Classification of Harmful Farm Insects in Agriculture

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***Abstract*—The "Dangerous Farm Insects Dataset" comprises images of harmful insects impacting the agricultural production. These consist of 15 distinct species of insects which are commonly found in an agricultural environment. The main purpose of this project is to develop robust models using different advanced machine learning methods to classify the dangerous insects by employing a variety of models - including the models built on convolutional neural networks (CNNs) [1]. This study not only focuses on achieving high classification accuracy but also explores the practical implementations of these models using transfer learning in real-world agricultural settings. The successful classification of these insects results in timely and effective pest management thereby contributing to increased yield paving way to promotion and raise of awareness of the pest management among farmers. This work underlines the potential of machine learning (Transfer learning) in transforming the traditional practices by integrating Internet-of-Things, data analytics and technological advancements into everyday norms and operations in agriculture sector. It portrays a comparative analysis of all the transfer learning models on the agriculture settings and depicts a case study.**

***Index Terms*—Classification of Farm insects, dangerous farm insects, pest control/management, crop protection, agriculture, entomology, integrated pest management, deep learning, machine learning.**

I. Introduction

Agriculture is one of the primary and critical sector that contributes enormously in local and global economies which feed the global population all around the world. However, there are several challenges and difficulties in the sector. One of the most significant of them is the threat of the harmful insects. These pests are capable of causing substantial damage to the crops, leading heavy losses in yield, quality and profitability. Therefore management of these pests are crucial and effective for food security and economic stability in farming communities.

There are various and diverse amount of insect pests making its identification, classification and management a complex task. The traditional methods of control and identification is often a tiresome, manual effort and has a extensive use of pesticides, which are harmful to the environment as well as human health. So, the agriculture sector is catching up with other fields by the raise of booming methods and technologies for innovative approaches that provide accurate, efficient, and sustainable solutions matching the demanding and rising population.

II. Objectives

The primary objective of this project is to enable the development of a robust system capable of effectively detecting and classifying theses insects. The implementation of such system holds an immense potential for pest control, benefiting both farms and residential areas alike.

- **Exploratory Data Analysis :** Exploration of the dataset and performing some basic Exploratory Data Analysis to understand the data structure and quality. This includes employing some data augmentation techniques, to diversify the data.
- **Model Training :** Experiment with some transfer learning models, including but not limited to models such as CNN, MobileNet, ResNet etc.
- **Model Evaluation :** Evaluation of the trained models using some of the metrics such as accuracy, precision, recall and F1-Score. Also, using some methods like cross-validation to evaluate the model in a better way, leading to better generalization of the model to unknown data.
- **Inference :** Test the final models with unseen data and evaluate the results.

III. Data

A. Description of the dataset

Since this a agriculture problem we require an authentic agriculture related dataset which is derived from the prominent website Kaggle [10]. The dataset is a curated collection of images of 15 distinct types of insects **(Fig-1)** which are threats to agricultural practices. They contain valuable and visual resources for studying, identifying and understanding the characteristics of these potentially harmful insects. Each class represents a specific type of insect, meticulously labeled to facilitate accurate detection and identification.

B. Insect classes

The 15 insect classes are

- **African Honey Bees (Killer Bees) :** The Africanized honey bees pose a high threat to animals as well as humans. They are extremely aggressive and defensive in nature which results in fatalities or deadly allergic reactions when people come into contact with them.

