

DETECTING CROP-HARMING INSECTS USING AI TRANSFER LEARNING MODEL

BY

MD HASSIBUL ISLAM

181-15-10884

FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfilment of the Requirements for the Degree of
Bachelor of Science in Computer Science and Engineering

Supervised By

Dr. Md. Fokhray Hossain

Professor

Department of Computer Science and Engineering
Daffodil International University

Co-Supervised By

Mr. Mushfiquir Rahman

Assistant Professor

Department of Computer Science and Engineering
Daffodil International University



DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

Fall 2024

APPROVAL

MD HASSIBUL ISLAM submitted this project, "Detecting Crop-Harming Insects Using AI Transfer Learning Models," to the Department of Computer Science and Engineering, Daffodil International University. It has been accepted as satisfactory for the partial fulfilment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation was held on 13 January 2025.

BOARD OF EXAMINERS



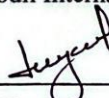
Dr. Sheak Rashed Haider Noori (SRH)
Professor & Head Chairman
Department of Computer Science & Engineering
Faculty of Science & Information Technology
Daffodil International University

Chairman



Most. Hasna Hena (HH)
Assistant Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Internal Examiner



Md. Ferdouse Ahmed Foysal (FAF)
Lecturer
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Internal Examiner



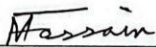
Dr. Md. Arshad Ali (DAA)
Professor
Department of Computer Science and Engineering
Hajee Mohammad Danesh Science and Technology University

External Examiner

DECLARATION

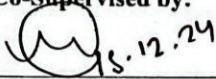
We hereby declare that this project has been done by us under the supervision of **Dr. Md. Fokhray Hossain, Professor, Department of CSE Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree.

Supervised by:



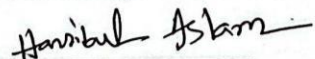
Dr. Md. Fokhray Hossain
Professor
Department of CSE
Daffodil International University

Co-Supervised by:



Mr. Mushfiqur Rahman
Assistant Professor
Department of CSE
Daffodil International University

Submitted by:



MD HASSIBUL ISLAM
181-15-10884
Department of CSE
Daffodil International University

ACKNOWLEDGEMENT

This work would not have been possible without the support and contributions of many individuals over the past two semesters. We are deeply grateful to everyone who has assisted us in one way or another.

First, we express our heartfelt thanks and gratitude to the Almighty for His divine blessing, which enabled us to complete the **Final Year Design Project (FYDP)** successfully.

We are grateful and wish our profound indebtedness to **Dr. Md. Fokhray Hossain, Professor**, Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh. Deep knowledge and keen interest of our supervisor in **AI Transfer Learning** to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

We would like to express our heartfelt gratitude to the Head of the Department of Computer Science and Engineering for his help finishing our project and to other faculty members and staff of the Department of Computer Science and Engineering, Daffodil International University.

We would like to thank all our Daffodil International University course-mates who participated in this discussion while completing the coursework.

Finally, we must acknowledge with due respect the constant support and patience of our parents.

ABSTRACT

Bangladesh is a six-season country and is also called a riverine country. New things are seen every six seasons, such as different types of flowers, fruits, pithapuli, festivals, seasonal animals, insects, etc. Seasonal changes such as river water level increases, demand for seasonal fruits is high, seasonal animals and birds can be observed, and the effects of various seasonal pests or insects can also be observed. As a result, many crops are destroyed by pests or insects, causing food shortages throughout the world. So, our work mainly aims to identify different types of insects or pests through artificial intelligence and data mining algorithms. The main objective of this work is to focus on agricultural practices so that farmers can detect and save their crops early as well as seeing how farmers can use less pesticides on their crops. As a result, the use of pesticides on the cropland can be avoided to a large extent, and the fertility of the land will remain the same. This means that farmers can protect their crops from harmful insects, they can use fewer pesticides on crops, and biological monitoring workers can save time. In this paper, three transfer learning models, namely VGG19, MobileNetV2, and ResNet152v2 and one deep learning model, namely Customize CNN, are used. VGG19, MobileNetV2, ResNet152v2 transfer learning models have 94% accuracy in VGG19, 90% accuracy in MobileNetV2, 96% accuracy in ResNet152v2. Also, the deep learning model Customize CNN has 80% accuracy. It can be seen that the ResNet152v2 model obtained the highest accuracy of 96% using transfer learning, and the Customize CNN model obtained 80% accuracy using deep learning. Here, it can be seen that the highest accuracy was obtained using the ResNet152v2 transfer learning model.

TABLE OF CONTENTS

CONTENTS	PAGE
Board of examiners	i
Declaration	ii
Acknowledgements	iii
Abstract	iv
List of Figures	vii
List of tables	viii
 CHAPTER	
 CHAPTER 1: INTRODUCTION	1-6
1.1. Background of the Research	1
1.2. Motivation	2
1.3. Problem Statement	2
1.4. Objective of Research	3
1.5. Research Methodology	3
1.6. Proposed Solution	4
1.7. Expected Outcome	4
1.8. Report Layout	5
1.9. Conclusion	6
 CHAPTER 2: LITERATURE REVIEW	7-9
2.1. Introduction	7
2.2. Literature Review	7
2.3. Comparison between existing works	9
2.4. Scope of the Problem	11
2.5. Challenges	12

2.6. Gap Analysis	13
2.7. Conclusion	13
CHAPTER 3: RESEARCH METHODOLOGY	14-17
3.1. Introduction	14
3.2. Data Pre-Processing	14
3.3. Dataset Description	15
3.4. Statical Analysis	16
3.5. Design Approach	17
CHAPTER 4: AI TRANSFER LEARNING MODEL	18-22
4.1. Introduction	18
4.2. VGG19 Model	18
4.3. MobileNetV2 Model	19
4.4. ResNet152V2 Model	20
4.5. Customize CNN Algorithm	21
4.6. Conclusion	22
CHAPTER 5: DETECTING CROP HARMING INSECT DETECTION	23-27
5.1. Introduction	23
5.2. Insect & Damage Description	23
5.3. Category wise Insect Description	24
5.4. Describe Crop-Harming Insect	25
5.5. Benefits of Insect Detection Using AI	26
5.6. Conclusion	27

CHAPTER 6: EXPERIMENTAL RESULTS AND DISCUSSION	28-47
6.1. Introduction	28
6.2. Discussion	28
6.3. VGG19	30
6.4. MobileNetV2	34
6.5. ResNet152V2	37
6.6. Customize CNN	41
6.7. Experimental Results and Analysis	45
6.8. Conclusion	46
CHAPTER 7: IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY	48-52
7.1. Introduction	48
7.2. Impact on Society	48
7.3. Impact on Environment	49
7.4. Ethical Aspects	50
7.5. Sustainability	51
7.6. Conclusion	52
CHAPTER8: SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLEMENTATION FOR FUTURE RESEARCH	53-54
8.1. Conclusion	53
8.2. Further Suggested Word	54
REFERENCE	54-55

LIST OF FIGURES

FIGURES	PAGE NO
Figure-1: Architecture of Working Process	17
Figure 2: Visual overview of VGG19	19
Figure 3: Visual overview of MobileNetV2	20
Figure-4: Visual overview of ResNet152V2	21
Figure 5: Visual overview of CNN	22
Figure-6: Training loss, validation loss and training accuracy, validation accuracy plot for VGG19	30
Figure-7: Training loss, validation loss and training accuracy, validation accuracy plot for VGG19	31
Figure 8: Error by class on test set	31
Figure-9: Confusion matrix for VGG19	33
Figure-10: Training loss, validation loss and training accuracy, validation accuracy plot for MobileNetV2	34
Figure-11: Training loss, validation loss and training accuracy, validation accuracy plot for MobileNetV2	34
Figure 12: Error by class on the test set	35
Figure-13: Confusion matrix for MobileNetV2	37
Figure-14: Training loss, validation loss and training accuracy, validation accuracy plot for ResNet152V2	38
Figure-15: Training loss, validation loss and training accuracy, validation accuracy plot for ResNet152V2	38
Figure 16: Error by class on the test set	39
Figure-17: Confusion matrix for ResNet152V2	41
Figure-18: Training loss, validation loss and training accuracy, validation accuracy table for Customize CNN	42
Figure-19: Confusion matrix for Customize CNN	44
Figure 20: Summary of all Models	46

LIST OF TABLES

TABLES	PAGE NO
Table 1: Summary of Related Works	9
Table 2: Category Name and Description	15
Table 3: Insect Name and Description	24
Table 4: Classifiers Description	29
Table-5: Model metrics of VGG19 Model	32
Table-6: Classification report of VGG19 Model	32
Table-7: Model metrics of MobileNetV2 Model	35
Table-8: Classification report of MobileNetV2 Model	36
Table-9: Model metrics of ResNet152V2 Model	39
Table-10: Classification report of ResNet152V2 Model	39
Table-11: Model metrics of Customize CNN Algorithm	42
Table 12: Classification report of Customize CNN Algorithm	43
Table 13: Test Customized CNN algorithm using dummy image	45
Table 14: Classifiers' accuracy, recall and precision	46

CHAPTER 1

INTRODUCTION

1.1. Background of the Research

Agriculture faces significant challenges due to insect pests that threaten crop health and productivity. The project Detecting Crop-Harming Insects Using AI Transfer Learning Models addresses this issue by leveraging Artificial Intelligence (AI) and Data Science to accurately detect insects harmful to crops. By applying transfer learning and computer vision techniques, the project focuses on automating insect detection to aid farmers and agricultural stakeholders in mitigating crop damage.

The methodology involves collecting image data for nine types of crop-harming insects, including species such as Asota moth caterpillars, cutworms, and mealy bugs, each associated with specific crops like rice, papaya, and citrus. Using advanced image preprocessing techniques, such as resizing and normalisation, the collected images are prepared for analysis. These preprocessed images are then subjected to training, testing, and validation processes. During training, AI models learn to identify distinct visual features of each insect type while testing and validation ensure the model's performance and adaptability to new datasets.

Transfer learning plays a pivotal role by utilising pre-trained models, which are fine-tuned for insect detection tasks. This approach not only enhances accuracy but also reduces computational requirements and training time. The project's results include performance metrics that demonstrate the model's capability to accurately detect insects and identify the crops they harm. By integrating these AI-driven insights, the project offers a practical solution to pest management in agriculture, enabling early intervention to minimise crop losses and promoting sustainable farming practices. This work highlights the potential of AI in addressing real-world agricultural challenges effectively and efficiently.

