Transfer Learning and Fine-Tuned Faster R-CNN for Improved Insect Detection in Agriculture

MSc Research Project
Data Analytics

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MSc Project Submission Sheet

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Abstract

Over the years, various insect pests have posed challenges to the agricultural sector with serious off-takers to the losses. Correct identification of insects and pests are important steps in pest control, while existing solutions for this problem can be imprecise and inhibit scalability. Traditional methodologies are gradually losing its effective role in terms of identification of insects due to its incapability in processing large amount, and versatility of data and real time detection. To this end, this research seeks to apply the advanced deep learning method to improve insect detection in agricultural environments where the pest issue is prevalent. In particular, the examined architecture is based on the Faster R-CNN model, which follows the transfer learning approach where the base networks are trained on the pre-collected datasets, and then adapted to the authors' custom collection of dangerous farm insects sourced on Kaggle. Various species of insects and temperature conditions are incorporated in this dataset making it rich for any training and testing of models. The primary innovation of this study lies in the development of a custom training pipeline that incorporates detailed accuracy calculations tailored for object detection tasks. This approach ensures the evaluation metrics accurately reflect the model's performance in detecting and localizing insects. The methodology also involves significant data augmentation to address the class imbalance inherent in the dataset, thereby improving the model's generalizability and robustness. Upon implementation, the fine-tuned Faster R-CNN model achieved a detection accuracy of 91%, demonstrating significant improvements compared to baseline models such as ResNet50V2, ResNet152V2, MobileNetV2, Xception which achieved accuracies of 72%, 63%, 70% and 53% respectively. Also after hyperparameter tuning efficiently, the best baseline model emerged to be the Xception model with an impressive accuracy of 78% on the validation data. These results highlight the superior performance of the Faster R-CNN and the Xception model in real-time pest monitoring and management. This enhanced detection capability can lead to more targeted pest control interventions, thereby reducing pesticide usage and promoting sustainable farming practices. This research contributes to the field of agricultural technology by providing a scalable and efficient solution for insect detection.

1 Introduction

According to FAO projections, there will be almost 33% more mouths to feed by 2050. It is recognized, therefore, that food production cannot sustainably provide ever-increasing amounts of food to feed the world's expanding population. This problem is made worse by the fact that humans need a steady and sustainable supply of food all year round but crops only grow during certain seasons. Especially in tropical countries, agricultural crops are one of the world's most important sources of food. It also keeps individuals prosperous globally and offers conveniences for economic impartiality. As a result, there has been a lot of focus on protecting agricultural crops in terms of both quantity and quality. Many scientific techniques have been applied in this area as a result to accomplish the previously specified goals. Insect infestation is the primary source of damage to agricultural crops. According to certain research, insects and diseases can directly harm healthy plants by spreading a variety of disorders. Many techniques are used all over the world to eradicate pests from farms. However, not all approaches are effective. Furthermore, using common insecticides to keep insects away has a lot of drawbacks. Overuse of pesticides reduces the effectiveness of prevention and increases the risk of immunotoxicity in workers and consumers, as well as domestic animal fatalities and transmission, pesticide resistance, and a lack of intrinsic antagonists to pests. Additionally, pesticides have the potential to contaminate the air, fertilized soil, and groundwater on a farm.

Beyond simply producing food, there are other ways to attain food security. Using proper food preservation and storage methods can help prevent food waste and ensure that food is available for a longer period. There are unique challenges to growing high-quality food, like integrating new technologies and satisfying the growing demand. Farmers still face difficulties long after the crops have been harvested. Activities carried out after harvest have similar significance and may determine whether consumers receive food of a high calibre. 10% to 20% of the world's grain production is thought to be lost worldwide, according to an FAO report. Additionally, the Food and Agriculture Organization of the United Nations (FAO) estimates that 17% of the world's food supply is lost during storage (10% by insects and 7% by mites, rats, and illnesses). Insect infestation of stored agricultural products results in significant quantitative damage. However, the products suffer from both quantitative and qualitative degradation due to the presence of insects or their body parts (legs, wings, molting, etc.) that are undesirable for food. Due to their activity in food and the production of their metabolic products, insects also alter the chemical composition of stored goods, lowering the product's quality.

The agricultural industry may be able to solve its present insect infestation issues by employing Internet of Things (IoT) based smart wireless technology to remotely spot early insect activity in crop development, storage, processing, handling, and transportation. The technology uses cloud computing, and a unique device called SmartProbe, which Pan and his colleagues built using wireless sensors and cameras, to identify and predict bug occurrences. This could reduce the amount of food lost, the necessity for fumigants in contemporary agricultural products, and insect pest control[1].

Automated insect monitoring systems are still required for food production and for the storage of both raw and processed food. But the current generation of technology either can't identify significant pests well enough or require human assistance in order to do so. Insect

[1] https://caes.ucdavis.edu/news/new-smart-technology-developed-uc-davis-professor-may-help-early-detection-insects-food-and

identification and counting using artificial intelligence (AI) is a potentially efficient means of satisfying the need for quick, precise, and timely insect information to improve integrated pest management (IPM) methods. Advances in computer vision technology coupled with deep learning algorithms enable artificial intelligence (AI) to identify insects. Continuous observations can be made using non-invasive devices like cameras. Deep learning models can be trained using photos to estimate insect biomass, diversity, and abundance. Near-infrared (NIR) spectroscopy and machine vision are two of the most recent techniques for fast, non-destructive, and effective insect detection and classification. NIR spectroscopy is accurate and dependable, however it cannot detect low infestation levels or distinguish between live and dead insects.

Recent work has merged machine vision and machine learning to increase the accuracy of stored insect grain identification and classification. One of the most widely used machine learning techniques is convolutional neural networks (CNNs), which have an intricate network topology and are capable of performing convolution operations. A deep neural network was utilized to recognize and identify six species of stored grain insects that were mixed with grain and dockage materials. They utilized different models for different insects and ran into issues such as categorizing one species as two, even though they achieved a high mean average precision (mAP) of 88%. Only one species of bug could be identified at a time by a deep CNN-based system in another insect identification system that was focused on a range of insect sizes and achieved mAP of up to 95%(Mendoza *et al.*, 2023).

1.1 Motivation

According to the Food and Agriculture Organization, insects cause up to 40% of the world's crop production to be destroyed annually (FAO). In addition to jeopardizing food security, this startling loss severely strains farmers and the world food supply network[2]. Pest insects account for 20% to 40% of global agricultural production losses annually, necessitating the use of insecticides in agricultural practices. With the advent of intensive agriculture, applying these chemical components has emerged as the most profitable crop protection strategy. Due to the chemical makeup of pesticides and their widespread use over decades, there has been a rise in resistant bugs, organism poisoning, air and water pollution, poisoning and other health issues. Some of the essential steps include insect monitoring through which pest identification is done to avoid misuse of chemicals. Technologically advanced Integrated Pest Management (IPM) programs that have been formulated in the recent past seek to use small quantities of pesticide only when a pest outbreak is identified. Thus, the overall objective of insect monitoring is to equip the farmer with tools that will help in decision making to increase on crops, have better and quality yields with regarding to the environment. Historically it entails counting the number of insects trapped within fields from where monitoring specialists regularly deliver traps. However, this process is rather a time-consuming method as well as not free from errors and individual approbation since each trap can contain a large number of insects of different species within it(Teixeira *et al.*, 2023).

Artificial intelligence algorithms improve data applicability and provide hypothesis for better decision making. Machine learning uses algorithms and statistical models to enhance the performance of tasks it has been assigned over time on the other hand, Deep learning applies

the use of neural networks with more than one layer to extract patterns, which is more beneficial when it comes to image tasks such as classification, segmentation, and detection.
Insect detection and crop disease recognition have suggested highly developed deep learning models to improve proficiency and reliability. The model which is YOLOv3 in which the backbone network was CSPDarknet-53 and regression prediction was Complete Intersection over Union (CIOU) which yielded an accuracy of 90.62%, while improving 3% compared to the original YOLOv3 model(Li, Zhu and Li, 2021). Another one, ResNet v2, Mask R-CNN, and YOLOv7 algorithms for pests and diseases on the tomato crop(Yang, Chen and Sonza, 2024).
This research seeks to use a fine-tuned Faster R-CNN model to overcome the traditional challenges by having transfer learned a pre-trained network on a dangerous farm insects' dataset. The data is collected from Kaggle containing various insect species which will serve the purpose of model training and validation properly. Training a custom pipeline that includes fine-grained accuracy measures specific to the object detection problem guarantees that it reflects the model's capabilities in recognizing the bugs. This method's benefit is especially noticeable when there is a scarcity of labeled data, as it is more effective than training a model from scratch, as seen in the YOLOv3 and YOLOv7 cases. And also makes the model less prone to overfitting and increases detection performance as compared with the comparative studies, adding to the model's redundancy and internal validity of the results.