- **Aphids :** The Aphids infect a vast range of plants. They are minute sap-sucking insects that deplete the plant's sap, causing crucial damage resulting on distorted leaves, stunted growth and reduced crop yield.
- **Armyworms :** The Armyworms are devouring worms (caterpillars) that fundamentally target cereal crops and grasses. They are capable of rapidly feeding huge areas of crops thereby destroying the whole field leading to critical losses in yield.
- **Brown Marmorated Stink Bugs :** The encroaching brown marmorated stink bugs use their mouth parts as their primary weapon to ruin crops by drilling into fruits, vegetables and other plant parts which leads to deformity, wreckage and decay of the produce resulting in decreased market value.
- **Cabbage Loopers :** The Cabbage loopers are fond of the leaves of broccoli, cabbage and vegetables under the Cruciferae family. They feast and destroy the plants leading to reduced yield and quality because of the pillage.
- **Citrus Canker :** The Citrus Cankers affects the citrus trees. These are bacterial diseases that causes abrasion on leaves, stems and fruits leading to early fruit drop thereby impacting and compromising the produce of tree, its health and citrus growers and industry.
- **Colorado Potato Beetles :** As the name suggests the Colorado potato beetles are assault potato plants, rapidly denuding them which significantly decreases the comprehensive quality of the tubers impacting the farmers and processors yields.
- **Corn Borers :** The Corn borers are commonly known as moth larvae that causes structural damage and reduced yield in corn plants. They burrow through into the stalks of corn plants which serve as entry points for pathogens further affecting corn growers and plant health.
- **Corn Earworms :** The Corn earworms infect the ears of corn and other crops by feeding on the kernels. These cause contamination of the crops which reduces its market value making it unsuitable for consumption and affecting the corn producers and consumers.
- **Fall Armyworms :** The Fall Armyworms are devouring pests that having destructive feeding habits that lead to extreme damages to various primary crops like corn, rice and sorghum. This results in significant economic losses for the farmers.
- **Fruit Flies :** The Fruit flies are known for laying their eggs on ripening produce, and then the hatched larvae consumes the flesh of the host fruit or vegetable which spoils the produce leading to significant crop losses. They are major threat to fruits and vegetables which impacts both consumers and farmers.
- **Spider Mites :** The Spider mites are very tiny arachnids that pose high threat to multiple crops inclusive of all fruits, vegetables and ornamental plants. They target and feed on the plant sap causing blemish, wilting and stunted growth that impacts gardening and horticulture sectors.
- **Thrips :** The Thrips are tiny insects that causes distorted growth, early leaf drop, browning and decreased crop quality by destroying plants by sucking their sap and spreading the viruses impacting a wide range of agricultural sectors.
- **Tomato Hornworms :** The Tomato hornworms are huge worms basically caterpillars that focuses and assaults tomato plants by consuming foliage and fruits. They can cause extreme levels of deformation and plunder resulting in reduced yields and compromised fruit quality affecting the tomato growers and processors.
- **Western Corn Rootworms :** The Western Corn Rootworms strikes corn crops by suckling on the plant's root. These activity are highly catastrophic that results in stunted growth and reduced yields by weakening the plant's stability and nutrient uptake, affecting the corn farmers and the food industry.

C. Exploratory Data analysis :

Here, our fundamental focus is to effectively and efficiently reprocess and load the images of all the insect class seamlessly for model training and evaluation. By loading the images into the storage, we ensure it is feasibly accessible and quick enough to manipulate the data during the learning process of the pipeline. Now , the pre-processing steps involve multiple transformations, normalization and resizing the image data into a suitable format for optimal performance. These steps collectively aim to create, facilitate effective learning and inference by our models using the well-prepared dataset.

*1) **Data Loading, Visualization and Preprocessing**:* Firstly, the images are loaded from the dataset directory to the computational source memory, which ensures that each image is properly labeled as per class. then the preprocessing involves the following steps:

- **Resizing :** The dimensions of all the images are adjusted to uniform size making sure it is compatible to the models.
- **Normalization :** The pixel values of the images are scaled to the range [0,1] to obtain a standardized input data.
- **Augmentation :** The various transformations like rotation, width/height shifts, zoom, shear, and horizontal flips are done to artificially increase the count and diversity of the available dataset which can be used for training.

*2) **Class distribution and Class imbalance**:* For robust inference and efficient training, it is significant for us to maintain a non-biased dataset with equal number of images for each insect class. This balanced distribution paves way for precise and accurate model training and prediction, if not some classes will be underrepresented, which can negatively impact the model's performance.