1.2. Motivation

Agriculture is a cornerstone of food security, yet it faces significant challenges from crop-damaging insects. Timely and accurate identification of these pests is crucial for minimising crop loss and ensuring sustainable farming practices. Traditional methods of pest identification are time-consuming and require expert knowledge, creating a need for automated and efficient solutions.

The advancements in Artificial Intelligence, particularly transfer learning models, provide an opportunity to revolutionise pest detection. By leveraging AI for insect identification, we can empower farmers with a tool that enhances precision and reduces manual intervention. This approach not only saves time but also aids in implementing targeted pest control strategies.

This project is driven by the vision of improving agricultural productivity through technology. Detecting and categorising harmful insects, such as rice bugs, mealy bugs, and caterpillars, provides actionable insights for farmers. By addressing this critical issue, we contribute to reducing crop losses, promoting sustainable agriculture, and ensuring food security.

1.3. Problem Statement

Crop damage caused by harmful insects is a critical issue in agriculture, leading to significant economic losses and threats to food security. Identifying these pests accurately and in a timely manner is challenging due to their diverse types, varying appearances across life stages, and environmental factors. Traditional pest management techniques often rely on manual observation, which is time-consuming, error-prone, and lacks scalability. This project addresses the urgent need for a technology-driven solution by leveraging Transfer Learning Models in Artificial Intelligence and Data Science to detect nine specific types of crop-harming insects, such as Asota moth caterpillars, cutworms, and rice bugs, which adversely impact various crops. By utilising image processing and computer vision techniques for model training, testing, and validation, this approach aims to enhance accuracy and efficiency in pest identification, ultimately enabling timely interventions, reducing crop damage, and supporting sustainable agricultural practices.

1.4. Objective of Research

- To develop an automated system for detecting and classifying crop-harming insects using AI and data science techniques.
- To utilise transfer learning models for precise and efficient insect detection.
- To collect and preprocess insect image data for training, testing, and validation purposes.
- To analyse and identify nine harmful insect species and associate them with the crops they affect.
- To evaluate the performance of trained models through accuracy metrics and validation results.
- To provide farmers and agricultural stakeholders with actionable insights for pest control and crop protection.
- To contribute to sustainable agriculture by reducing crop loss through early and accurate insect detection.

1.5. Research Methodology

The research methodology for this project focuses on detecting crop-harming insects using Transfer Learning Models in Artificial Intelligence. The process begins with data collection, where image datasets of nine specific insects harmful to various crops were gathered from reliable sources. These images underwent preprocessing using techniques such as resizing, noise reduction, and normalisation to enhance their quality for analysis. The preprocessed data was then divided into training, testing, and validation sets to ensure robust model development. Transfer Learning Models, known for their efficiency in computer vision tasks, were utilised to train the system using labelled images. The trained models were subsequently tested and validated to evaluate their performance and accuracy in identifying different insects. The results obtained from the testing phase provided insights into the effectiveness of the models, enabling further optimisation for improved precision. This approach ensures an efficient, scalable, and accurate solution for pest detection in agriculture.

1.6. Proposed Solution

- Image Dataset Creation: Develop a comprehensive and high-quality image dataset featuring nine types of crop-harming insects and their related crops.
- Image Preprocessing: Apply preprocessing techniques like resizing, normalisation, and noise removal to enhance image quality for accurate model input.
- Utilising Transfer Learning: Employ transfer learning models, leveraging pre-trained architectures like ResNet or VGG to ensure efficient and scalable insect classification.
- Training Phase: Train the models using labelled datasets, associating each insect type with its corresponding harmful crops.
- Testing and Validation: Test the trained models on unseen data and validate their performance to ensure robustness and accuracy.
- Accuracy Optimization: Refine models by adjusting hyperparameters and augmenting data to improve detection precision and reliability.
- Practical Implementation: Deploy the model as a user-friendly application or API to aid farmers in identifying harmful insects and protecting their crops effectively.

1.7. Expected Outcome

- Successfully implemented transfer learning models to detect and classify nine types of crop-harming insects.
- Developed a robust image preprocessing pipeline to optimise insect image datasets for model training, testing, and validation.
- Achieved reliable insect classification by training AI models with high accuracy rates for specific pests and their associated crops.
- Identified harmful effects of insects, such as Asota moth caterpillars damaging papaya and Ficus species and cutworms affecting tender seedlings.
- Validated the model's effectiveness in predicting insect types and their potential impact on crops like rice, citrus, and vegetables.
- Delivered insights for pest control strategies, reducing crop losses and enhancing agricultural productivity.

1.8. Report Layout

This report is structured into six comprehensive chapters that guide the reader through the process and findings of the project.

Chapter 1: Introduction outlines the foundational aspects of the study, including the motivation behind the project, its objectives, and the scope. It also discusses the relevance of the research and presents the primary research questions guiding the inquiry. The chapter concludes with an overview of the expected project outcomes and the layout of the report.

Chapter 2: Background provides essential terminology and context, reviews related works, and compares existing studies to highlight the scope of the problem and the challenges faced. This chapter also conducts a gap analysis to identify areas lacking in previous research.

Chapter 3: Research Methodology details the proposed method and its components, including data collection and dataset description. It elaborates on the statistical analysis and preprocessing techniques applied, culminating in a description of the proposed model.

Chapter 4: Experimental Results and Discussion focuses on the discussion of the experimental findings, providing a thorough analysis of the results.

Chapter 5: Impact on Society, Environment, and Sustainability examines the broader implications of the research, including societal impacts, environmental considerations, ethical aspects, and sustainability plans.

Chapter 6: Conclusion and Future Scope summarizes the study's findings, draws conclusions, and suggests implications for future research.

The report concludes with a reference section that lists all sources cited throughout the study.

1.9. Conclusion

The project successfully addresses the challenge of detecting crop-harming insects using AI and transfer learning techniques, providing an innovative solution to safeguard agriculture. By leveraging image processing and computer vision methodologies, we identified nine specific insect types and their harmful impact on various crops. The use of training, testing, and validation processes ensured that the developed models achieved high accuracy in identifying harmful insects. This approach not only improves the efficiency of insect detection but also offers a scalable and practical tool for farmers to protect their crops.

The integration of advanced AI techniques enables proactive pest management, reducing crop damage and increasing agricultural productivity. This project highlights the potential of AI in revolutionising traditional agricultural practices and sets the foundation for future advancements in pest detection and crop protection.

CHAPTER 2

LITERATURE REVIEW

2.1. Introduction

This project utilises key terms associated with Artificial Intelligence (AI), data science, and agricultural pest management. Transfer Learning refers to leveraging pre-trained AI models for insect detection, reducing the need for extensive data. Image Processing involves preprocessing and analysing visual data to extract features for model training. Computer Vision is the application of AI to interpret and classify images of insects. Training Data are labelled images used to teach models, while Testing Data evaluates model performance, and Validation Data fine-tunes accuracy. Key insect terms include Asota Moth Caterpillars, Cutworms, Henosepilachnaviginotopunctata, and others known for damaging specific crops like papaya, rice, and citrus. The project outcomes support agricultural sustainability by identifying crop-harming insects and their impact, enabling data-driven pest management strategies.

2.2. Literature Review

Wenyong Li et al. [1] developed the Smart Pest Monitoring (SPM) system using CNN for insect identification and classification. Their method combines image preprocessing, modelling, and framework development, achieving maximum accuracy in identifying pests to mitigate impacts on crops and food quality. Zeba Anwar et al. [2] utilised CNN and ensemble-based models like Inception v3, Xception, and ResNet50 for insect classification. Using the IP102 dataset of 75,222 images, their ensemble model achieved an accuracy of 82.5%. Nour Eldeen M. Khalifa et al. [3] implemented AlexNet, GoogleNet, and SqueezeNet with data augmentation on the IP102 dataset, comprising 27,500 images. AlexNet achieved 89.33% accuracy, highlighting its efficacy in insect detection. Mohammad Kamran Khan et al. [4] applied InceptionV3 and VGG19 models on the IP102 dataset, obtaining accuracies of 81.7% and 80%, respectively. Their work emphasises identifying crop-threatening pests. Yiwen Liu et al. [5] combined CNN models (VGG16, Inception-ResNet-v2) and multilayer networks using the IDAP dataset for pest detection. They achieved a remarkable accuracy of 97.71%. Wei Li et al. [6] applied Faster-RCNN, Mask-RCNN,

and Yolov5 on IP102 and Baidu AI Pests datasets. Mask-RCNN achieved the highest accuracy of 99%, showcasing DCNN's capability in crop pest detection. Ana Cláudia Teixeira et al. [7] analysed 92 studies (2016–2022) on pest classification and identification. They highlighted dataset and methodology challenges, recommending 36 classification and identification criteria. João Gonçalves et al. [8] used the SSD ResNet50 model on yellow sticky and delta trap datasets, achieving accuracies between 82–99%. Their work supports mobile device-based pest identification. Ming-Fong Tsai et al. [9] integrated time-series feature extraction with transfer learning for pest detection. The approach increased prediction accuracy by up to 15%, demonstrating machine learning's potential. Chen Li et al. [10] used ResNeXt-50 (32×4d) on the IP102 dataset, achieving 86.95% accuracy with transfer learning and cutmix augmentation for insect detection. Iftikhar Ahmad et al. [11] deployed YOLOv5x on the IP23 dataset, detecting 23 insect species with 98.3% average precision and an F1-score of 97%, ensuring fast and reliable pest detection. Xu Cao et al. [12] applied CNN models like VGG19 and InceptionV3 on the ImageNet dataset for insect classification. VGG19 achieved 97.39% accuracy, highlighting simplicity and time efficiency. Tuan T. Nguyen et al. [13] employed EfficientNet models for insect classification, achieving 95% precision across 10 epochs. EfficientNet-b3 provided optimal performance in this study. Catherine M. Little et al. [14] discussed the dual aspects of insects, emphasising their role in crop destruction and beneficial functions like pollination and biological control. Kim BjergeID et al. [15] used YOLOv5 on a dataset of 29,960 annotated images to detect nine species, achieving an accuracy of 92.7% and recall of 93.8%. Eray Önlü et al. [16] applied YOLOv5 to detect *Vanessa Cardui* from 2,416 video frames using transfer learning. The method proved efficient for object detection. Michael Gomez Selvaraj et al. [17] utilised transfer learning on 18,000 banana crop images for pest detection, achieving 70–99% accuracy in identifying harmful insects. Dušan Marković et al. [18] used machine learning to predict insect presence based on temperature and humidity, achieving an accuracy of 86.3% over a five-day interval. Nathan Moses-Gonzales et al. [19] explored drone-based pest detection, emphasising enhanced visualization and detection efficiency, particularly for agricultural research applications. Liu Yang et al. [20] applied MobileNet with transfer learning to classify nine tomato insect diseases in China. The model achieved an accuracy of 97.5%, supporting agricultural pest management.