1.2 Research Question

A research topic has been established for this study based on the subject presented above

- How does the employed transfer learning techniques, when improved by hyperparameter tuning, along with the proposed fine-tuned Faster R-CNN model, improve insect detection performance and accuracy in agriculture, making farming methods more sustainable?

2 Related Work

2.1 Grain Storage Techniques and Insect Management in Agricultural Crops for Food Security

The lack of enough food to feed the world's expanding population has become a major challenge. Since arable land areas cannot be greatly extended, almost all of the world's fertile land is currently occupied. Securing high-quality harvests while making agricultural production environmentally sustainable is a global challenge (Jankielsohn, 2018).
The Sustainable Development Goal 2 (ending hunger and achieving food security) is a high priority set forward by the United Nations. However, in 2021, there were between 702 and 828 million hungry people in the world, and approximately 2.3 billion people worldwide suffered from moderate-to-severe food insecurity. Climate change is a serious issue because the Food and Agriculture Organization (FAO) has noted that adversely affect everyone's access to food because of its effects on agriculture. As a result, there will be more financial

strain on food access. Based on simulations using the International Model for Policy According to analysis, the three most important staple cereals in the world—rice, wheat, and maize—should face price hikes of between 31 and 106% by 2050, adjusted for inflation. Food loss during storage is seen to be the most important stage of food value chain losses, especially in developing countries where the majority of losses occur during this period. But there are losses all the way from manufacture to distribution. However, food storage can improve food security and ensure that there is enough food accessible for customers provided adequate effort is done to encourage efficient food storage techniques and the use of improved storage buildings (Afriyie *et al.*, 2023).

People's nourishment is met on a fundamental level by crop cultivation. Crop production in increasingly large-scale, intense, and simple agricultural settings is frequently threatened by several factors, including a lack of pollinators and pest damage from weeds, rodents, pathogenic microorganisms, nematodes, and insect pests. While crop pests can result in significant losses during crop production and food storage, efficient pest management helps to lower crop loss and misuse of pesticides. To ensure good yields and quality, insect pollination is also necessary for most of the vegetable and fruit tree crops. For sustainable crop production, research on pest management tactics and methods and their possible effects on pollination and pest control in agricultural landscapes is crucial(Ouyang *et al.*, 2022).

Grain is the essential material that keeps humans alive, and both the sustainability of human expansion and our future are inextricably related to it. First, this crop provides the body with the nourishment and energy required to maintain regular physiological functions. It is high in lipids, proteins, and carbs, dietary fibre, vitamins, and minerals are essential for sustaining human health and life. Low-temperature grain storage technology primarily uses natural or artificial cooling during the storage process in order to keep grain in the depot at a lower temperature and prevent or slow down the invasion of harmful organisms and the deterioration in quality. Depending on the climatic circumstances of the grain storage locations, solutions for reducing the temperature of grain piles include covered and closed grain storage, mechanical or natural refrigerator cooling, and rebuilt warehouse thermal insulation. Grain storage system with a regulated atmosphere stops dangerous insects from growing by altering the air quality in the grain storage facility by hand. This delays the deterioration of grain quality, inhibits the growth of mildew and pests, and slows down the rate at which grain respiration and physiological metabolism occur(Zhao, Lv and Li, 2023).

Crop pests can be controlled in two different ways: "top down," where pests are controlled by natural enemies and biodiversity, and "bottom up," where pests are controlled by plant defensive mechanisms. Frontier areas in research and technology for crop disease prevention and insect pest management are always crucial, and ecological regulation and control of pests in agricultural landscapes are no exception(Fang, XingYuan and Feng, 2020).

The following section details the detrimental effects that bug infestations on product have on farmers and how this forces them to maintain appropriate storage conditions, in addition to the increased global efforts to battle hunger through various food storage strategies.

2.2 Effects of Insect Infestation on Crop Growth and Commodity Storage

The modernization of the agricultural production system resulted in a significant annual rise in food output to fulfil the continuously expanding demand from customers. In many countries, the majority of food grains produced are stored for regular and emergency usage. Security and safety of food are at risk because major grain destruction and storage losses result from these grains' frequent direct or indirect insect infestation. Many bug species that cause significant damage to commodities stored in storage account for between 10 and 20 % of all storage losses. Insects that commonly cause losses of stored objects of agricultural and animal nature include more than 600 different species of beetles, 70 species of moths, and 355 species of mites. Both the quantity and quality of the stored goods are severely lost as a result of this massive pest arena. Insect pests that harm storage products usually originate in the field and become established at the storage location due to the favourable environment(Guru *et al.*, 2022).

One of the main causes of agricultural loss that occurs annually throughout the world is pests. Chemical pesticides have long been the primary means of agricultural pest prevention and control. Nevertheless, there is never a single pesticide that works for every type of pest, and the number (as well as their distribution and categories) of agricultural pests in the field greatly influences the performance of pesticides, even though these factors are necessary for precision pest management. Because of this, chemical pesticide overdosage is widespread, leading to high insecticidal costs and issues with food safety resulting from pesticide residues in actual use.

Across the globe, agricultural pests seriously reduce food yields in both developed and developing nations. Recent studies reveal that agricultural diseases and insect infestations cause about half of the world's crop production to be lost. Real-time monitoring of the types and distributions of agricultural pests has become essential with the introduction of precision agriculture in recent years, since it enables effective and precise management of agricultural pests in the field. Traditionally, manual counting and visual inspection have been the main methods used to gather data on the population of pests. However, because of worker exhaustion and skill deficiencies, this task requires a lot of labour and takes a long time with inconsistent accuracy(Li *et al.*, 2020).

An Insect infestation of stored agricultural products results in significant quantitative damage. However, in addition to causing quantitative harm, the inclusion of insects or their bodily parts—legs, wings, molting, etc.—degrades the items' quality. In food, these components are also undesirable. Because they produce metabolic products and are active in food, insects also contribute by changing the chemical composition of preserved things, degrading their quality. A portion of the commercial and nutritional value of foods and raw materials is lost, which may have negative health effects on consumers. Jood et al. investigated the possibility that the insect infestation of T. granarium (Everts) and R. dominica (Fabricius) would change the proteins in cereals. It was discovered that a 50:50/0 mixed population infestation of these insects resulted in a decrease in the amount of important amino acids present in wheat, maize, and sorghum. In particular, the results indicate a drop in methionine per wheat of 38.9%, in isoleucine per maize of 30.8%, and in lysine per sorghum of 32.9%. When it comes to cultivating crops, insects primarily do two kinds of harm. First, the plant is harmed directly by the feeding insect, which burrows in stems, fruit, or roots and eats on leaves. This kind of pest includes hundreds of species of adult and larval orthopterans, homopterans, heteropterans, coleopterans, lepidopterans, and dipterans. An indirect damage occurs when an insect does little to no harm to a crop but instead disperses a bacterial, viral, or fungal illness(Stathas *et al.*, 2023).

2.3 Conventional Techniques for identifying Insects in Agricultural Food Storage

The management of grains after harvest mostly entails treating the grains in a scientific manner and storing them in safer ways. The field-harvested commodity also features their stored food grain which is attacked by the following insect pests. Mating behaviour, feeding habits, life cycle, effect on plants and harm they cause are different in each case of an insect. In management, it is therefore important that the presence of insects or signs of insect damage is detected as early as possible. Both the visual examination and observation of insects at different stages represent the core of all assessment methods. Among the novel strategies covered in this course and structure are techniques that have allowed researchers to pinpoint the insects infesting products that are being stored. For instance, Hagstrum et al. (1996) used acoustical detection to successfully separate one contaminated kernel from 650 g of wheat grains. In order to find unseen interior insect hideouts in wheat kernels, Pearson et al. (2003) used electrical conductivity. The results were somewhat successful; 88% of large-sized larvae and 87% of pupae were found. Moreover, Brabec et al. (2017) used electrical conductivity and a lab roller mill to find Sitophilus zea- mais larvae inside popcorn kernels. Additionally, the detection accuracy varied between 75% and 81% for pupae and between 80% and 91% for medium larvae., and 43–47% of the tiny larvae; depending on the roller speed(Ranganathan *et al.*, 2022).

Traditional Insect classification has for a long time been an important element for agricultural practice especially for food crops and storage facilities. Identifying insects based on their shape still remains, the primary method of classifying insects. This method entails the observation of physical characters namely: size, color, shape, and those of some body appendages like wings, antennae, and genitalia. The first major benefit of morphological identification is that in most cases, it is the simplest method and it relies on a tool such as microscopes. Also, it is non-destructive in a way that after a test, the specimens are left intact for further use. Nevertheless, this method has some major disadvantages. It demands comprehensive familiarity with entomology and is frequently limited to the adults especially the males because of the diagnostic physical characteristics. A dichotomous key is a tool for the identification of insects, where it offers the user a way of reaching the species of an insect beginning with a series of decisions. Every move in the key offers two statements concerning a feature of the insect that are opposite in meaning. This method is sort of standardized therefore the process is well outlined and can be greatly used in teaching new entomologists. However, dichotomous keys may be somewhat difficult and time consuming to work with, particularly if the users are not professional entomologists and the variation in traits of the insects may pose some sort of challenge(Banga *et al.*, 2020).