In occasions where there are significantly fewer samples compared to others, it would lead to imbalance learning. In such cases, the model will have difficulties to learn significant features from the underrepresented classes, which will lead to poor performance and biased predictions. The model instead

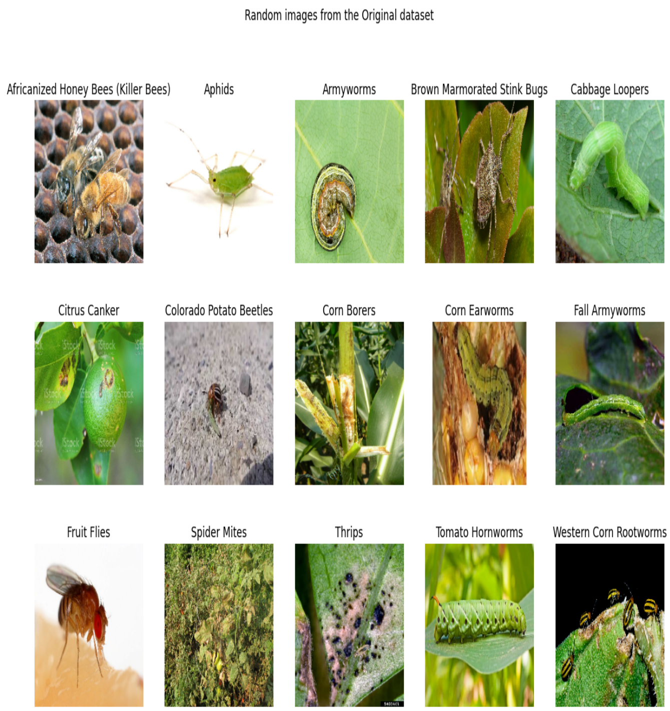

Fig. 1. The figure shows the random images of insects from each class **before pre - processing.**

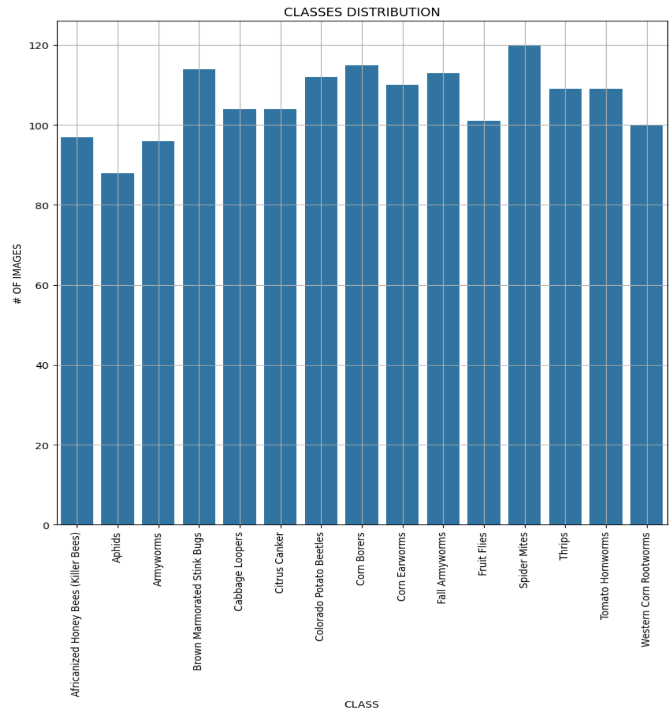

Fig. 2. The image shows the class distribution of the dataset.

learning the meaningful patterns it starts to resort or guessing or favouring the majority class, compromising the overall performance, efficiency and effectiveness.

By ensuring an equal sample size for each class, the model has a leveled data to learn from which allows for a fair and square unbiased representation of all classes, enabling the model to make accurate predictions.

The class distribution plot shown in the **Fig-2** reveals the number of images across the different insect classes showing the balance or imbalance within the dataset. For instance, we have 119 images for *"Spider mites"* making it the class with highest number labelled as common classes while *"Aphids"* only has 88 images, marking it the rare classes. This class imbalance poses a major challenge for training and model performance, as the model struggle to learn and generalize the classes effectively.

- **Rare Classes :** The classes like *"Africanized Honey Bees (Killer Bees)", "Aphids" and "Armyworms"* are considered rare due to their less number of samples when compared to the rest of the classes. This scarcity of images representing the classes gives raise to challenges when the model is being trained, it hinders the model's ability to capture the unique features and patterns, thereby resulting in lower accuracy, precision and performance by mis-classifying and identifying the rare insects.
- **Common Classes :** Converse to rare classes, The common classes exhibit a high numer of samples making them more abundant and prevalent. In our dataset classes like *"Spider Mites", "Corn Borers" and "Fall Armyworms"* are some which has relatively high sample size than others. This provides the model with more occasions to understand, learn the distinctive characteristic features of each class thereby allowing the model to leverage and capture the features, potentially leading to improved accuracy and performance in identification and classification of these insects.