2.3. Comparison between existing works

Table 1: Summary of Related Works

Paper No	Authors & Year	Dataset	Used All Models	Height Accuracy Model	Height Model (%)
1	Wenyong Li, Tengfei Zheng (2021)	-	CNN	CNN	-
2	Zeba Anwar, Sarfaraz Masood (2023)	IP102 (75,222 images in 102 classes)	Inceptionv3, Xception, VGG19, VGG16, ResNet50 and Ensemble	Ensemble	82.5%
3	NOUR ELDEN M. KHALIFA, MOHAMED LOEY (2020)	IP102 (27500 images in 102 classes)	AlexNet, GoogleNet, and SqueezeNet	AlexNet	89.33%
4	Mohammad Kamran Khan, Muhammad Obaid Ullah	IP102 (27500 images in 102 classes)	InceptionV3 and VGG19	InceptionV3	81.7%
5	Yiwen Liu, Xian Zhang (2022)	IDAP dataset	VGG16 and Inception-ResNet-v2	-	97.71%
6	Wei Li, Tengfei Zhu (2022)	Baidu AI Pests & Insects dataset and IP102 dataset	Faster-RCNN, Mask-RCNN and Yolov5	Faster-RCNN, Mask-RCNN	99%

7	Ana Cláudia Teixeira, José Ribeiro (2023)	-	Ninety-two papers published from 2016 to 2022 have been surveyed.		
8	João Gonçalves, Eduardo Silva (2022)	168 images of 8966 key insects	SSD ResNet50	SSD ResNet50	84%
9	Ming-Fong Tsai, Chun-Ying Lan (2023)	-	Time-series feature extraction with transfer learning technology	-	Increase accuracy 3-15%
10	Chen Li, Tong Zhen (2022)	IP102 dataset	fine-tuning and cut mix with transfer learning	-	86.95%
11	Iftikhar Ahmad, Yayun Yang (2022)	IP-23 dataset	YOLOv5, YOLOv3, YOLO-Lite, and YOLOR	YOLOv5x	98.3%
12	Xu Cao, Ziyi Wei (2020)	-	VGG16, VGG19, InceptionV3 and InceptionV4	VGG19	97.39%
13	Tuan T. Nguyen, Quoc-Tuan Vien (2021)	-	EfficientNet	EfficientNet-b3	95%
14	Catherine M. Little, Thomas W. Chapman (2019)	-	This paper discusses all aspects of pests and insects good and bad, etc.		
15	Kim BjergerID, Jamie Alison (2023)	29,960 images	YOLO	YOLOv5	93.8%
16	Eray Önler (2021)	2416 images	YOLOv5	YOLOv5	

17	Michael Gomez Selvaraj, Alejandro Vergara (2019)	18,000 images	DCNN and Transfer Learning Algorithm	DCNN and Transfer Learning	70-99%
18	Dušan Marković, Dejan Vujić (2021)	-	Machine learning algorithm	Machine learning algorithm	86.3%
19	Nathan Moses-Gonzales, Michael J. Brewer (2021)	-	This paper discusses how to detect pests and insects using drones.		
20	Liu Yang, Limin Yu (2021)	-	Convolutional Neural MobileNet	Convolutional Neural MobileNet	97.5%

2.4. Scope of the Problem

- **Crop Damage and Yield Loss:** Harmful insects such as cutworms, rice bugs, and mealy bugs cause significant crop damage by feeding on leaves, stems, fruits, or roots, leading to reduced agricultural productivity and economic losses.
- **Limited Pest Detection:** Traditional pest detection methods are time-consuming, prone to human error, and lack scalability, making it difficult for farmers to identify and mitigate insect infestations effectively.
- **Increased Use of Pesticides:** Without accurate identification of crop-specific pests, excessive or inappropriate pesticide use can harm the environment and human health, while failing to target harmful insects efficiently.
- **Data Complexity:** Insect identification involves analyzing complex image data, which requires advanced preprocessing techniques and robust AI models for reliable detection.
- **Food Security Challenges:** Unchecked pest infestations threaten global food security by affecting staple crops like rice, soybeans, and vegetables, necessitating innovative solutions for sustainable pest management.

2.5. Challenges

- **Data Collection:** Obtaining high-quality, labelled images of crop-harming insects for effective training and testing of AI models is challenging and time-consuming.
- **Data Preprocessing:** Preparing image data for analysis, including handling noise, varying lighting conditions, and differences in image quality, requires meticulous effort and advanced preprocessing techniques.
- **Model Training:** Training transfer learning models to accurately detect multiple insect types with minimal errors demands significant computational resources and fine-tuning of parameters.
- **Model Validation:** Ensuring the models perform consistently across diverse datasets and environmental conditions is a complex task that requires rigorous validation.
- **Real-Time Application:** Deploying the trained models for real-time pest detection in agricultural fields introduces challenges in scalability and integration.
- **Insect Diversity:** Variations in insect size, colour, and patterns make it difficult to create models that can reliably detect all types of harmful insects.
- **Environmental Factors:** External variables such as weather, crop density, and soil conditions can affect insect visibility and detection accuracy, posing additional hurdles for AI-based solutions.

2.6. Gap Analysis

- **Limited Dataset Availability:** The scarcity of comprehensive, labelled datasets for diverse crop-harming insects poses a challenge for building robust AI models. This gap hinders the generalizability of the models.
- **Insect Variability:** Differences in the appearance of insects across life stages and environmental conditions are not fully addressed, impacting detection accuracy in real-world scenarios.
- **Real-Time Deployment:** The current approach lacks emphasis on implementing the models for real-time monitoring in agricultural fields, which is essential for timely interventions.
- **Integration Challenges:** There is limited focus on integrating AI models with existing agricultural systems, such as IoT devices or farm management tools, for seamless usage.
- **Adaptability to New Insects:** The models are not equipped to detect insects outside the pre-defined dataset, limiting their scalability for emerging threats or unfamiliar insect species.

2.7. Conclusion

The project successfully addresses the challenge of detecting crop-harming insects using AI and transfer learning techniques, providing an innovative solution to safeguard agriculture. By leveraging image processing and computer vision methodologies, we identified nine specific insect types and their harmful impact on various crops. The use of training, testing, and validation processes ensured that the developed models achieved high accuracy in identifying harmful insects. This approach not only improves the efficiency of insect detection but also offers a scalable and practical tool for farmers to protect their crops. The integration of advanced AI techniques enables proactive pest management, reducing crop damage and increasing agricultural productivity. This project highlights the potential of AI in revolutionising traditional agricultural practices and sets the foundation for future advancements in pest detection and crop protection.

CHAPTER 3

RESEARCH METHODOLOGY

3.1. Introduction

Agriculture faces significant challenges from crop-harming insects, which can drastically reduce yield and threaten food security. To address this issue, this project explores the use of Transfer Learning Models in Artificial Intelligence and Data Science to detect harmful insects and mitigate their impact on crops. Leveraging image processing and computer vision techniques, the project focuses on identifying nine specific insect types, such as Asota moth caterpillars, cutworms, and rice bugs, along with their associated crop damage. By preprocessing image data and applying training, testing, and validation stages, the models developed aim to achieve accurate and efficient detection of these pests. This approach not only enhances early detection and management strategies but also demonstrates the potential of AI to revolutionise pest control in agriculture, ensuring sustainable crop production and food security.

3.2. Data Pre-Processing

Data collected online is typically unstructured. Therefore, processing the data after collection is essential. Online and social media sources often provide redundant, unclear, and messy data. The dataset needs refinement to eliminate noisy data, discard low-quality images, remove outliers, eliminate duplicates, sanitise the data, and make it more interpretable. Tasks like listing images, organising image dictionaries, calculating image counts per category, determining total and unique images, and segmenting the dataset are extracted from the data. Hence, applying data preprocessing techniques to the dataset becomes necessary. The steps we follow for preprocessing include:

- Eliminate raw and poor-quality images.
- Exclude blank or zero-value images, inappropriate emojis, and symbolic visuals.
- Discard all retweets and irrelevant images.
- Filter out images with insufficient dimensions or sizes.

3.3. Dataset Description

The primary dataset utilised in this study consists of 4509 images in total. This entire dataset is categorised into 9 groups, including Asota Moth Caterpillar, Caterpillars, Cutworm, Henosepilachnavigintioctopunctata, Heteropterus, Lawn Grubs, Long-Horned Grasshopper, Mealy Bug, and Rice Bug. After performing preprocessing and data cleaning, the dataset is split into a fundamental partition containing 100% or 4509 original samples, with 80% (3607 samples) allocated for training, 10% (451 samples) for testing, and 10% (451 samples) for validation. Following the preprocessing, a total of 4509 samples are distributed into three sets: training, testing, and validation, each of which is further subdivided into nine categories. The dataset comprises 4509 original samples, of which 501 are distributed across the nine subsets.