There is another traditional method That is the pheromone and light traps, whereby insects are drawn to light traps in order to be captured. Pheromone traps utilise species-specific chemicals to attract the insects hence are efficient in pest surveillance. There is light traps that take advantage of the ultraviolet light to lure the insects. Once trapped, the insects are generally Sorted out by entomologist who has better understanding of insects. These are commonly used in monitoring and early detection techniques in pest infested areas although they have some shortcomings in that they cannot be specialized for a certain species and may not be very efficient in capturing the pests. Furthermore, the identification process still depends on a manual inspection and experience that can cause a problem in terms of processing volume(Abbas *et al.*, 2019). Next, as a further step to address the issues raised by the current control system, the Sunlight Trap is created. Using electronic devices like hormone spray traps and photo taxis—light rays connected to a high-voltage power network—these pests are eradicated and harvested within chambers. Insects favor solar LEDs due to their ability to increase consumer convenience. Here, the solar panel's daytime energy is stored in the battery to power the pest control LED light circuit at night(Jose and U P, 2023).

Despite their negative effects on farmland, crop quality, human health, and the biodiverse, chemical pest treatments are widely utilized because the problem of agricultural pests poses a danger to world food security. SILs, or solar-powered insecticidal lamps, are a physical control strategy that doesn't include chemicals to protect agricultural from pests. As a result, the assimilation of agricultural Internet of Things (IoTs) in the recent past means that the integration of SILs and IoTs creates a brand-new overall concept, which is subtitled as solar insecticidal lamps Internet of things (SIL-IoTs). Regarding the current research projects of the team regarding the SIL – IoTs domains, it was pointed out that they relate to pest counting and transmission until the fast information on the pest can be acquired and pest-concentrated areas, as well the fixed-point pest control is made target. Li et al. (2023).

2.4 Agricultural insect identification using deep learning technique

There are traps that use cameras and traps that use sensors in the insect pest monitoring techniques. Camera-taught traps use cameras and computers to detect digital pests using sensors and sticky surfaces that pheromones adhere to. Convolutional neural networks (CNNs) are the mainstay of most traditional approaches to image analysis and pest categorization problems. Several sensors are used in integrated pest management traps to help identify pests and assess whether the environment is conducive to pest populations. A central server gathers data from both kinds of traps in order to evaluate and determine the outcomes, indicating more accurate and successful pest surveillance and management in agricultural settings(Passias *et al.*, 2023).

Another method includes where researchers used deep learning methods for detection and image recovery of pest from the IP102 dataset having 75 K images, K-means clustering as a tool for pest detection even though there is a complicate classification and imbalance pest variety. Training and performance assessment include sample from 18000 pests for implementation of the project. These include sensitivity, specificity, precision, recall, F1 score and G mean of the performance. MATLAB R2021a is used as platform to implement, which feature extraction is done based on each pixel and geometric transformations are also done. Thus, the validation accuracy is 97%. Obtaining a 98% reliable test means that at a point when there were 1,000 samples to be tested, the results were earned. The disadvantage here is that: it might be impossible for the deep learning technique to enable the K-means clustering to effectively train the algorithm for pest distinction and classification if it was not trained in a similar scenario to the dataset here meaning that there could be mis classification of pests or low accuracy in pest detection where the area is not covered by the dataset. Thus, given some randomness in the pest's movements, there is always a possibility that some pests will be left unnoticed and escape extermination(Kundur and Mallikarjuna, 2022).

Advanced methods of deep learning have recently been incorporated into the identification process of insects within agricultural practices in order to improve the efficiency and reliability of the same. Another exemplary work by Amrani et al. (2023) successfully used YOLOv3 for objectives linked to the identification of insects in imagery, based on a newly presented adaptive feature fusion convolution network. This technique enhanced the YOLOv3 model by adding the adaptive feature fusion module that increases the ability of detecting smaller objects such as insects. The presented network was trained in Pest24 dataset containing more than 25000 images and obtained 72 % accuracy. 10% while a fast detection rate was recorded at 63%. 8 images per second. This study proved that the proposed model can yield better probability accuracy as well as better computational time than the previous methods used and can be used for the real-time monitoring and controlling of pests in agricultural farms(Amrani *et al.*, 2022). Nevertheless, there are also some issues with using deep learning in the identification of insects that should be noted. A limitation as identified by Manchanda et al. (2024) is the fact that huge annotated datasets are usually required to train the models adequately. This procedure may take sometime and may be very tasking hence, may need a lot of resources. Also, deep learning models require significant computation resources and hence may be unsuitable for deployment in scenarios that do not have a lot of computational power. Nevertheless, the study pointed to some factors that are worthy of consideration They identified that transfer learning which uses pre-trained models on large and general data bases and subsequently fine tuned on insect data sets displayed promising results in enhancing the results on insect classifications. This issue was closely discussed and it was concluded that careful tuning of hyperparameters and data augmentations in dataset are critical to improve performance and generalize the model across different agricultural domains(Manchanda *et al.*, 2024). Projects involving deep learning, such as DeepPestNet, exist with the framework for pest recognition and subsequent classification and are 100% effective. While the initial focus was put on the major pest species, the next steps for the future research of the given framework shall aim to expand the framework in order to also respond to the presence of other types of insects in their later developmental stages. The performance enhancement in the framework of the presented pest identification is anticipated to be greatly enhanced as a result of the further introduction of more species and the addition of life stages (i.e., larvae and adults). This research path offers experts and farmers the chance to fully obtain the more advanced tools for quicker and more accurate illness suspicion. Therefore, economic loss is prevented, and the yields produced in crops are protected(Ullah *et al.*, 2022).

3. Research Methodology

The objective of this study is to propose and compare an enhanced insect identification model based on deep learning approach; the selected deep learning framework is called Faster R-CNN to improve pest control in agriculture. There is a sequence of basic stages that are involved in the methodology which include data selection, pre-processing and data preparation, model creation, model training and model assessment. This research adopts the CRISP-DM business analytics framework to guide the pre-processing, information selection, data analysis, and modelling processes. The Figure 1 depicts the class distribution the dataset.

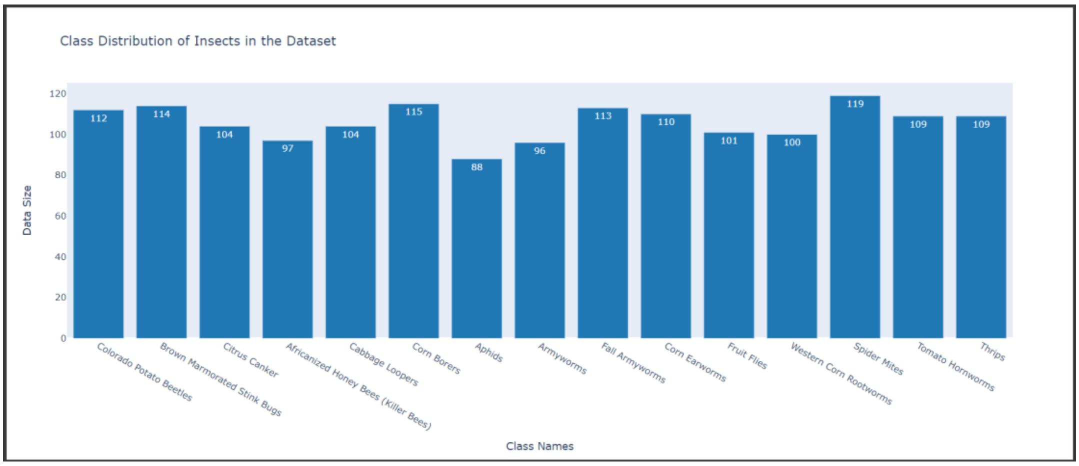

Figure 1: Class Distribution of the data

3.1 Data Selection

The data used in this research was obtained from Kaggle and it includes 15 different classes of insects that are very dangerous to farming practices and crop yields. Every class is given a distinctive name of the insect type and is well categorized to enhance the recognition process of the bugs. Each class contain different numbers of images; however, all together, the dataset contains 1481 images. The Figure 2 represents a snapshot of the dataset. The images are normalized, resized etc to pose them suitable for the model's learning and make them uniform. The data augmentation methods are also employed to handle the class imbalance problem as well as to enhance the model's ability to generalize.