IV. Methodologies :

From the class distribution analysis, it is imperative to employ a suitable data splitting ratio that incorporates stratification. The failure of this step may render the whole analysis ineffective. The stratified data split makes sure that the training and testing sets represent the same distribution mirroring the original dataset thereby preventing bias and facilitates an accurate evaluation of model's performance.

The data was split into following ratios

- **Training Set :** 863 images belonging to 15 classes.
- **Validation Set :** 274 images belonging to 15 classes.
- **Test Set :** 284 images belonging to 15 classes.

Now after successful split of the data and further process of augmentation, normalization and preprocessing. we load the data up and take a closer look of some random images from the training data for rough estimate of split distribution, appearance and characteristics of the training set.

The images are of good quality and provide a clear representation of farm insects which enable our models to learn the distinctive characteristics and features. however, some classes like cabbage loopers and citrus canker depict affected plant parts than insects. This won't significantly impact the training

Fig. 3. The figure shows the random sample images of insects from each class (Training set) **after pre - processing, Augmentation and Normalization.**

of our model's ability but if more images of same kind are found it would be a challenge for the model to focus more on detecting the symptoms of diseases than identifying the insects thereby deviating from the primary objective.

A. Class Weights :

After all the above steps, in order to address the class imbalance issue in our data, we are trying to resolve it using one of the methods known as the Class weights. The class weights are a concept in which different weights are assigned to each class based n their frequency of samples in the dataset. The model are highly influenced by adjusting the weights thereby giving selective importance to the rare classes during training. This helps us to mitigate the impact of class imbalance.

The precised outcome that we aim for cannot be achieved just by the original dataset. So by leveraging the class weights along with the stratified data split technique help us to resolve the class imbalance difficulty, ensuring the balanced and representative training across all classes therefore resulting a reliable and robust model, setting the stage for precise, comprehensive and accurate prediction system for real-world scenarios.

B. Model :

*1) **Model Selection** :* With the limited amount of images in the dataset, it is crucial to select appropriate models. So based on that adopting transfer learning approach will offer significant advantages over others. These are models built on using Convolution neural networks. It has several advantages in capturing the relevant features present in the farm insects. This methodology also allows to leverage the pre-trained models such as ResNet [7], MobileNet [3], VGG [8], and so on. They have exceptional performance on several tasks. Our primary objective ti to build a suitable model and network architecture for specific classification task. To streamline and to facilitate the models, a class object is built that encompasses functions for model training, model visualization and model comparison.

For this project the models like **MobileNetV2 [3], Xception [9], VGG19 [8], InceptionV3 [4], ResNet50V2 [7]** are chosen which enable us to set up the pipeline and effectively streamline the model training process and provide a comparative analysis of the different models.

From these pre-trained models, Some layers are removed and additional layers are added upon the each models based on the dataset to increase the performance and accuracy. These layers add and helps the model to pick up the key features thereby contributing in identification of the characteristics of the data. Some of the layers like dropout, global average pooling and dense layers are added which are triggered and activated using activation layers like rectified linear Unit and softmax. Further tuning of the layers is done based on trial and error and how each model interpruts our data.

- **MobileNetV2 :** The MobileNetV2 [3] architecture has a perspective to our objective. It is designed to focus on efficiency with less computational resources making it a choice for more streamlined architecture and depthwise separable convolutions. It consists of lightweight convolutional Neural Network [1]. This architecture aims to strike a balance between accuracy and resource efficiency in our classification task. as we incorporate the model and build our models over it, we can unravel it's potential as a backbone and its adaptability to our farm insect classification requirements.
The performance of the model is evaluated by the metrics and the accuracy and loss of training and validation are plotted. The MobileNetV2 [3] has an accuracy of 55.47 %