Table 2: Category Name and Description

Source Data	Category	Description	Number of Images	Label
1200 data collected in Raw and others 3306 data collected from online, social media, Google.	Asota Moth Caterpillar	Asota Moth Caterpillar pictures will be shown from all types of insects and insects.	501	Asota Moth Caterpillar, Caterpillars, Cutworm, Henosepilachnavigintioctopunctata, Heteropterus, Lawn Grubs, Long Horned Grasshopper, Mealy Bug, Rice Bug.
	Caterpillars	Caterpillars pictures will be shown from all types of insects and insects.	501	
	Cutworm	Cutworm pictures of all types of insects will be shown.	501	
	Henosepilachnavigintioctopunctata	Pictures of all types of insects will be shown in the Henosepilachnavigintioctopunctata.	501	
	Heteropterus	Heteropterus pictures will be shown of all types of insects and insects.	501	

	Lawn Grubs	Lawn Grubs pictures will be shown of all types of insects and insects.	501	
	Long Horned Grasshopper	Long Horned Grasshopper pictures will be shown from all types of insects and insects.	501	
	Mealy Bug	Mealy Bug pictures of all types of insects will be shown.	501	
	Rice Bug	Rice bug pictures of all types of insects will be shown.	501	

3.4. Statistical Analysis

- The dataset consists of a total of 4509 images.
- The dataset includes 4509 original samples, of which 501 are allocated across nine different subsets.
- The dataset contains a total of 3607 samples for training.
- The dataset holds a total of 451 samples for testing.
- The dataset includes 451 samples for validation.
- The labels are divided into nine distinct categories: Asota Moth Caterpillar, Caterpillars, Cutworm, Henosepilachnavigintioctopunctata, Heteropterus, Lawn Grubs, Long-Horned Grasshopper, Mealy Bug, and Rice Bug.

3.5. Design Approach

The provided architecture illustrates a machine-learning pipeline for image classification tasks. It begins with Images Data Acquisition, followed by Pre-Processing and Cleaning to prepare the data. The refined Dataset is then split into a Training Set and a Testing Set.

The Training Set is fed into a Classification Algorithm for model training. Various CNN-based models are explored, including VGG19, MobileNetV2, ResNet152V2, and a Custom Layer CNN. The trained models are evaluated using the Testing Set during the Testing Phase.

Post-testing, the results undergo Result Analysis to evaluate model performance. This leads to Performance Prediction, where metrics like accuracy and loss are assessed. Finally, the process concludes by selecting the Best Model based on performance criteria, ensuring optimal results for the image classification task.

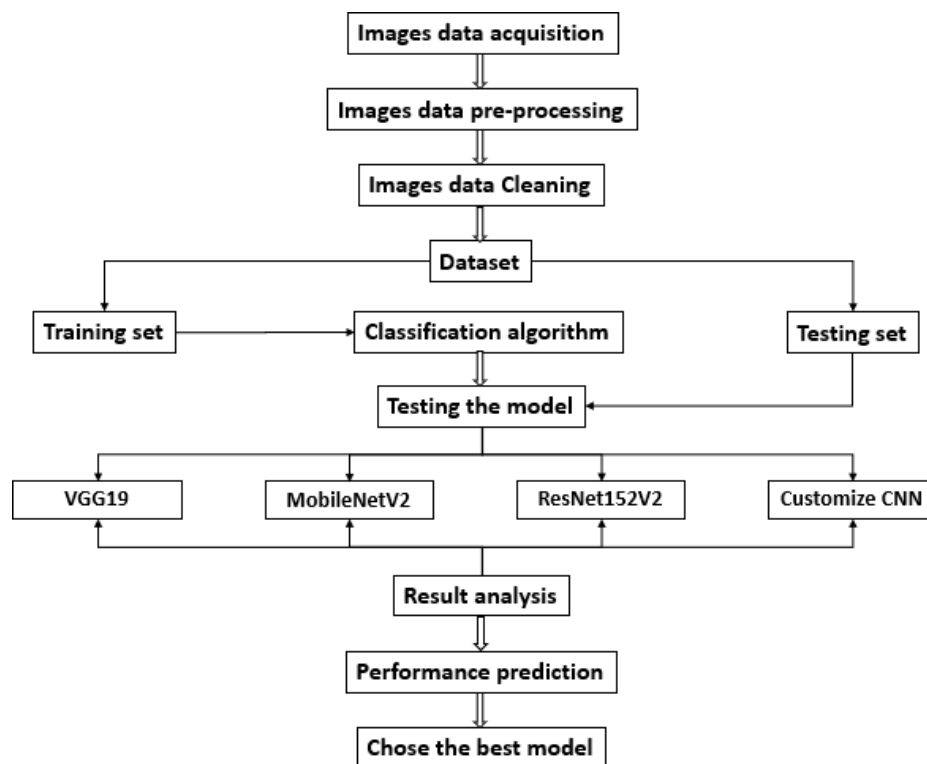


Figure-1: Architecture of Working Process

The diagram depicts a machine learning pipeline for image classification, starting with data collection, followed by preprocessing and cleaning to prepare a dataset split into training and testing subsets. Various classification algorithms, including VGG19, MobileNetV2, ResNet152V2, and a custom-layer CNN, are trained on the training set and tested on the testing set. The process includes result analysis, performance prediction, and, ultimately, selecting the most effective model for the classification task.

CHAPTER 4

AI TRANSFER LEARNING MODEL

4.1. Introduction

Transfer learning is a powerful concept in artificial intelligence (AI) and machine learning, enabling models to leverage knowledge gained from solving one problem and apply it to a different but related problem. Unlike traditional training, where models start learning from scratch, transfer learning accelerates the training process by utilising pre-trained models that have already been optimised on large-scale datasets like ImageNet. This approach is particularly valuable when working with limited data or computational resources.

Transfer learning is widely applied in deep learning for computer vision, natural language processing (NLP), and speech recognition. Pre-trained models, such as VGG19, ResNet, MobileNet, and Xception, act as feature extractors, capturing generalised patterns from massive datasets. Fine-tuning these models on task-specific data ensures improved performance without extensive training time or resources.

This method is advantageous because it reduces overfitting, improves accuracy, and enhances the efficiency of model training. For example, a model trained on millions of general images can be fine-tuned to classify medical images or detect objects in autonomous driving.

4.2. VGG19 Model

VGG19 is a convolutional neural network (CNN) developed by the Visual Geometry Group at Oxford University, renowned for its deep yet simple architecture. It consists of 19 layers, including 16 convolutional layers, three fully connected layers, and a softmax output layer. VGG19 uses 3x3 convolutional filters with a stride of 1 and 2x2 max-pooling layers with a stride of 2, ensuring spatial hierarchies are preserved. Its design emphasises increasing depth with small filters to extract intricate features while maintaining computational efficiency.

The model processes input images of size 224x224x3 (RGB). ReLU activation functions introduce non-linearity, and ImageNet pre-training allows VGG19 to perform well on tasks like

classification and feature extraction. Despite its high accuracy, it is computationally intensive due to the large number of parameters (~144 million). VGG19 remains a popular backbone for transfer learning in image recognition and computer vision applications.

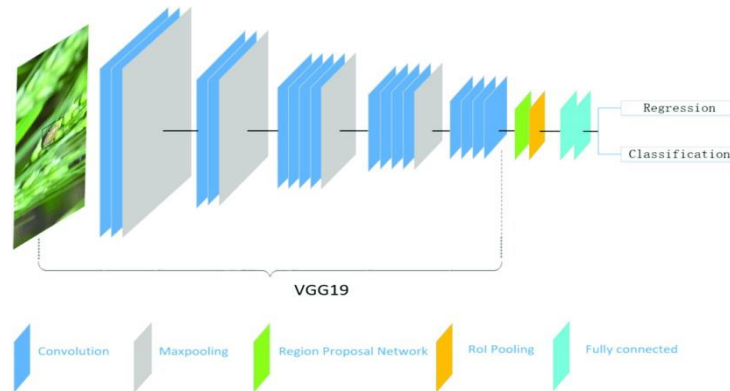


Figure 2: Visual overview of VGG19

4.3. MobileNetV2 Model

MobileNetV2 is a lightweight, efficient deep learning architecture designed for mobile and edge devices, providing a balance between performance and computational efficiency. It builds upon the success of MobileNetV1 with improved accuracy and reduced complexity. The core innovation of MobileNetV2 lies in its use of inverted residual blocks and depthwise separable convolutions, which significantly reduce the number of parameters and computations while maintaining performance.

Inverted residual blocks introduce a shortcut connection between the input and output layers, enhancing feature extraction and gradient flow. Depthwise separable convolutions decompose standard convolutions into two steps: depthwise convolution, which applies filters to each channel individually, and pointwise convolution, which combines these outputs into a single layer. This reduces computational costs while preserving spatial and channel-wise information.

MobileNetV2 is ideal for resource-constrained environments and excels in tasks like object detection, image segmentation, and classification. Its modular design enables flexibility for various applications.

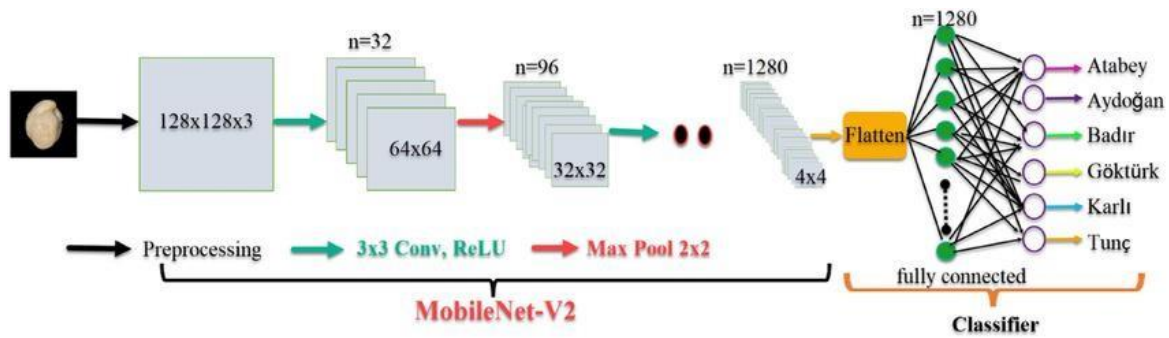


Figure-3: Visual overview of MobileNetV2

4.4. ResNet152V2 Model

ResNet152V2 is an advanced deep learning architecture in the ResNet (Residual Networks) family, designed to address the vanishing gradient problem in training deep neural networks. It is a refined version of the original ResNet model, incorporating batch normalisation layers before activation functions and improved initialisation techniques. With 152 layers, it is one of the deepest ResNet variants, enabling it to extract intricate features from complex datasets.

The model uses residual connections, or skip connections, which allow gradients to flow through the network more effectively during backpropagation. This helps the model maintain performance even with increased depth, avoiding issues like overfitting and degraded accuracy.