Figure 2 : Preview of the dataset

3.2 Data Preprocessing and Transformation

After analysing the image dataset and researching about the work done on this, the author has decided to apply various data transformation techniques and it deems as an import factor. This step is crucial in data processing and warehousing because it formats the data for insertion into deep learning models. The preprocessing pipeline for this research involves several key steps: Data Resizing, Data Shuffling, Class Distribution and Normalization. Further, to improve the performance of the deep learning model data augmentation was used. Then, the data set was pre-processed and then split into training, validation, and test sets to avoid overfitting and necessitate the evaluation of the models. The respective classes of the dataset are as follows:

- Africanized Honeybees (Killer Bees)
- Aphids
- Armyworms
- Corn Borers
- Colorado Potato Beetles
- Fruit Flies
- Cabbage Loopers
- Citrus Canker
- Corn Earworms
- Fall Armyworms
- Spider Mites
- Thrips
- Tomato Hornworms
- Western Corn Rootworms
- Brown Marmorated Stink Bugs

The problem of class imbalance is evident from the dataset obtained from Kaggle where certain classes contain much fewer samples than the other classes. To overcome this, the class weights were calculated and incorporated in the training process of the models. This adjustment prevents the model from focusing only on the majority class and keeps all the classes in consideration. This detailed preprocessing method is important for building an effective insect detection system that meets the requirements of agricultural pest identification.

Class Distribution: The dataset's class distribution throws light on the dataset's balance or imbalance by revealing how many photos there are in each class. The number of photos in this collection fluctuates according to the insect classes, suggesting an uneven distribution. As "Spider Mites" (119 images) demonstrates, some classes have larger sample sizes than others; "Aphids" (88 images) is one example of a smaller class. Because of this intrinsic imbalance, the model may find it difficult to learn and generalize across all classes, which presents a problem for training and model performance.

Rare Classes: Because their sample numbers are smaller than those of other classes in the dataset, some classes are regarded as rare. The collection contains notable instances of unusual classes, such as "Africanized Honeybees (Killer Bees)," "Aphids," and "Armyworms." Because there are only few instances of these classes, training the model will become difficult and could lead to poorer performance in correctly detecting and categorizing these uncommon insects. Reduced accuracy and precision in forecasting the presence of rare classes may result from the model's inability to adequately describe their distinctive traits and patterns.

Common Classes: On the other hand, a few classes in the dataset have bigger sample sizes, which indicates that they are more common and plentiful. Examples of these common classes that are noteworthy are "Corn Borers," "Spider Mites," and "Fall Armyworms." These classes gain from having more training instances available, which gives the model more chances to pick up on and comprehend their unique traits. Because there are many examples of the same classes, the model may identify and use these characteristics to its advantage, which could result in better performance and accuracy when classifying these insects.

Class Weights: Using class weights the issue of class imbalance has been addressed during training. Based on each class's frequency in the dataset, class weights allocate distinct weights to each one. Class imbalance is lessened by the model giving the minority class greater weight during training by altering the weights. After addressing the class weights, concerning the efficacy of training, it can be stated that the similarity of the distribution of the original classes and the classes of the trained images ensures that the model will be trained as planned, effectively avoiding problems related to class imbalance that could be present in the data. With the help of class weights and using the strategy of stratified split, the problem of class imbalance will be taken care of, and the model receives a balanced and representative training across the classes. Such a level of performance of the model provides confidence in its reliability and in the ability of the latter to effectively forecast in real-life conditions.

Image Loading and Preprocessing: The specific paths are used to load images according to the requirement. The loaded images are decoded into tensor format with the help of `tf. image. While decoding an image, it was ensured that all images have three color channels, RGB. Each image is resized to the specified dimensions (`256x256` or `224x224` depending on the size of image passed) along with the information to be extracted is obtained from each image. This makes the size of the input to the model is standardized with resize. The pixel values of the images are scaled to the range between 0 and 1/255 by dividing the images by 255. This step makes it certain that the model is fed with data that is normalized and this is known to enhance the training process of the model.

Label Extraction: The class labels are derived from the image paths according to the subdirectories created during the data organization. These labels are then either kept as the string names of these classes or are converted to the numerical indices as per their position in the list of classes. If specified, the class labels are one hot encoded, which converts the categorical labels into binary vectors. This is good for the categorical cross entropy commonly used in the training phase.

Stratified Data Splitting: Although the class distribution analysis helps to mitigate the problem of class imbalance during training, there is still a need to use an appropriate data splitting technique that takes stratification into account. If this isn't done, the class distribution analysis might not be useful. By using stratified data splitting, the train and test sets are guaranteed to maintain a representative class distribution that is identical to the original dataset. This method avoids bias introduction and aids in a precise assessment of the model's performance by maintaining the relative proportions of each class. The author has applied the train-test split function from the scikit-learn to carry out a stratified data split. Therefore, through performing a verification to the train section images, one can bolster up the validation of the data split process and consequently the training phase. This cross-checking will prove beneficial and will give the necessary confidence and guidance to ensure the creation of the training data, and eventually the for the betterment of model training.

3.3 Model and Data Mining Design

Data mining is generally understood as the technique of search for regularities, trends, and anomalies in the given data and forecasting the result. The objective of this work is to create an accurate insect detection model with the help of modern deep learning methods as depicted Figure 3.

Due to the small size of the dataset, the objective is to employ transfer learning since it is well suited for classifying the farm insects. The use of this approach helps to recognize the pre-trained models to work with such as ResNet, MobileNet. Further to enhance the performance. Further, the fine-tuned Faster R-CNN model will be applied on the dataset for the current classifying task at hand. And in the end, the ultimate aim is to determine the best network architecture that can be used for the real-world application of identifying insects in an agricultural setting.

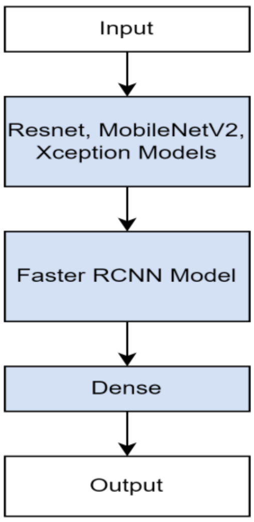

Figure 3: Proposed Model

3.4 Model Assessment and Interpretation

Another important step that is characteristic for deep learning processes is the evaluation of results. This step also helps to determine the best approach depending on the metrics of the models and a comparison of their performances will be made. In this study, the evaluation entails the use of multi-class metrics because of the multiple classes of insects. The measures of effectiveness that have been applied in the process of comparing the models include accuracy, precision, recall as well as F1 score. Besides, the multi-class confusion matrix is used to analyse the efficiency of the classification in terms of various insect types. The last procedure involves presenting all the results through graphs and charts as a means of evaluating the competency of the models to identify and categorize farm insects.

4 Design Specification

Basic introduction of implemented system for this research is presented in this section as depicted in the Figure 4. And each phase of this design is discussed in detail.

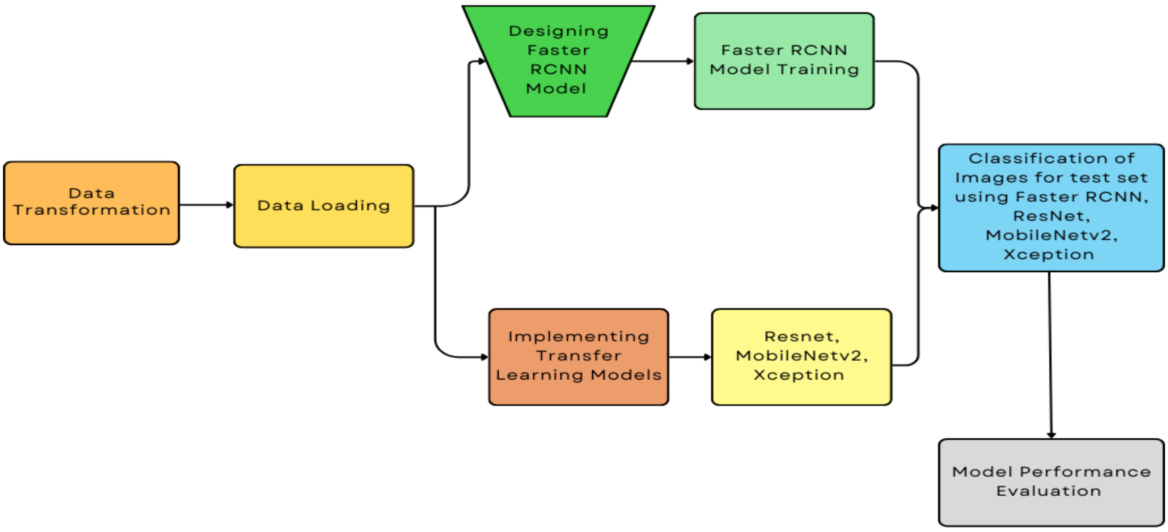

Figure 4: Design of Project

4.1 Faster RCNN

Deep learning has come to be regarded as one of the most efficient methods of feature learning and object recognition. Faster R-CNN is one of the Deep Neural Networks which outperforms other machine learning algorithms because it is capable of learning hierarchical features from data on its own. It presents a novel concept of a Region Proposal Network (RPN) that is connected directly to the detection network utilizing full-image convolutional feature so that generating region proposals can practically be done at almost no extra computational cost. This approach helps the model to identify the objects with ease and less time and at the same time, improve the accuracy of the model. The basic idea in Faster R-CNN is that convolutional layers of the network can learn features from the input image, while the region proposals and their classifications as well as the boundaries can be further improved. The model is divided into two main stages: the proposal stage of a region and classification stage. In order to acquire the predicted class labels and bounding box locations, the Region Proposal Network and ROI pooling in conjunction with a classifier and regressor head are the primary components of the Faster R-CNN as depicted in the Figure 5.