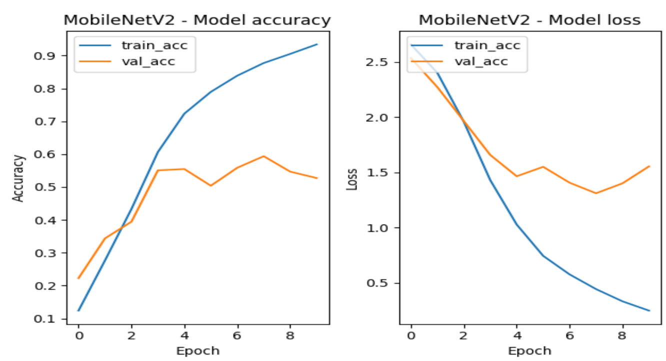

Fig. 4. The figure shows MobileNetV2 [3] model's accuracy and loss plot against No. of epochs for the training and validation set

It is apparent that MobileNetV2 [3] model demonstrates consistent performance across both training and validation. But its testing performance is less favourable and has a detoriated trend. Further fine tuning and reevaluation of its model will result in better testing performance.

- **Xception :** Xception [9] is a deep neural network architecture which is a derived version of inception [6]architecture. It is also known as extreme inception [6] which has shown impressive performance on several computer vision tasks. It is best known for its contemporary approach to CNNs [1] by spatial and channel-wise filtering operations.Its deep architecture of having 71 convolutional layers has particularly been efficient and effective in classification of images. It's better suited for capturing intricate patterns in images making suitable for object detection and image segmentation. It's ideology is to enhance learning capability of the pipeline network by minimizing computation complexity. Its also one of the depthwise separable convolutions that has efficient use of parameters that contribute to the efficiency, which makes it suitable for tasks where there is a budget in computational power.

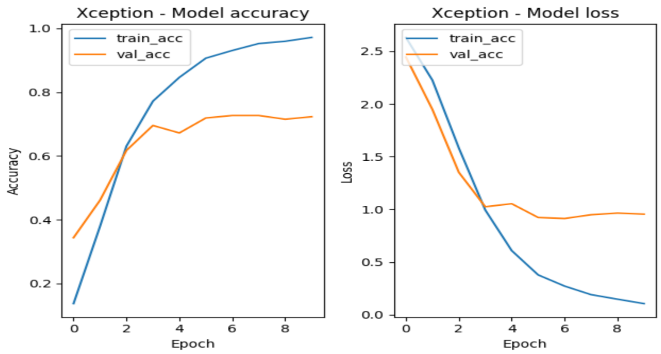

Fig. 5. The figure shows Xception [9] model's accuracy and loss plot against No. of epochs for the training and validation set

We can observe a testing accuracy of 74.9% which is remarkable enhancement in performance of the model than before models. The training and validation results show a performance, the progress seen in testing performance is a formidable cornerstone for our framework of classification unrevealing it's potential through further refinement of hyper-parameter tuning thereby ensuring robustness and precision.

- **VGG19 :** The VGG19 [8] is also a deep convolutional neural network [2] architecture that is characterized its simplicity and uniform architecture compromising 19 layers which makes it easy for understanding and implementing. The VGG19 [8] was proposed by visual Geometry Group at the University of Oxford. It stacks multiple Convolutional layers followed by max-pooling layers with fully connected layers at the end for classification.

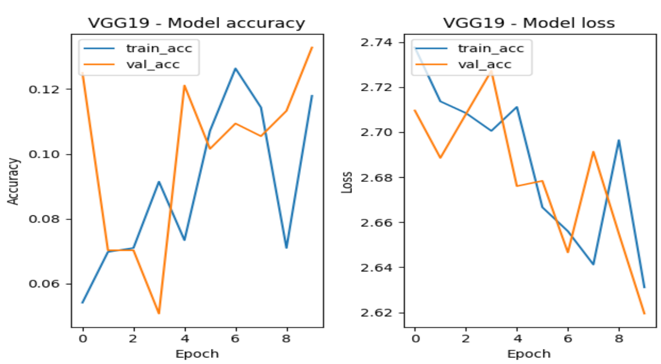

Fig. 6. The figure shows VGG19 [8] model's accuracy and loss plot against No. of epochs for the training and validation set

we can see very poor performance of VGG19 [8] model on our dataset. It only has 16.6% of test accuracy. This is because the transfer learning did not match the dataset's intricate features. it all depends on how the model interprets the characteristics of the image. In this case, it poorly performed and was all over the place.