ResNet152V2 is widely used in computer vision tasks such as image classification, object detection, and segmentation. It has achieved significant success on benchmark datasets like ImageNet, offering a robust balance between depth, computational efficiency, and performance accuracy, making it a preferred choice for high-performance applications.

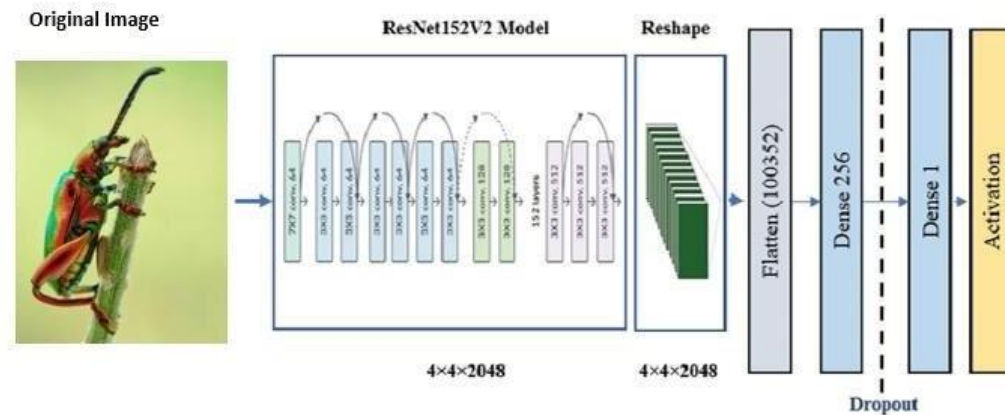


Figure-4: Visual overview of ResNet152V2

4.5. Customize CNN Algorithm

A Customized Convolutional Neural Network (CNN) is a tailored architecture designed to optimise performance for specific tasks, such as image classification or object detection. Unlike pre-built models, a customised CNN is designed by selecting the number of layers, kernel sizes, activation functions, and hyperparameters to suit the dataset and problem requirements.

The architecture typically starts with convolutional layers to extract spatial features from input images, followed by pooling layers to reduce dimensionality while retaining essential features. Additional layers, such as dropout, may be added to prevent overfitting. Fully connected layers at the end aggregate the learned features for classification or regression tasks.

Customisation includes defining the number of filters, learning rates, optimisers (e.g., Adam or SGD), and loss functions. Data augmentation techniques and regularisation are often integrated to improve generalisation. A tailored CNN can outperform generic models by focusing on task-specific features, ensuring higher accuracy and efficiency for the target dataset.

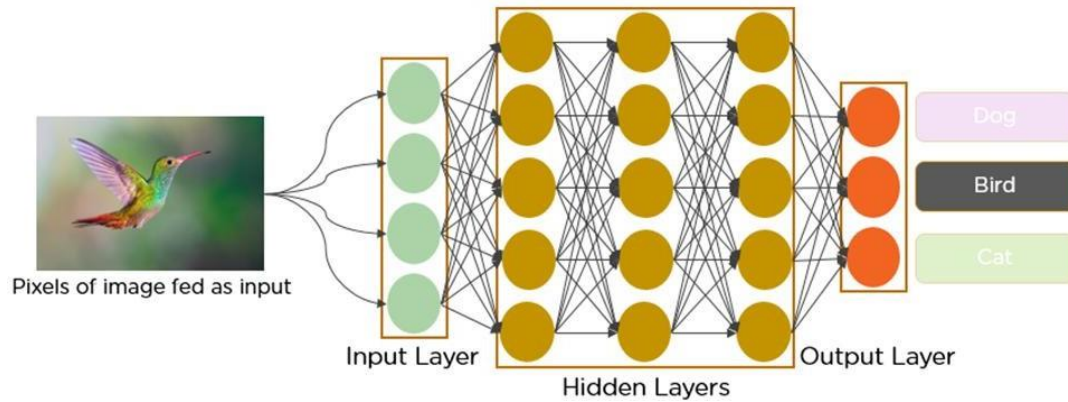


Figure 5: Visual overview of CNN

We have used a sequential model in insect work. Total parameters (11,170,121), trainable parameters (11,170,121) and non-trainable parameters (0) are fitted to the dataset using this model.

4.6. Conclusion

The project successfully addresses the challenge of detecting crop-harming insects using AI and transfer learning techniques, providing an innovative solution to safeguard agriculture. By leveraging image processing and computer vision methodologies, we identified nine specific insect types and their harmful impact on various crops. The use of training, testing, and validation processes ensured that the developed models achieved high accuracy in identifying harmful insects. This approach not only improves the efficiency of insect detection but also offers a scalable and practical tool for farmers to protect their crops. The integration of advanced AI techniques enables proactive pest management, reducing crop damage and increasing agricultural productivity. This project highlights the potential of AI in revolutionising traditional agricultural practices and sets the foundation for future advancements in pest detection and crop protection.

CHAPTER 5

DETECTING CROP HARMING INSECT DETECTION

5.1. Introduction

The detection of crop-harming insects plays a crucial role in safeguarding agricultural productivity and ensuring food security. Pests and insects significantly contribute to crop damage, leading to substantial losses for farmers and exacerbating food shortages worldwide. Traditional pest management methods, such as the excessive use of pesticides, not only harm the environment but also degrade soil fertility over time.

This project introduces an innovative approach to identifying harmful insects using Artificial Intelligence (AI) and Transfer Learning models. Leveraging advanced image processing and computer vision techniques, the system accurately detects and classifies insects that threaten crops. By integrating models like ResNet152v2, VGG19, MobileNetV2, and a customised CNN, the system demonstrates high precision in pest identification.

The proposed solution enables early pest detection, helping farmers take proactive measures to protect crops, reduce pesticide dependency, and promote sustainable farming practices, ensuring long-term agricultural success.

5.2. Insect & Damage Description

- **Asota Moth Caterpillars:** Asota moth caterpillars pose a significant threat to Ficus species and papaya plants, causing damage by feeding on their leaves and stems. Their feeding habits can lead to reduced growth, compromised plant health, and economic losses.
- **Caterpillars:** Caterpillars are harmful to a variety of plants, including docks, bramble, plantains, dandelions, nettles, and bedstraws. Their voracious feeding can defoliate plants, weaken their structure, and hinder their ability to thrive and reproduce.

- Cutworms: Cutworms damage tender seedlings and young transplants by cutting stems at the base, often killing the plants. They target a wide range of crops, causing significant yield loss and requiring vigilant monitoring and management for effective control.
- HenosepilachnaVigintioctopunctata: Henosepilachnavigintioctopunctata, commonly known as the 28-spotted ladybird, damages solanaceous and cucurbitaceous crops. Its feeding on leaves and stems reduces photosynthetic activity, leading to weakened plants and lower agricultural productivity.
- Heteropterys: Heteropterys insects threaten rice and soybeans, causing direct damage by feeding on plant tissues. Their activity results in reduced crop yields, stunted growth, and increased vulnerability to diseases, impacting agricultural sustainability and food security.
- Lawn Grubs: Lawn grubs are destructive to the roots of turfgrasses, ornamentals, and vegetables, leading to plant wilting and death. Their feeding disrupts root systems, reducing water and nutrient uptake and causing severe damage to agricultural and landscape plants.
- Long-Horned Grasshopper: Long Horned grasshoppers feed on the leaves, stems, fruits, and seeds of crops. Their feeding behaviour results in defoliation, reduced crop quality, and economic losses, making them a significant pest in agricultural systems.
- Mealy Bug: Mealybugs primarily harm citrus plants, feeding on sap and excreting honeydew that promotes fungal growth. This weakens plants, reduces fruit quality, and lowers yields, posing challenges for citrus growers worldwide.
- Rice Bugs: Rice bugs are major pests of rice crops, feeding on developing grains and causing "pecky rice." This damage reduces grain quality and market value, making their management critical in rice cultivation areas.

5.3. Categorywise Insect Description

Table 3: Insect Name and Description

Category	Description
Asota Moth Caterpillar	Asota Moth Caterpillar pictures will be shown from all types of insects and insects
Caterpillars	Caterpillars pictures will be shown from all types of insects and insects.
Cutworm	Cutworm pictures of all types of insects will be shown.
Henosepilachnavigintioctopunctata	Pictures of all types of insects will be shown in the Henosepilachnavigintioctopunctata.
Heteropterus	Heteropterus pictures will be shown of all types of insects and insects.
Lawn Grubs	Lawn Grubs pictures will be shown of all types of insects and insects.
Long Horned Grasshopper	Long Horned Grasshopper pictures will be shown from all types of insects and insects.
Mealy Bug	Mealy Bug pictures of all types of insects will be shown.
Rice Bug	Rice bug pictures of all types of insects will be shown.

5.4. Describe Crop-Harming Insect

Crop-harming insects are a major threat to agricultural productivity and food security. These pests infest crops during different growth stages, causing extensive damage to plants by feeding on their leaves, stems, roots, flowers, or fruits. Each insect species has specific feeding patterns, habitats, and target crops, making their identification crucial for effective management.

For instance, Asota moth caterpillars harm Ficus species and papaya plants, while Henosepilachnavigintioctopunctata targets solanaceous and cucurbitaceous crops. Cutworms destroy tender seedlings, and Rice bugs damage rice crops by sucking out grains. Lawn grubs affect turfgrass and vegetables by attacking their roots, while Mealy Bugs feed on citrus plants, causing stunted growth and reduced yields. Other harmful insects include Long-horned

grasshoppers, which consume leaves, stems, and fruits, and Heteropterys, which infest rice and soybeans.

The impact of these pests goes beyond crop destruction, as they also increase farming costs due to the heavy reliance on chemical pesticides, which can harm the environment. Early detection and classification of these harmful insects are essential to mitigate crop losses, reduce pesticide dependency, and enhance agricultural sustainability. Addressing these challenges effectively requires integrating advanced technologies like AI, image processing, and machine learning for proactive pest management.