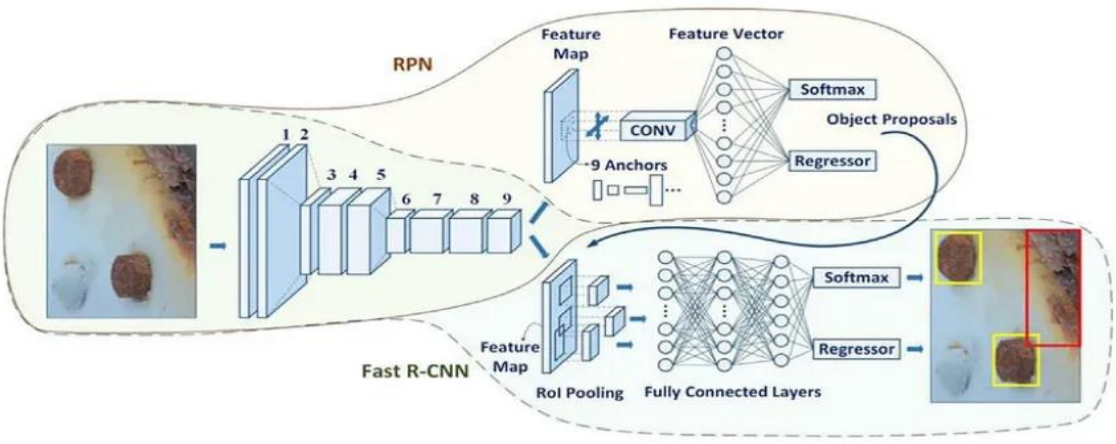

Figure 5: Faster R-CNN

4.2 ResNet, MobileNet, and Xception Models

Besides, the other state-of-art deep learning models like ResNet, MobileNet, and Xception are studied in this research concerning insect classification. These models are used through the transfer learning technique to utilize the weight and to improve the feature extraction element.

ResNet is a very powerful deep learning model that has been designed with the use of residual blocks in an effort to minimize the vanishing gradient issue in very deep networks. ResNet enables the training of deep models by adding shortcuts, which skip one or more layers, into the network. This design enhances the learnability of residual functions making the convergence and performance better. To extract complicated features from the insect images, ResNet50V2 and ResNet152V2 models are employed in this project.

MobileNetV2 is an efficient convolutional neural network proposed for use in mobile and IoT devices applications. It employs depth wise separable convolutions to scale down the parameters as well as the computational intensity, which makes it very efficient. MobileNetV2 is relatively small but is effective, therefore it can be used in cases where it is necessary to save computational power. In this case, the effectiveness of this model for insect classification problems is measured.

Xception, which is an acronym for Extreme Inception is a deep convolutional neural network which builds on Inception architecture by replacing traditional Inception. This architecture leads to a more efficient and powerful model to learn the fine-grained features. Due to the design of Xception, the algorithm can provide a high level of accuracy in different activities related to image classification.

Thus, by comparing these models at first, one can obtain preliminary information concerning their effectiveness and appropriateness for the given dataset. This approach also aids to set a base for the design and working of the Faster R-CNN model.

4.3 The Method

The data is initially loaded into google collab from google drive after the drive is mounted through the code. To reduce the data loading process and overcome the memory problems, the batch processing method is applied where the sets of 32 images are used. The data is loaded into memory using custom data loaders in such a way that each batch of data is preprocessed and in a format that can be used by the models. For the model training, several state-of-art deep learning models are used which includes ResNet, MobileNet and Xception via transfer learning to set up a good initial base. These models utilize transfer learning to improve the feature learning process. In these models, the classifier layers are tweaked to provide the output of 15 classes that are associated with various species of insects. Following the benchmarking with transfer learning models, the Faster R-CNN model is employed to enhance the use of object detection. Faster R-CNN employs an RPN to produce region proposals, subsequently, the model performs classification and bounding box regression. All the models are trained for the desired number of epochs and the model which yielded the best accuracy in the validation set is used for further testing. The outputs of these models are assessed using other basic measures like accuracy, precision, recall, and F1 score.

5 Implementation

This section deals on the methods of utilizing different types of deep learning models to classify the insect species in the dataset. The basic architecture models applied in this research are Faster R-CNN, ResNet, MobileNet, and Xception, which employ transfer learning to improve the outcomes of the models.

5.1 Faster R-CNN Implementation

Based on the dataset of the images of insects within fifteen classes, the detailed approach was constructed in this paper to perform the automatic detection and recognition of the various kinds of insects. To perform this task, the Faster R-CNN model that integrates the Region Proposal Networks (RPN) with Fast R-CNN was used.

Backbone: ResNet50 which is trained on the ImageNet database is used as the feature extractor. The backbone takes features of the input images and passes them to the RPN.

Region Proposal Network (RPN): Produces region proposals, which are boxes possibly containing an object. The RPN provides candidate regions of interest (ROIs) that may contain an object.

ROI Pooling: Generates fixed size feature maps from the proposed regions. This makes sure that each region proposal is of a fixed size that can be passed to the fully connected layers of the network.

Fully Connected Layers: These layers sort and narrow down the objects and sharpen the bounding boxes. The classification layer provides the probable object class for each region proposal and the bounding box regression layer fine tunes the coordinates of the bounding boxes as depicted in the Figure 6.

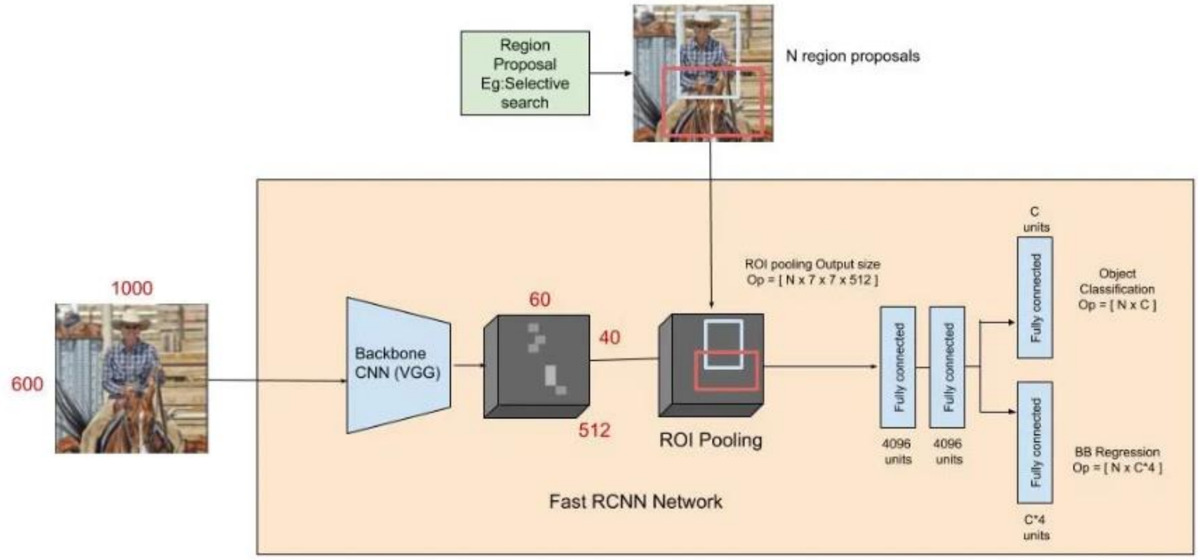

Figure 6: Faster R-CNN Pipeline

The features of the network include 50 convolutional layers that are followed by max-pooling layers for feature extraction and ReLU activation function for non-linearity. The last layer of the network is the output layer by which the identified insects are classified into fifteen classes using SoftMax function.
Fully Connected Layers: These layers sort and narrow down the objects and sharpen the bounding boxes. The classification layer provides the probable object class for each region proposal and the bounding box regression layer fine tunes the coordinates of the bounding boxes.