- **ResNet50V2 :** The ResNet50V2 [7] architecture is the most fundamental and widely used deep learning network. It is a simple and highly effective which performs well in most of the cases. It's deep structure and residual connections contains a total of 50 convolutional layers that helps us to vanish the gradient problem. this enable us to train deeper networks makes information flow smoothly through the layers, making it easier for model to learn intricate features from the data. The ResNet50V2 [7] lays a strong solid foundation initially, which helps to leverage strong feature extraction capabilities to fine tune dor a specific task.

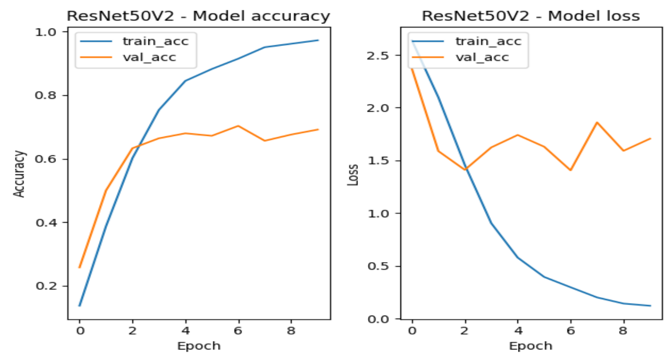

Fig. 7. The figure shows ResNet50V2 [7] model's accuracy and loss plot against No. of epochs for the training and validation set

The plot shows that there is overfitting in the model which stands in line with our expectations.though with accuracy of 67.8% accuracy, there is a noticeable gap of between training and validation loss. This variance significantly affects our requirements This discrepancy may imply many things, they are the real world data should be a mimic the characteristics of the model or it needs further optimization. The accuracy curves suggests a promising trajectory. with the aid of hyperparameter tuning and subsequent optimization, we can make the model more consistent and accurate.

- **InceptionV3 :** InceptionV3 [4] is one of the convolutional neural network [1] architecture developed by the google research team. It is a part of the inception [6] family architecture that is designed to balance the computational efficiency and accuracy. It introduces the concept of inception [6] modules, which has several parallel cNN [3] branches, each with different filter sizes. It has 48 layers including inception [6] modules and convolutions which utilizes global average pooling at the end of the network to reduce overfitting. It is pretrained on ImageNet and majorly facilitates in transfer learning. The inceptionV3 [4] is more suitable for tasks like image classification and feature extraction that requires a good balance of computation, efficiency and accuracy.
We can see a high accuracy of 75.6% of the model performed on our training and validation set. This indicates that the model was able to recognize the intricate features

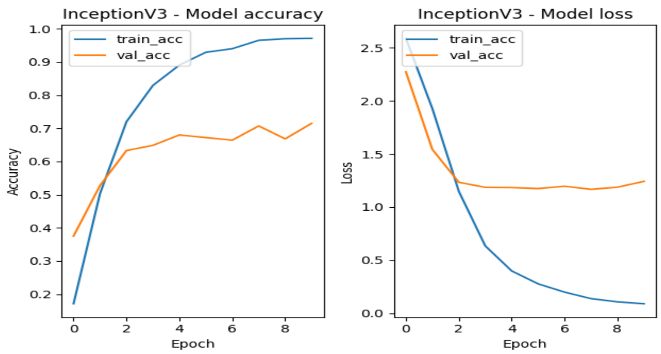

Fig. 8. The figure shows Inception [4] model's accuracy and loss plot against No. of epochs for the training and validation set

of the images.

*2) **Model Evaluation** :* After training the above models we are able to see that Xception [9] and Inception [6] models have performed better and are more or less have the same accuracy in out test set. To further evaluate the model's performance we use the evaluation metrics like Precison, Recall, F1 score and support along with the confusion matrix to evaluate and decide the best of the models. The evaluation metrics are

- **Precision :** Presicion is the evaluation of accuracy of the postive predictions made by the model. It is the ratio of correctly predicted postive observation to total prediction positives. It is very useful when the cost of false positives are high.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

- **Recall :** Recall also called as sensitivity measures the model's ability to correctly identify the instances in the data. It is the ratio of correctly predicted positive observations to all actual positives. Recall is a significant when the cost of false negatives is high.