5.5. Benefits of Insect Detection Using AI

The application of Artificial Intelligence (AI) for insect detection offers a range of transformative benefits to agriculture, ensuring both economic and environmental sustainability. Below are the key advantages:

- **Enhanced Accuracy:** AI-powered systems, such as Transfer Learning models (ResNet152v2, VGG19, MobileNetV2), provide high accuracy in identifying and classifying crop-harming insects. This precision minimises errors in pest detection, allowing farmers to address infestations effectively.
- **Early Warning System:** Early identification of harmful insects enables farmers to take proactive measures, preventing significant crop damage. Timely intervention reduces the risk of crop failures and ensures stable agricultural outputs.
- **Reduced Pesticide Usage:** Accurate insect detection minimizes unnecessary pesticide application, lowering chemical exposure to crops and soil. This not only preserves soil fertility but also promotes healthier, organic farming practices.
- **Cost Efficiency:** By reducing pesticide usage and crop losses, AI-driven insect detection systems lower overall farming costs, improving farmers' financial stability.
- **Environmental Sustainability:** The reduction in pesticide use helps protect biodiversity, including beneficial insects and pollinators. It also decreases water and soil contamination, contributing to a healthier ecosystem.

- Scalability and Adaptability: AI-based systems can analyze large datasets, making them suitable for diverse agricultural settings. They are adaptable to various crop types and regional pest behaviors.
- Food Security: By mitigating crop losses due to pests, AI solutions contribute to increased agricultural productivity, ensuring a steady food supply and addressing food scarcity challenges.

5.5. Conclusion

The detection of crop-harming insects is a critical step in safeguarding agricultural productivity and ensuring food security. This study highlights the application of advanced technologies such as artificial intelligence and machine learning to identify harmful insects accurately and efficiently. By leveraging AI-driven models, farmers can detect pests early, reducing reliance on chemical pesticides and promoting sustainable farming practices. Early identification enables timely interventions, preventing extensive crop damage and minimizing economic losses.

Moreover, integrating transfer learning models such as VGG19, MobileNetV2, and ResNet152v2 has proven effective, with ResNet152v2 achieving the highest accuracy of 96%. These models provide scalable and practical solutions for proactive pest management. This approach not only addresses the immediate issue of pest infestations but also contributes to environmental preservation and long-term agricultural sustainability. Overall, AI-based insect detection offers a promising pathway to revolutionize traditional agricultural practices and combat the challenges posed by harmful pests.

CHAPTER 6

EXPERIMENTAL RESULTS AND DISCUSSION

6.1. Introduction

Agriculture faces significant challenges from crop-harming insects, which can drastically reduce yield and threaten food security. To address this issue, this project explores the use of Transfer Learning Models in Artificial Intelligence and Data Science to detect harmful insects and mitigate their impact on crops. Leveraging image processing and computer vision techniques, the project focuses on identifying nine specific insect types, such as Asota moth caterpillars, cutworms, and rice bugs, along with their associated crop damage. By preprocessing image data and applying training, testing, and validation stages, the models developed aim to achieve accurate and efficient detection of these pests. This approach not only enhances early detection and management strategies but also demonstrates the potential of AI to revolutionize pest control in agriculture, ensuring sustainable crop production and food security.

6.2. Discussion

Different types of destructive insects appear during various seasons, leading to significant crop losses for farmers. Early detection of these harmful pests is crucial to provide timely warnings and reduce crop damage. Farmers frequently resort to using pesticides on their agricultural fields to combat these destructive insects. However, if these pests are identified and managed promptly, the use of pesticides can be substantially minimized. This, in turn, helps preserve the soil's fertility and maintain sustainable agricultural practices. Across the globe, food shortages and famines occasionally emerge, posing severe challenges to human survival. Among these, food-related famines—caused by the failure of crops—are particularly devastating. One major cause of crop failure is the widespread infestation of pests and insects, which often destroys crops in different regions, leading to food scarcity and economic hardships.

To address this critical issue, we have developed a digitized approach powered by artificial intelligence, data science, and modern technological advancements such as machine learning and

deep learning. This innovative system enables the early detection and classification of insects or pests into distinct categories. By leveraging this system, we can distinguish between harmful and beneficial insects and pinpoint areas where pests are likely to gather in large numbers. This predictive capability provides farmers with advance warnings, helping them prepare and implement effective measures to safeguard their crops from impending pest attacks.

In this study, transfer learning algorithms such as VGG19, MobileNetV2, ResNet152v2, and a customized convolutional neural network (CNN) have been utilized to identify and classify pests. These algorithms allow for accurate pest identification, enhancing the farmers' ability to take proactive measures, thereby reducing crop losses and ensuring food security. This approach represents a significant step toward mitigating the impact of pest infestations on agricultural productivity.

In this study, three transfer learning models—VGG19, MobileNetV2, and ResNet152v2—and one deep learning model, Customized CNN, were employed to detect crop-harming insects. The performance evaluation of these models reveals that the transfer learning model ResNet152v2 achieved the highest accuracy of 96%, followed by VGG19 with 94% and MobileNetV2 with 90%. On the other hand, the Customized CNN model, developed using deep learning techniques, attained an accuracy of 80%. The superior accuracy of the ResNet152v2 model highlights its effectiveness in leveraging pre-trained weights for identifying pests with greater precision. While the Customized CNN model performed relatively well, it fell short compared to the transfer learning models, indicating the significant advantage of transfer learning in achieving higher accuracy. Overall, the findings demonstrate that transfer learning, particularly the ResNet152v2 model, is a highly reliable approach for detecting and classifying harmful insects in agricultural settings.

Table-4: Classifiers Description

Classifier	Description
VGG19	VGG19 is a convolutional neural network (CNN) developed by the Visual Geometry Group at Oxford University, renowned for its deep yet simple architecture. It consists of 19 layers, including 16 convolutional layers, 3 fully connected layers, and a softmax output layer. VGG19 uses 3x3 convolutional filters with a stride of 1 and 2x2 max-pooling layers with a stride of 2, ensuring spatial hierarchies are preserved.
MobileNetV2	MobileNetV2 is a lightweight, efficient deep learning architecture designed for mobile and edge devices, providing a balance between performance and computational efficiency. It builds upon the success of MobileNetV1 with improved accuracy and reduced complexity.
ResNet152V2	ResNet152V2 is an advanced deep learning architecture in the ResNet (Residual Networks) family, designed to address the vanishing gradient problem in training deep neural networks. It is a refined version of the original ResNet model, incorporating batch normalization layers before activation functions and improved initialization techniques.
Customize CNN	A Customized Convolutional Neural Network (CNN) is a tailored architecture designed to optimize performance for specific tasks, such as image classification or object detection. Unlike pre-built models, a customized CNN is designed by selecting the number of layers, kernel sizes, activation functions, and hyperparameters to suit the dataset and problem requirements.

6.3. VGG19

6.3.1. Training Loss, Validation Loss and Training Accuracy, Validation Accuracy:

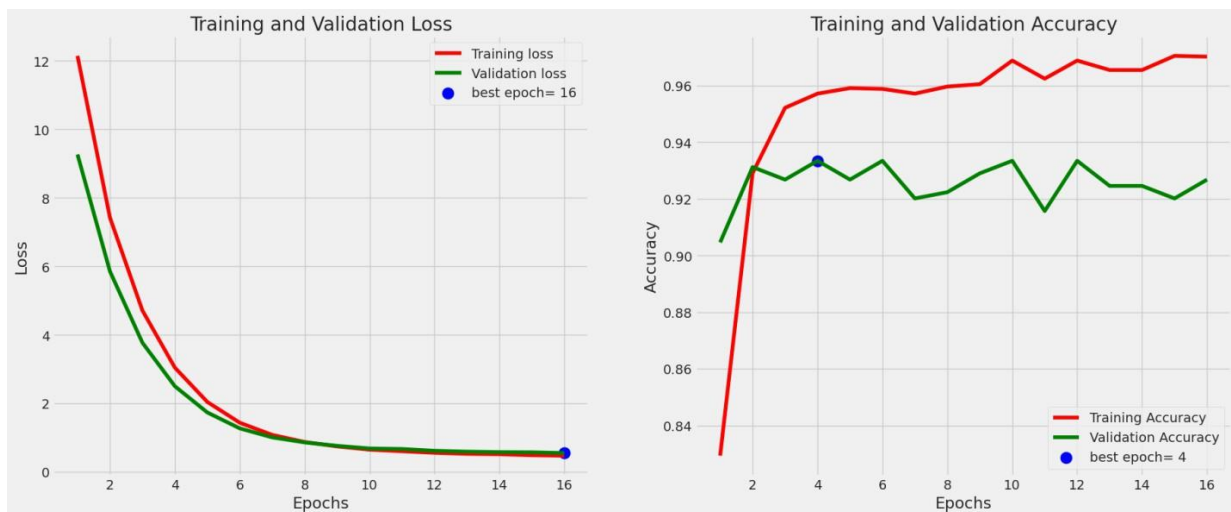


Figure-6: Training loss, validation loss and training accuracy, validation accuracy plot for VGG19

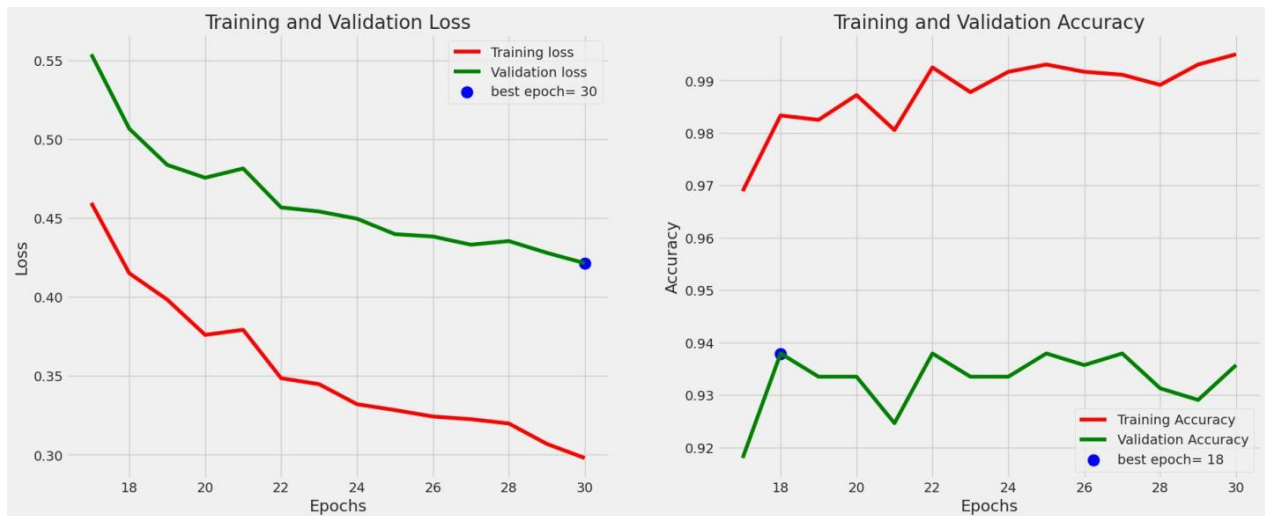


Figure-7: Training loss, validation loss and training accuracy, validation accuracy plot for VGG19

6.3.2. Test Set Error:

Some errors can be observed in the test set of 9 classes using our dataset. We have calculated the error goal for each class. 3 errors found in Long Horned Grasshopper class. 4 errors found in Rice Bug class. 2 errors found in Mealy Bug class. 2 errors found in Lawn Grubs class. 1 error found in class Heteropterus. 1 error found in class Henosepilachnavigintioctopunctata. 1 error found in Cutworm class. 9 errors found in Caterpillars class. 3 errors found in Asota Moth Caterpillar class. A total of 26 errors were found in 9 classes.