5.2 Transfer Learning Models

ResNet is another powerful deep learning model that became very popular because of its residual blocks that prevent from vanishing gradient issue in very deep networks. ResNet enables one to train very deep networks by incorporating a shortcut connection that jumps over one or more layers. This design enhances the learning of residual functions, and at the same time it enhances the rate of convergence and performance. In this project both the ResNet50V2 and ResNet152V2 architectures are used to extract fine details of the images of insects. The input layer takes images of size 224 x 224 x 3, which is passed through residual blocks comprising of convolution layers, batch normalization, and ReLU activation. Shortcuts skip one or more layers of convolution in order to allow for the learning of residuals.
MobileNetV2 is quite compact, yet it is very efficient, which will make it suitable for many scenarios with restricted computational capabilities. The model in this project takes input images of size 224*224*3 and applies depth wise separable convolutions which decreases the computation and the model size. Bottleneck layers are made up of thin layer with a few channels, dilated by pointwise convolution and then passed through depthwise convolution.

Xception – ‘’Extreme Inception’, is a deep convolutional neural network that is an extension of the Inception model whereby standard Inception modules are replaced with depthwise separable convolutions. This architecture leads to designing a more efficient and powerful model of capturing better features at a more detailed level. The model processes input images of size 224*224*3 and in the Inception modules, standard convolution is replaced with depthwise separable convolution for better efficiency and accuracy.

In this project, for the input data, in all the above-mentioned models, the average Pooling layers sum all the feature maps to produce a single value for each map before going to fully connected layers with 256 and 128 neurons and the ReLU activation function. A dropout layer set to a dropout rate of 0. 4 is used to avoid overfitting by performing input unit sampling that sets a portion of the input units to 0 during the training phase. To improve the learning and model convergence, the Adam optimizer was used in their training process.

6 Evaluation

The performance of the models was tested on the test set. The following results summarize the evaluation metrics for each model:

6.1 ResNet50V2 Model

As depicted in Figure 7 it is noted that for the ResNet50V2 model the accuracy output for the training set was 66% and the number of images correctly classified for the training set was 840 with an image count of 1272. The validation accuracy was also 66% and 189 correct classifications out of 287, which means that there is some overfitting. The testing accuracy was 66% almost similar to the validation accuracy and was able to correctly predict 21 out of 32 images. The accuracy of the training set improved, while the over fit measurements such as validation accuracy remained behind by 0.2, highlighting overfitting. Through the confusion matrix presented in Figure 8 the author was able to see that certain classes had perfect results while there were extremely poor results for Aphids and Armyworms. However, great recall values were observed for Africanized Honeybees though precision for the same bees was significantly low because although the model identified the bees correctly, it also gave high probabilities to other bees that were not necessarily the Africanized Honeybees.

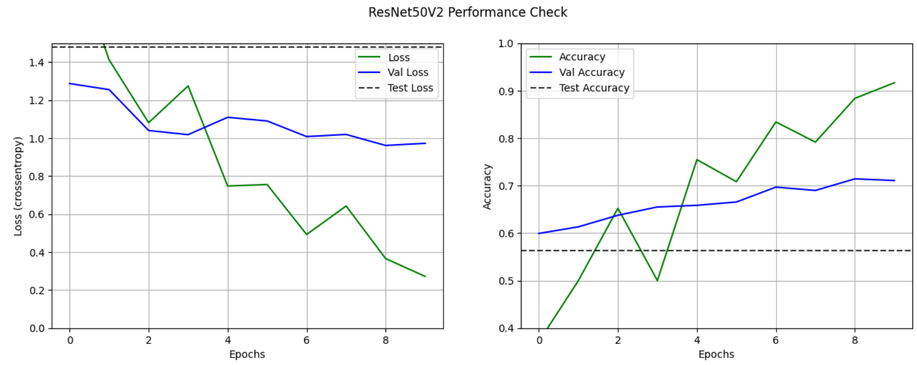

Figure 7: ResNet50V2 Performance

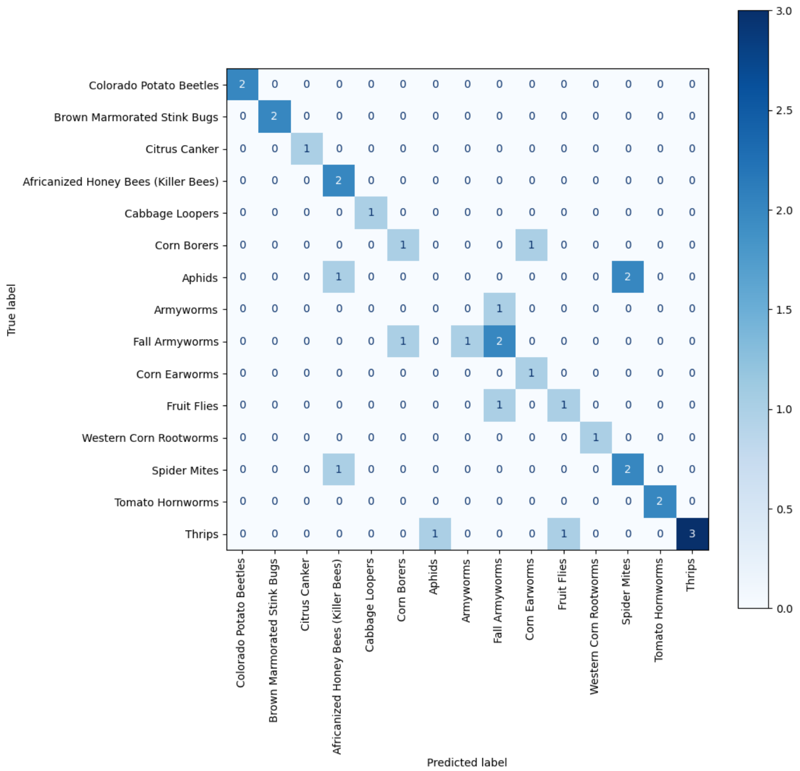

Figure 8: ResNet50V2 Confusion Matrix

6.2 ResNet152V2

The performance of ResNet152V2 model shifts in tandem with the ResNet50V2. Even with the deeper architecture of ResNet152V2 in a bid to capture more features, its gains are negligibly small. The training accuracy level for ResNet152V2 was around 60%, and validation was around 70% as seen in Figure 9, followed by the testing accuracy almost equal to the validation. The characteristics of the learning and validation losses prove that there is no significant overfitting here.

Figure 9: ResNet152V2 Performance

The confusion matrix as shown in the Figure 10, and the metrics of the classification report show that, although ResNet152V2 reaches a very good accuracy in the Colorado Potato Beetles, Brown Marmorated Stink Bugs and none or very low values for the others, where it is even impossible to recognize any percentages of precision and recall for some classes. The means of precision, recall, and F1 score are respectively, 61. 6%, 62. 7%, and 60. 3%, respectively. Based on these outcomes, it would appear that the effort should be made to fine-tune rather the ResNet50V2 model because of the similar performance metrics while having better computational demands.

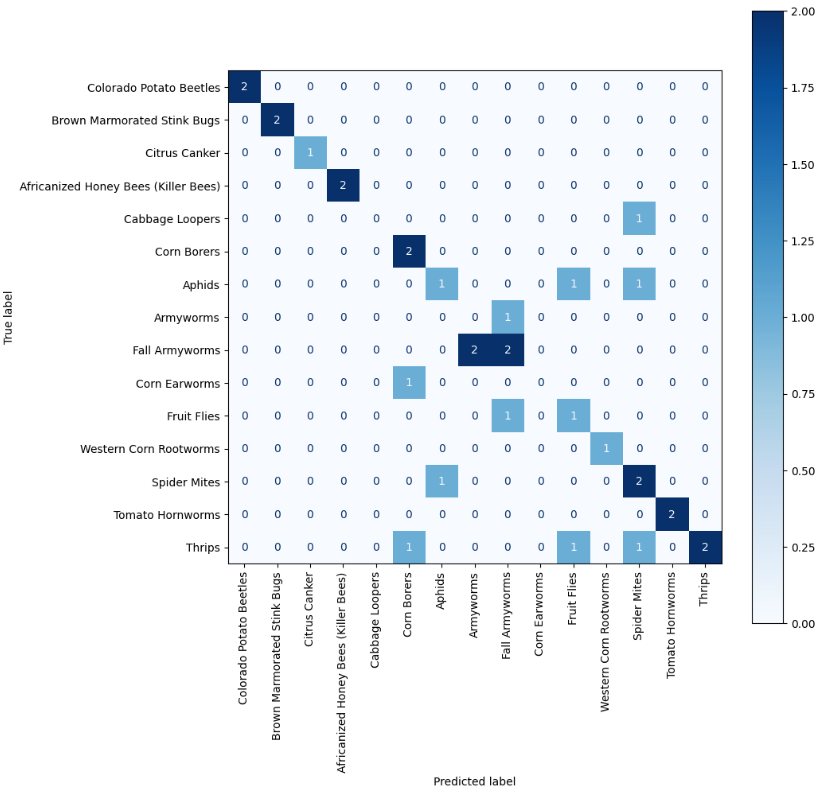

Figure 10: ResNet152V2 Confusion Matrix

6.3 MobileNet V2

Through the classification report, the model shows better and worse performance on the different classes of insects. Nevertheless, some classes like Colorado Potato Beetles, Brown

Marmorated Stink Bugs and Africanized Honey Bees performers perfectly to the precision and recall measures while others like Cabbage Loopers and Armyworms undergo low levels of precision and recall measures. The evaluation of the overall performance which includes precision, recall and F1 score which is values at 0. 677, 0. 697, and 0. 611, respectively. This, in turn, shows that the model has a decent performance in some classes while having a poor performance in the other, hence, an average performance. The confusion matrix also underlines these statements, as it indicates the distribution of true positive and true negative, depending on classes.