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

- **F1 Score :** The F1 Score is the mean of precision and recall, which provides balance between the two and evaluates the model's performance. It is considered especially when there is a class imbalance in dataset.

$$F1Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{3}$$

- **Support :** Support is the number of actual occurrences of each class which is usually notes as N for the total number of samples of each class.
- **Confusion Matrix :** The confusion matrix consists of 4 components which are
  - **True Positives (TP) :** : Correctly predicted positive instances.
  - **True Negatives (TN):** Correctly predicted negative instances.
  - **False Positives (FP) :** Incorrectly predicted positive instances.
  - **False Negatives (FN) :** Incorrectly predicted negative instances.

TABLE I
CONFUSION MATRIX

	Predicted Positive	Predicted Negative
Actual Positive	TP	FN
Actual Negative	FP	TN

C. *Results :*

Therefore, the above results are obtained after training our models. The below table 2 shows the testing and validation accuracy of all the models. There are 2 models Xception [9] and Inception [6] with almost same accuracy. To evaluate the best model of the 2, the other evaluation metrics are used and Since this is a classification task, confusion matrix has more influence in selecting the best of models.

TABLE II
ACCURACY

Model	Test Accuracy	Validation Accuracy
Xception	74.91%	72.27%
VGG19	16.6%	13.28%
ResNet50V2	67.84%	69.14%
InceptionV3	75.61%	71.48%
MobileNetV2	55.47%	52.73%