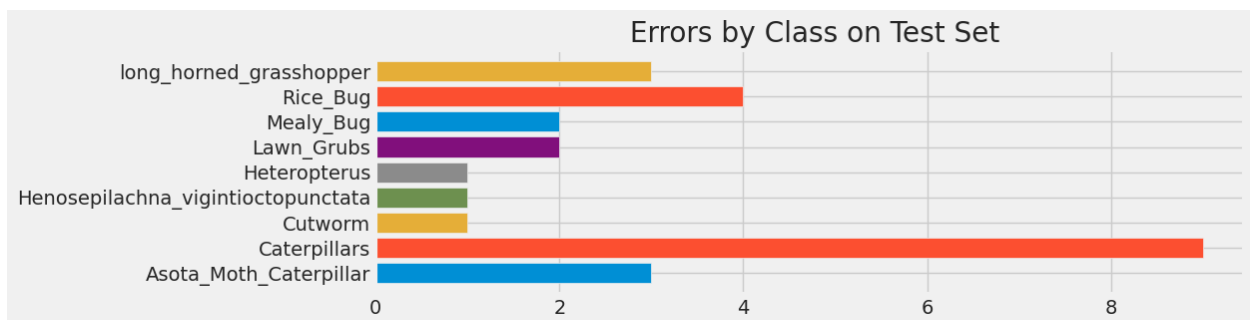


Figure-8: Error by class on test set

6.3.3. Model Metrics after Training:

After dataset training, the model is divided into 2 matrices namely - Loss matrix and Accuracy matrix. The value of Loss matrix is found to be 0.46699 and the value of Accuracy matrix is found to be 0.94209. That is, the accuracy of the test dataset is found to be 94.21%.

Table-5: Model metrics of VGG19 Model

Matric	Value
Loss	0.46699
Accuracy	0.94209

6.3.4. Classification Report Model Performance:

Insect image collection - Asota Moth Larvae, Caterpillars, Cutworm, Henosepilachnavigintioctopunctata, Heteropterus, Lawn Grubs, Long-Horned Grasshopper, Mealy Bug, Rice Bug, by examining the categories, categorization report i.e., precision, recall, f1_score, and support demonstrated that VGG19 Model achieved 94% Accuracy report.

Table-6: Classification report of VGG19 Model

	precision	recall	f1-score	support
Asota_Moth_Caterpillar	0.97	0.95	0.96	61
Caterpillars	0.91	0.82	0.86	49
Cutworm	0.80	0.97	0.88	37
Henosepilachna_vigintioctopunctata	1.00	0.98	0.99	50
Heteropterus	0.98	0.98	0.98	45
Lawn_Grubs	1.00	0.97	0.98	64
Mealy_Bug	0.94	0.96	0.95	53
Rice_Bug	0.92	0.90	0.91	39
long_horned_grasshopper	0.92	0.94	0.93	51
Accuracy			0.94	449
Macro avg	0.94	0.94	0.94	449
Weighted avg	0.94	0.94	0.94	449

In the classification report, we can observe that Precision, Recall, F1-Score, and Support are extracted for all insect image dataset categories (Asota Moth Caterpillar, Caterpillars, Cutworm, Henosepilachnavigintioctopunctata, Heteropterus, Lawn Grubs, Long Horned Grasshopper, Mealy Bug, Rice Bug). In addition to determining accuracy, the macro average and weighted average values were computed. By analysing precision, recall, and f1-score, it is evident that all the classes are effectively classified. The accuracy of the VGG19 Model stands at 94%.

6.3.5. Confusion matrix

		Confusion Matrix								
Actual	Asota_Moth_Caterpillar	58	0	3	0	0	0	0	0	0
	Caterpillars	1	40	4	0	0	0	3	0	1
	Cutworm	1	0	36	0	0	0	0	0	0
	Henosepilachna_vigintioctopunctata	0	1	0	49	0	0	0	0	0
	Heteropterus	0	1	0	0	44	0	0	0	0
	Lawn_Grubs	0	0	2	0	0	62	0	0	0
	Mealy_Bug	0	1	0	0	1	0	51	0	0
	Rice_Bug	0	1	0	0	0	0	0	35	3
	long_horned_grasshopper	0	0	0	0	0	0	0	3	48
		Asota_Moth_Caterpillar	Caterpillars	Cutworm	Henosepilachna_vigintioctopunctata	Heteropterus	Lawn_Grubs	Mealy_Bug	Rice_Bug	long_horned_grasshopper
		Predicted								

Figure-9: Confusion matrix for VGG19

The confusion matrix offers valuable insights into how many images are accurately categorised in each class and which classes are misclassified during the process. In this case, we observe that the real category results in a higher number of incorrectly classified outcomes.

6.4. MobileNetV2

6.4.1. Training Loss, Validation Loss and Training Accuracy, Validation Accuracy:

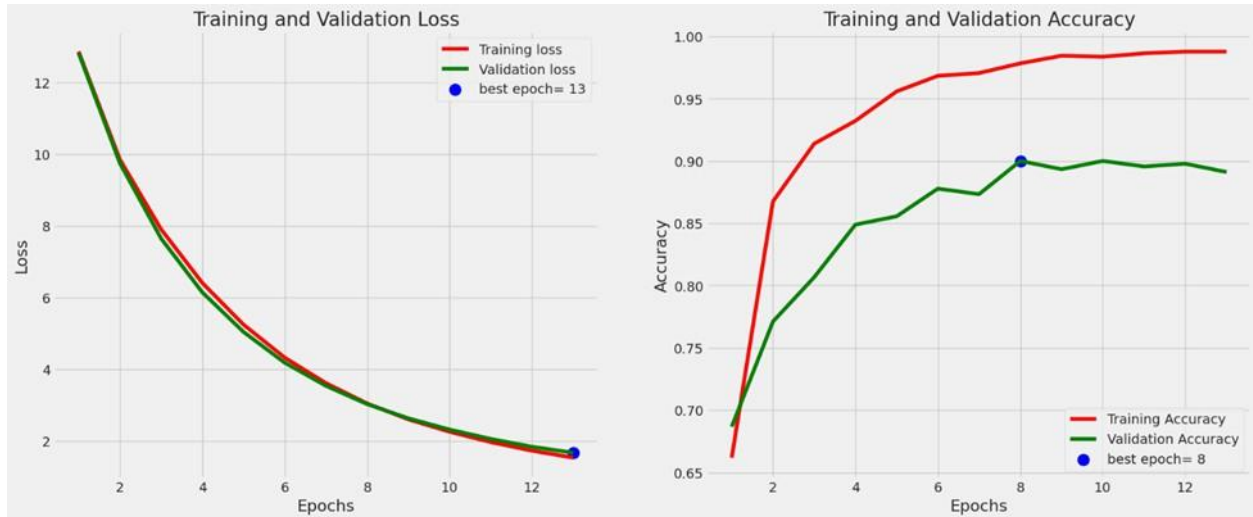


Figure-10: Training loss, validation loss and training accuracy, validation accuracy plot for MobileNetV2

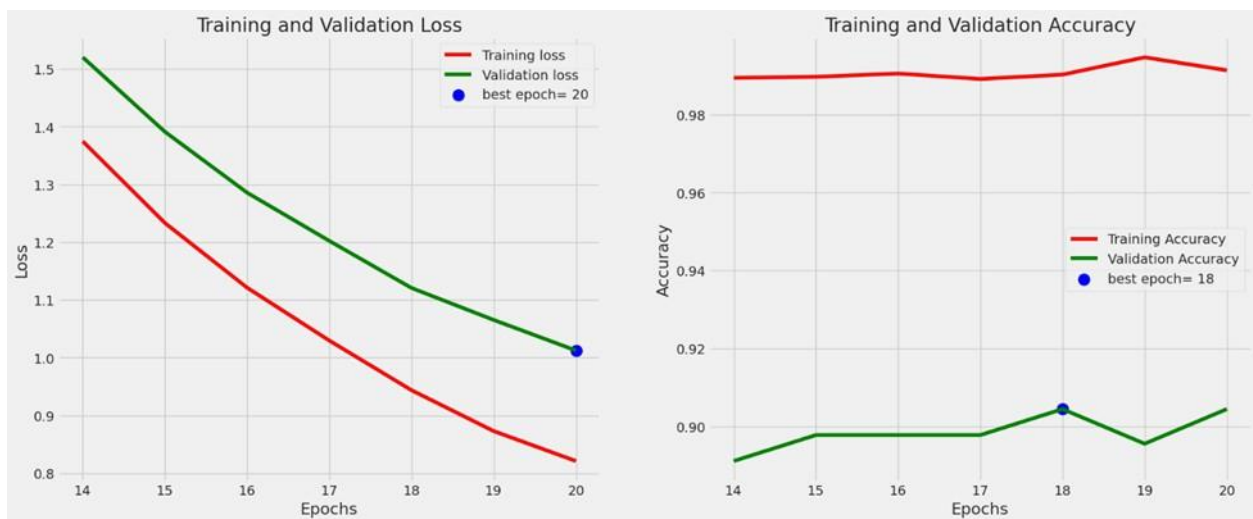


Figure-11: Training loss, validation loss and training accuracy, validation accuracy plot for MobileNetV2

6.4.2. Test Set Error:

Some errors can be observed in the test set of 9 classes using our dataset. We have calculated the error goal for each class. 13 errors were found in the Long-Horned Grasshopper class. Eight errors

were found in the Rice Bug class. 5 errors were found in the Mealy Bug class. One error was found in the Lawn Grubs class. Four errors were found in class Heteropterus. Three errors were found in the henosepilachnavigintioctopunctata class. 4 errors were found in the Cutworm class. Four errors were found in Caterpillar's clones. 1 error was found in the Asota Moth Caterpillar class. A total of 43 errors were found in 9 classes.