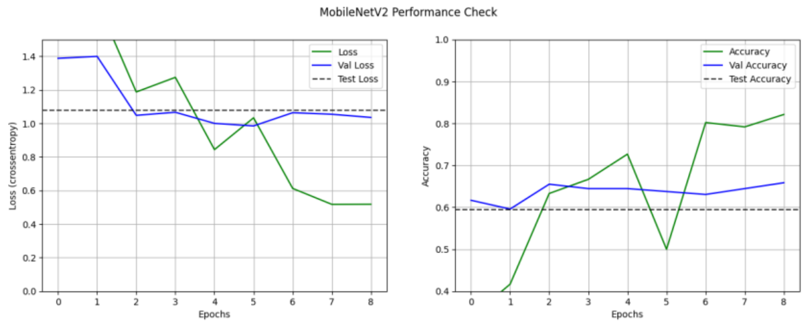

Figure 11: MobileNet V2 Performance

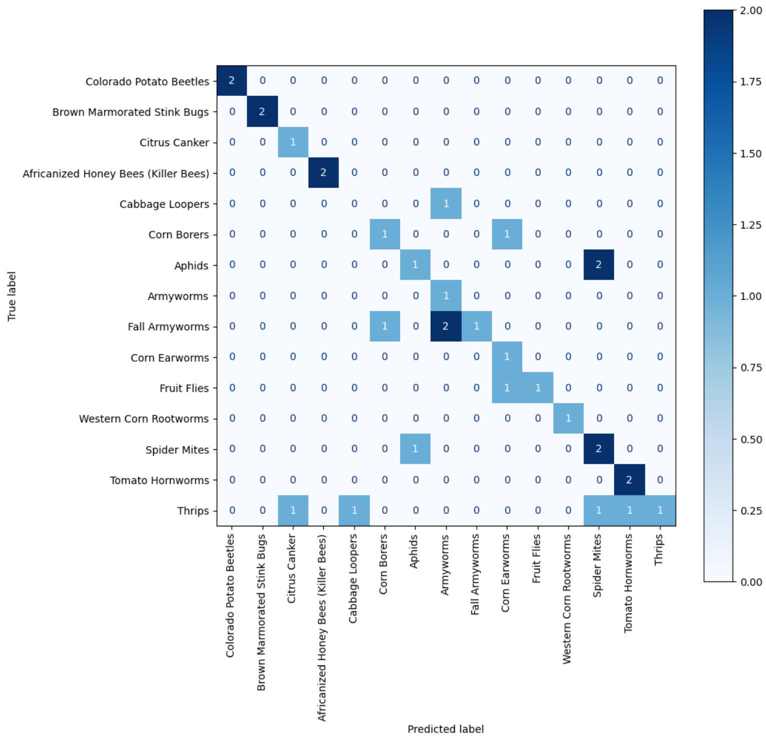

Figure 12: MobileNet V2 Confusion Matrix

6.4 Xception

Interestingly, the case with the Xception model is impressive in terms of testing compared to other models. As it can be noted, the training and validation losses, as well as the accuracy, are almost identical for the two networks meaning that Xception has the potential of being the optimum backbone since there is a significant boost in testing accuracy. Specifically, this model obtained an accuracy of 50% as visible from the Figure 13, in general and a precision of 0. 461 and other relevant symbolisms, while the rate of recalls was 0. 532.

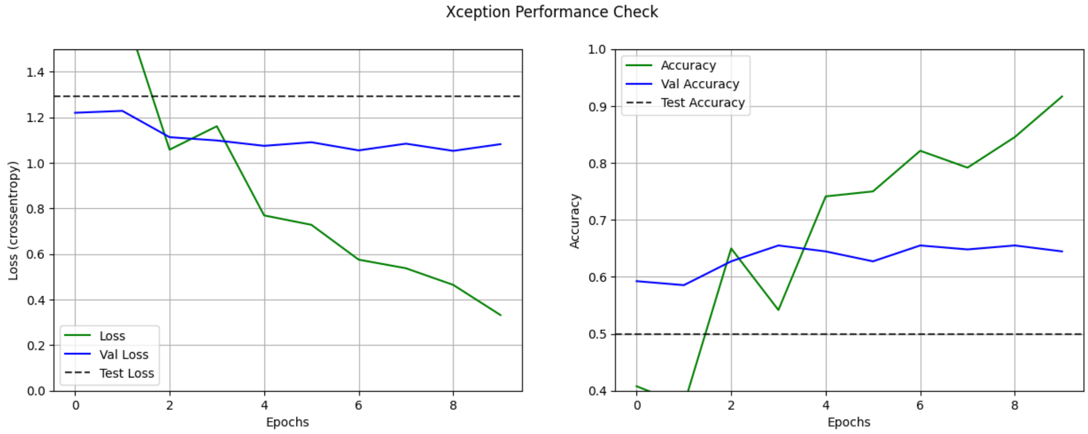

Figure 13: Exception Performance

From the classification report depicted in the Figure 14 it can be seen that the model is good with certain classes but doesn't recognise certain classes such as Aphids and Armyworms, but the model possesses good accuracy with classes such as Colorado Potato Beetles and Brown Marmorated Stink Bugs. This implies that by optimizing the proper hyperparameters, the Xception model could be further enhanced for the betterment of its accuracy in all the classes.

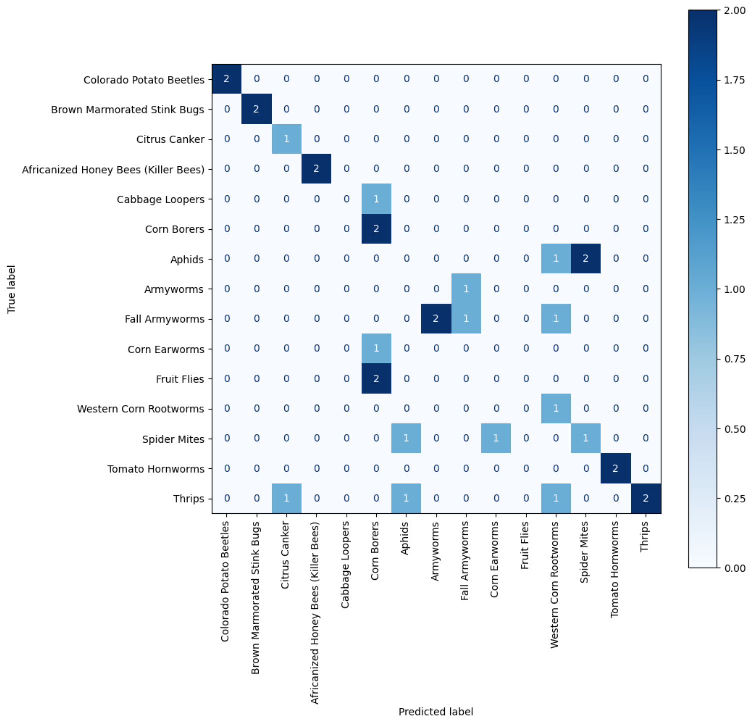

Figure 14: Xception Confusion Matrix

6.5 Hyperparameter Tuning

In this paper, the author presents the results after hyperparameter tuning with a Hyperband method in 13 trials and, on the validation dataset. The model was fine-tuned to perfection to achieve a 5 % enhancement than the actual benchmark of 72%, giving an accuracy of 77% as shown in the Figure 15. This significant improvement should be placed the Xception model as one of the most potent peers to the earlier models while surpassing other models.