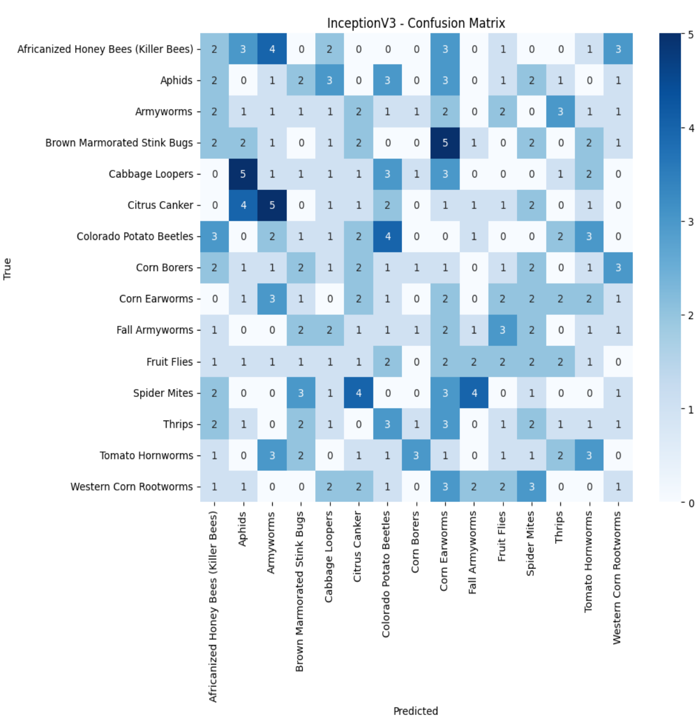

Fig. 9. The figure shows InceptionV3 [4] model's confusion Matrix

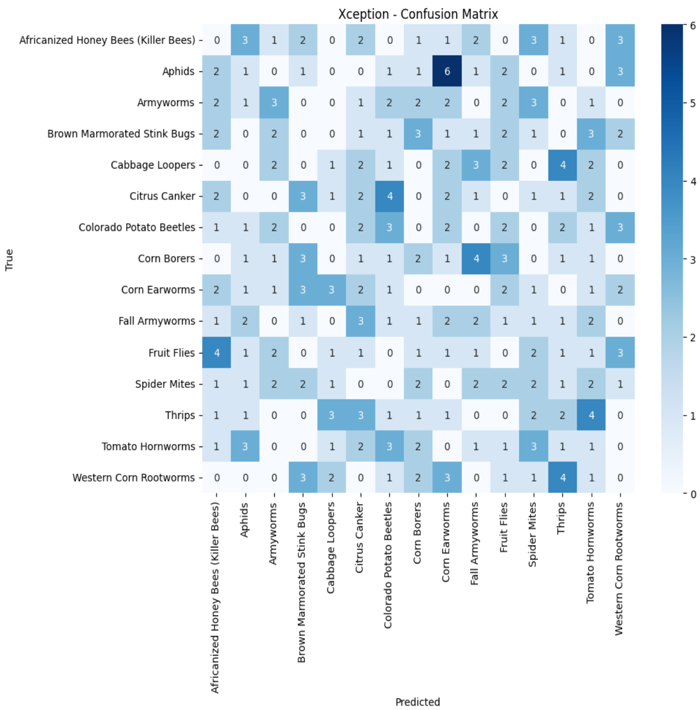

Fig. 10. The figure shows Xception [9] model's confusion Matrix

As we can see the two confusion matrices (Fig 9 and Fig 10) of both Xception [9] and InceptionV3 [4] models. There is clear difference in number of false positives between the two matrices. the InceptionV3's [4]prediction has recorded a high scale of false positives when compared to Xception [9] model's confusion matrix. This can highly affect the model performance. This being a classification task. It is significant for the system to identify and classify the image in real-world scenario. If we use model's that give false identification, this may induce heavy losses to the end user.

V. Applications of the System

There are several use cases and applications available for the problem statement and dataset we have. They are

A. Early Detection and Intervention :

The system allows farmers and homeowners to prepare and get equipped for timely measures as a result of early detection of insect infestations. Thereby enabling them to prevent the widespread damage of yield and crops and also help them to implement targeted pest control strategies, minimizing crop losses and economic impacts.

B. Precision Pest Control :

The system aids in implementing targeted and precise pest control methods by accurately identifying specific insect species. The dependency on broad-spectrum pesticides can be reduced there by optimizing the resource utilization and minimizing the environmental impact.

C. Yield Enhancement and Crop Protection :

The system contributes largely to increased food supply, economic stability and improved farm productivity by detecting and identifying the harmful insects which further aids in protecting crops from damage by preserving their quality.

D. Integrated Pest Management :

The real-time insights and alerts from the system aids and enhances in informed decision making, which includes the cultural practices, use of biological controls and select insecticides. We can integrate the system with existing agricultural practices, farmers can adopt integrated pest management strategies.

E. Disease Prevention :

There are several occasions where the insects act as carriers of plant diseases. Monitoring and detecting their presence with the help of the system helps us to prevent the spread of diseases thereby maintaining healthy agricultural ecosystems minimizing crop losses.

F. Cost Reduction :

The system can help farmers to reduce a major chunk of financial losses linked to insect damage. It also helps in optimizing pest control efforts and minimizing crop losses also avoiding unnecessary pesticide applications, resulting to cost savings in terms of chemical inputs and promoting sustainable farming practices.

G. Research and Analysis :

The system can also produce valuable resources for conducting research and behaviour analysis including ecological impact of dangerous farm insects and distribution. It can be a highly valuable asset for anyone involved in the agricultural industry, entomology research and computer vision applications in the field of farming. The system also facilitates the studies on various control methods and effectiveness on the development of innovative solutions for sustainable agriculture.

VI. Discussion

After successful completion of selection of a best model which will be Xception [9] model. Now this model's performance can be further improved by fine tuning the hyperparameters which will increase and improve its performance in real world settings and data. But due to the time and computational resource constraint. I was unable to fine tune the model's pperformance. But this can be done by employing cross validation. The cross validation can be done by employing several methods which are *hyperband [12] strategy, Bayesian Optimization [13], Random Search [14] and Sklearn [15].* These are the potential future works that enhances the best model and makes it more suitable for our objective.

VII. My Documents

The below documents are attached for your reference.

- **Dataset :** Click Here
- **Code :** Click Here
- **Presentation :** Click Here

VIII. Conclusion

Therefore from following all the above the process, Xception [9] was chosen as the best model and was further built on and used to predict the ral world images. It was able to correctly classify the test set images but struggled a bit when a new image outside the dataset was introduced to it and made the prediction wrong 2 out of 4 times. Most of the time it predicted the insect class as spider mites because of class imbalance and less number of samples. this can be resolved by further increasing the number of images in the dataset, fine tuning the hyper parameters. Using different class weights and so on. Then the developed robust and precise system is used for the appropriate applications to further increase the yield by effective pest management.

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