Inception-V3: The class-wise model performance for the Inception-V3 is displayed in Table 1.6 along with a visual depiction in Fig. 1.8, which demonstrates that the 'Snail' class has the highest accuracy and lowest error rate, respectively,

Table 1.5 Tabulate format of confusion matrix for DenseNet-201 model (Converted 2×2).

Model	Class	TP	FN	FP	TN
DenseNet-201	Ants	93	3	5	1051
	Bees	81	21	7	1047
	Beetle	68	36	22	1030
	Caterpillar	75	19	35	1027
	Earthworms	50	21	16	1069
	Earwig	79	15	25	1037
	Grasshopper	81	20	27	1028
	Moth	99	2	3	1052
	Slug	71	20	14	1051
	Snail	98	1	2	1055
	Wasp	93	7	10	1046
	Weevil	91	8	7	1050

with an accuracy rate of 99.65% and an error rate of 0.35%. In contrast to other instruction, the snail class's TPR, FNR, FPR, TNR, precision rate, and F1-Score are 98.98%, 1.02%, 0.28%, 99.72%, 99.71%, and 99.35%, respectively.

Table 1.6 Class-wise performance metrices for Inception-V3 model.

Model	Class	Accuracy	Error	TPR	FNR	FPR	TNR	Precision	F1 Score
Inception-V3	Ants	98.70	1.30	93.00	7.00	0.76	99.24	99.19	96.00
	Ants	98.70	1.30	93.00	7.00	0.76	99.24	99.19	96.00
	Bees	98.44	1.56	87.25	12.75	0.47	99.53	99.46	92.96
	Beetle	95.07	4.93	64.42	35.58	1.90	98.10	97.13	77.47
	Caterpillar	94.20	5.80	73.40	26.60	3.95	96.05	94.89	82.77
	Earthworms	96.54	3.46	60.56	39.44	1.11	98.89	98.21	74.92
	Earwig	95.42	4.58	77.66	22.34	3.01	96.99	96.26	85.97
	Grasshopper	94.90	5.10	80.20	19.80	3.70	96.30	95.59	87.22
	Moth	99.48	0.52	95.00	5.00	0.09	99.91	99.90	97.39
	Slug	97.40	2.60	74.73	25.27	0.66	99.34	99.13	85.21
	Snail	99.65	0.35	98.98	1.02	0.28	99.72	99.71	99.35
	Wasp	98.01	1.99	88.24	11.76	1.04	98.96	98.83	93.23
	Weevil	98.79	1.21	97.98	2.02	1.14	98.86	98.85	98.42
Average		97.22	2.78	82.62	17.38	1.51	98.49	98.10	89.24

DenseNet-201: The class-wise model performance for the DenseNet-201 is displayed in Table 1.7 along with a visual depiction in Fig. 1.9, which demonstrates that the 'Snail' class has the highest accuracy and lowest error rate, respectively, with an accuracy rate of 99.74% and an error rate of 0.26%. In contrast to other instruction, the snail class's TPR, FNR, FPR, TNR, precision rate, and F1-Score are 98.99%,1.01%, 0.19%, 99.81%, 99.81%, and 99.40%, respectively.

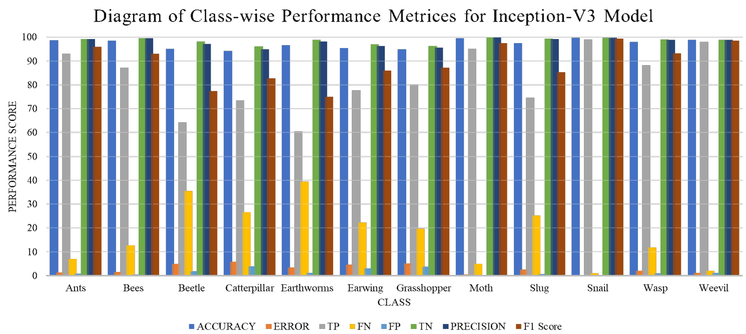


Figure 1.8 Visual representation of class-wise performance matrices for DenseNet-201 model.

Table 1.7 Class-wise performance metrices for DenseNet-201 model.

heightModel	Class	Accuracy	Error	TPR	FNR	FPR	TNR	Precision	F1 Score
DenseNet-201	Ants	99.31	0.69	97.00	3.00	0.47	99.53	99.51	98.24
	Ants	99.31	0.69	97.00	3.00	0.47	99.53	99.51	98.24
	Bees	97.58	2.42	79.41	20.59	0.66	99.34	99.17	88.20
	Beetle	94.98	5.02	65.38	34.62	2.09	97.91	96.90	78.08
	Caterpillar	95.33	4.67	79.79	20.21	3.30	96.70	96.03	87.16
	Earthworms	96.80	3.20	70.42	29.58	1.47	98.53	97.95	81.94
	Earwig	96.54	3.46	84.04	15.96	2.35	97.65	97.28	90.18
	Grasshopper	95.93	4.07	80.20	19.80	2.56	97.44	96.91	87.76
	Moth	99.57	0.43	98.02	1.98	0.28	99.72	99.71	98.86
	Slug	97.06	2.94	78.02	21.98	1.31	98.69	98.34	87.01
	Snail	99.74	0.26	98.99	1.01	0.19	99.81	99.81	99.40
	Wasp	98.53	1.47	93.00	7.00	0.95	99.05	98.99	95.90
	Weevil	98.70	1.30	91.92	8.08	0.66	99.34	99.28	95.46
Average		97.51	2.49	84.68	15.32	1.36	98.64	98.32	90.68

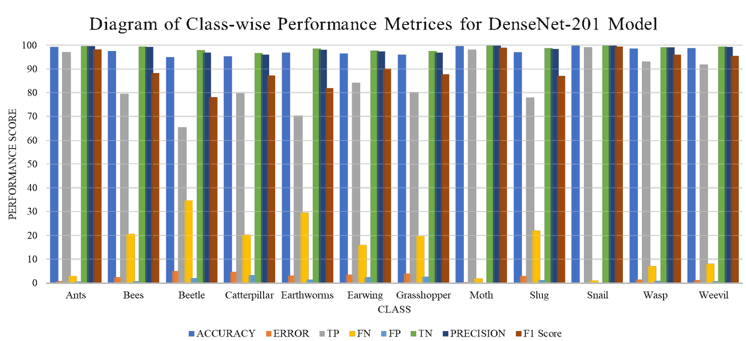


Figure 1.9 Visual representation of class-wise performance metrices for DenseNet-201 model.

1.5 CONCLUSION AND FUTURE WORK

In this study, a technique for recognizing and classifying crop pests using deep learning, transfer learning, and fine-tuning pre-trained models is presented. Two trendy pre-trained models are examined, and the DenseNet201 model is found to be the most accurate, with a 97.51% accuracy rate by DenseNet-201. This method has the potential to revolutionize pest control in agriculture by enabling farmers to detect and classify crop pests with precision, allowing them to take necessary precautions to protect their crops in a timely manner. Additionally, a simple application is intended to be created, which will enable farmers to take real-time photographs or videos of pests and obtain information on the appropriate pesticides, fertilizers, and necessary directions to protect their crops from pests. This application will help bridge the gap between technology and agriculture, providing farmers with easy access to the latest advances in deep learning and computer vision. In summary, this research has the potential to contribute to society and the economy by increasing agricultural productivity and food security, reducing economic losses caused by crop pests, and providing farmers with tech-nology-driven solutions. It is expected that the proposed approach and application will be widely accepted and further improved to assist farmers and the agriculture industry worldwide.

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