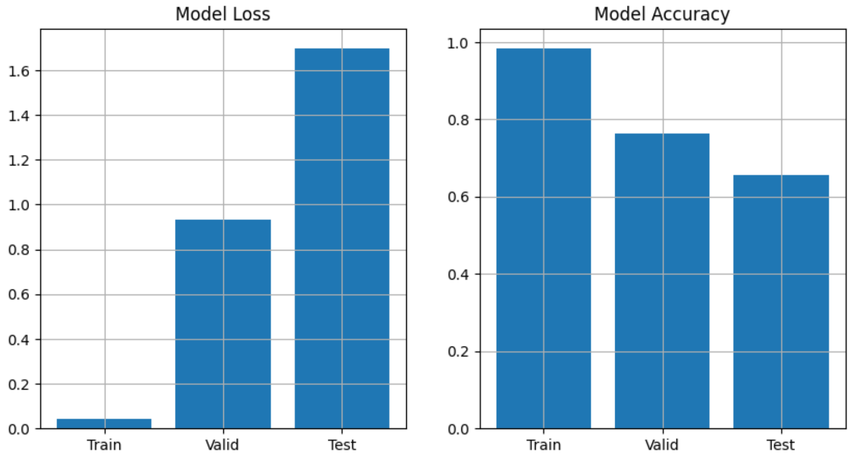

Figure 15: Model Accuracy and Loss

It is once again noted that the Xception model's performance stays well within the validation data, thus making it suitable for real-life use. As with many other models that displayed a significant difference in performance between a validation set and a testing set, this issue has been particularly reduced via hypertuning. In summary, the training curve gives a better perspective of the model's ability and sturdiness in handling our classification task rather than the overfitting inference from the loss curve. Such consistency and the significant enhancement in the testing outcomes prove that the Xception model holds great potential to be developed as an excellent backbone for the classification framework.

Thus, the predictions of the Xception model and the corresponding true labels suggest fairly high accuracy in the classification of various species of insects. The grid of images from the Figure 16 essentially allows the user to compare the images according to the true/predicted labels. Also, the structure of the Xception model is described in detail, which allows showcasing the model's depth and performance. It has 24,024,631 parameters in total, 23,970,103 of which are trainable, and 54,528 are non-trainable. A high value of parameters is suggestive of the model's ability to capture complex relationships and characteristics of the inputs. These are followed by the layers like GlobalAveragePooling2D layers and multiple dense layers with dropout to make the model more generalizable. Even though there is a warning about the optimizer during loading, the model performance is not harmed, and the developed hypertuning approach confirms the model's stability and high efficiency after hypertuning.

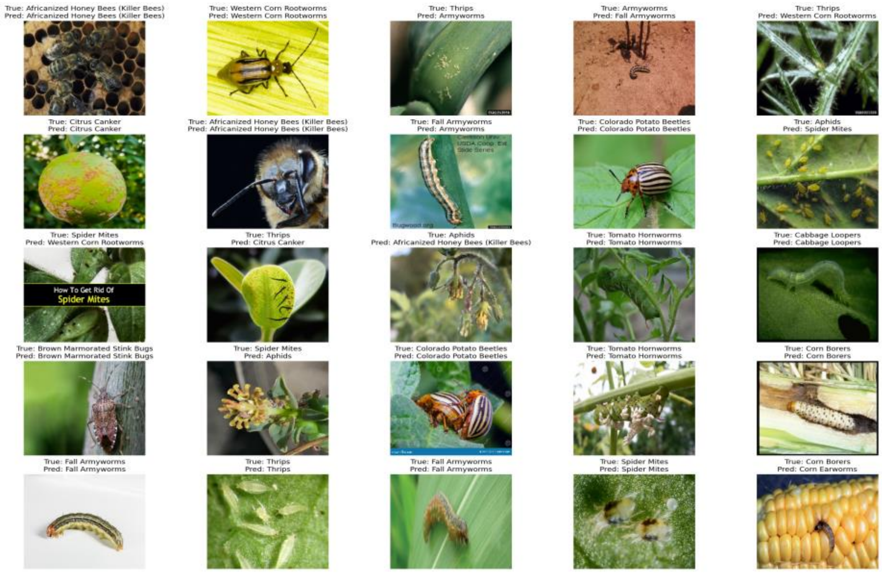

Figure 16: Model Predictions

6.6 Faster RC-NN

Faster R-CNN model was trained with ResNet-50 as the backbone which was pre-trained on the ImageNet dataset. The model was trained with minor modifications to our insect detection task, which is of detecting 15 insect classes and a background class. The training process was carried out for 10 epochs, at the end of which model was tested on the validation data.
The training procedure was performed by making certain preparations to the dataset where the data was stratified split with an aim of partitioning the classes fairly. The InsectDataset class was declared to load the images and the labels associate with them, and the set of transformations were used to normalize the inputs. For batch and shuffle creation, DataLoader objects were created with phases including the training, validation, and testing phases. Based on the suggested model architecture, the author changed the box predictor to a predictor of the suitable number of classes. The used optimizer for the specified network was Stochastic Gradient Descent (SGD) with the learning rate of 0. 005, momentum of 0. 9, and weight decay of 0. 0005. These parameters were chosen to keep the training process steady and reach a good convergence. While training the model, the performance parameters gradually increased in the training phase. The initial training accuracy was. 94. 5% while the validation accuracy of the model is 92. 3%. Further, the accuracy in the course of 10 epochs has shown significant oscillations, although there is a clear movement towards the increase in the adequate measures of the model. Finally, for the last Epoch it was 91.5% in the training accuracy, 91.99% for the validation accuracy which indicates a better generalized model.

7 Conclusion and Future Work

This section, therefore, narrows down its focus on discussing and comparing the various models employed in this research concerning insect identification as presented in the Figure 17. While the first initial steps like the pre-processing of images and the transformations that occurred were similar to all models, the results they had were different.

Model	Train	Test	Validation
ResNet50V2	77%	67%	72%
ResNet152V2	62%	62%	63%
MobileNetV2	59%	59%	70%
Xception	50%	50%	53%
Xception (After Hypertuning)	92%	77%	78%
Faster R-CNN	92%	92%	92%

Figure 17: Comparision of Models

The ResNet50V2 model demonstrated good performance on the training dataset that had a training accuracy of 77 % and validation accuracy of 76 % only. However, the overall recall and F1 score remained below 50%, which suggested the model's weaknesses at working with data not included in the training set. This might be because of the datasets used or there is a possibility of potential over fitting to data.

The ResNet152V2 model under the premise of the ResNet lineage didn't bring many improvements in performance compared to ResNet50V2. Though its deeper architecture, this model achieved an accuracy of 91.5% on the training set, validation accuracy of 91.99% respectively and an accuracy of 62% on the test set. The result holds steady as the major trend indicates that although there could be instances that, utilizing deeper models does not enhance scores for this certain data set.

Again, while the accuracy of its training and the validation was impressive, the testing was a bit of a letdown. It resulted in a precision of 0. 677 accompanied by a recall of 0. 697, the slight drop in the testing performance of the MobileNetV2 model indicates that this should not be preferred for this application.

Nevertheless, rather surprisingly, Xception turned out to be the most suitable choice of the backbone to be used. After fine-tuning all hyperparameters of the model, it is possible to obtain the maximum validation accuracy of 77%. A significant 5% raise has been seen which is slightly above the benchmark of 72%. This model also had excellent separation of training/validation/testing phases with very little overlap, hence its variance was very low between the validation and testing phases. It can be concluded that the stability and high resistance of the Xception model's values, compliance with which has been consistently demonstrated when working with validation data, make the model suitable for practical implementation.

In the case of object detection, the Faster R-CNN model, with the ResNet- 50 back bone, offered the highest detection rates. The training accuracy was seen to go up to highlight at 94.5%, and the validation accuracy got to the level of 92 during the first epoch and minimal deviations across next subsequent epochs. The final epoch provided a train accuracy of 91.5 % and 91.99% as its validation accuracy respectively.

Therefore, it is possible to conclude that the method used in this research has allowed to determine that Xception and Faster R-CNN models are the best backbones for identifying insects in an agricultural setting for the utilized dataset in this research. Thus, the proposed

Xception model performs better in the validation phase and the Faster R-CNN with its noteworthy accuracy has a higher possibility to be used in a real-world environment.

Apparently, further work should be devoted to a number of directions that will help enhance the model's performance. First, a larger and more varied set of images will mean that the models are trained on a better and more diverse set of images, thus increasing their capacity to correctly identify previously unseen images.

The integration of the models into a total pest management system that incorporates pest trolls as well as monitoring and alert processes enable farmers and other agricultural experts to come up with effective practices. Such a system could use IOT devices and edge computing to analyze the images from the field in real time and provide accurate and timely interventions. Finally, entomologists, and agronomists' feedback including field data for further validation of the models adopted will guarantee that the developed system is informed by current practice and is the most accurate and reliable in detecting and managing pests.

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