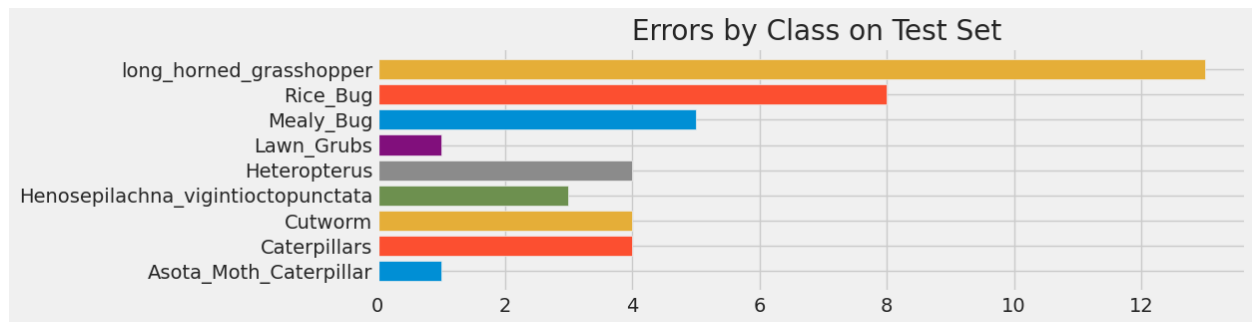


Figure 12: Error by class on the test set

6.4.3. Model Metrics after Training:

After dataset training, the model is divided into two matrices, namely the loss matrix and the Accuracy matrix. The value of the Loss matrix is found to be 0.98802, and the value of the Accuracy matrix is found to be 0.90423. That is, the accuracy of the test dataset is found to be 90.42%.

Table-7: Model metrics of MobileNetV2 Model

Matric	Value
Loss	0.98802
Accuracy	0.90423

6.4.4. Classification Report Model Performance:

Insect image dataset – Asota Moth Caterpillar, Caterpillars, Cutworm, Henosepilachnavigintioctopunctata, Heteropterus, Lawn Grubs, Long Horned Grasshopper, Mealy Bug, Rice Bug, by examining the categories, classification summary i.e., precision, recall, f1_score, and support revealed that MobileNetv2 Model has 90% Accuracy summary.

Table-8: Classification report of MobileNetV2 Model

	precision	recall	f1-score	support
Asota_Moth_Caterpillar	1.00	0.98	0.99	48
Caterpillars	0.88	0.92	0.90	53
Cutworm	0.90	0.93	0.91	56
Henosepilachna_vigintioctopunctata	1.00	0.94	0.97	53
Heteropterus	0.89	0.91	0.90	45
Lawn_Grubs	0.94	0.98	0.96	46
Mealy_Bug	0.84	0.90	0.87	51
Rice_Bug	0.88	0.84	0.86	51
long_horned_grasshopper	0.82	0.72	0.77	46
Accuracy			0.90	449
Macro avg	0.90	0.90	0.90	449
Weighted avg	0.90	0.90	0.90	449

In the classification report, we can observe that Precision, Recall, F1_Score, and Support have been derived for all Insect image dataset categories (Asota Moth Caterpillar, Caterpillars, Cutworm, Henosepilachnavigintioctopunctata, Heteropterus, Lawn Grubs, Long Horned Grasshopper, Mealy Bug, Rice Bug). Along with determining accuracy, macro average and weighted average values were also calculated. By examining precision, recall, and f1-score, it is evident that all the classes are adequately categorised. The Accuracy of the MobileNetv2 Model is 90%.

6.4.5. Confusion matrix

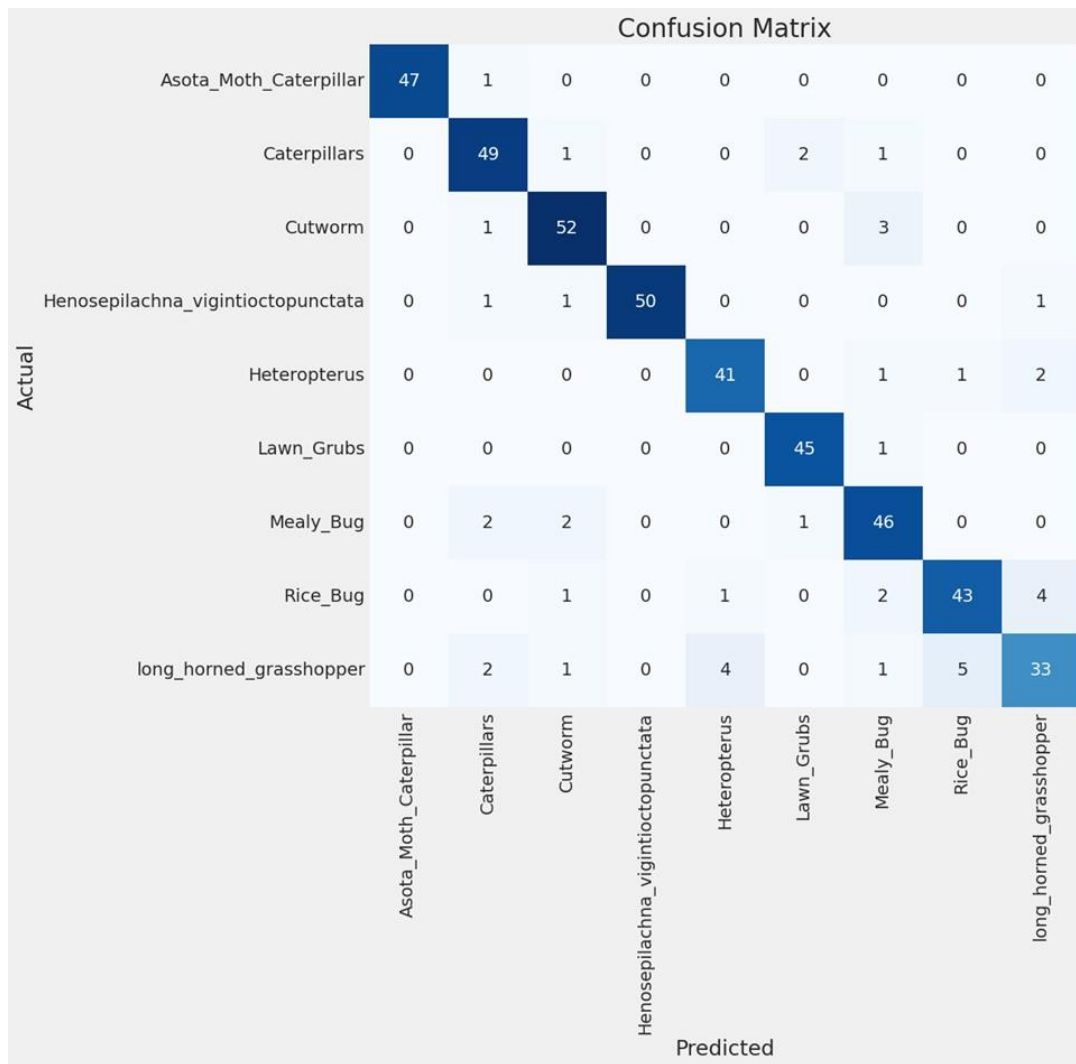


Figure-13: Confusion matrix for MobileNetV2

The confusion matrix offers valuable insight into how many images are accurately categorised in each class and which classes are misclassified during the process. In this case, we observe that the real category produces a higher number of incorrectly classified outcomes.

6.5. ResNet152V2

6.5.1. Training Loss, Validation Loss and Training Accuracy, Validation Accuracy:

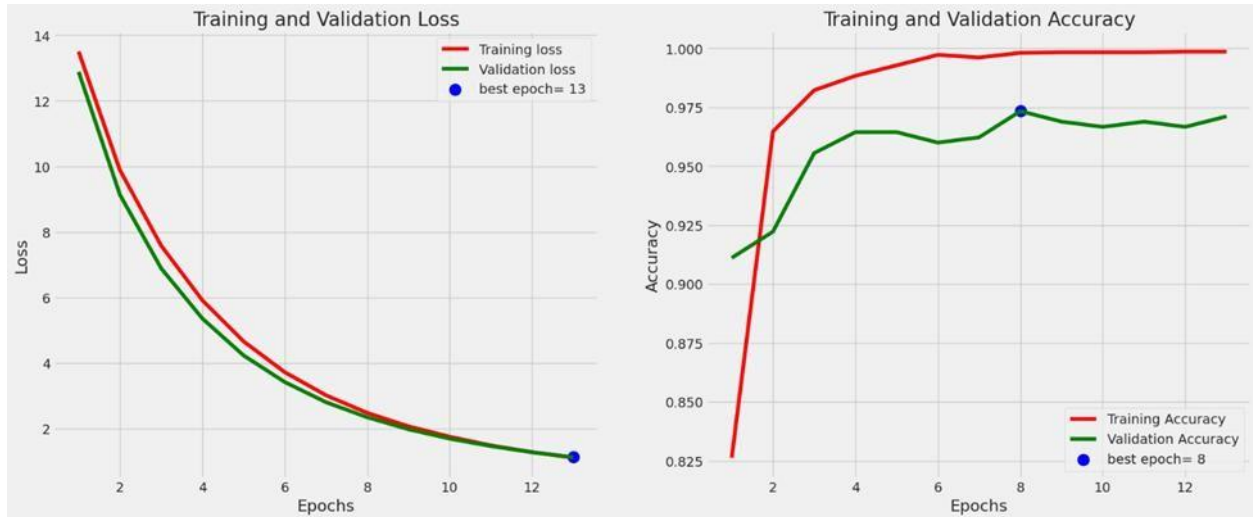


Figure-14: Training loss, validation loss and training accuracy, validation accuracy plot for ResNet152V2

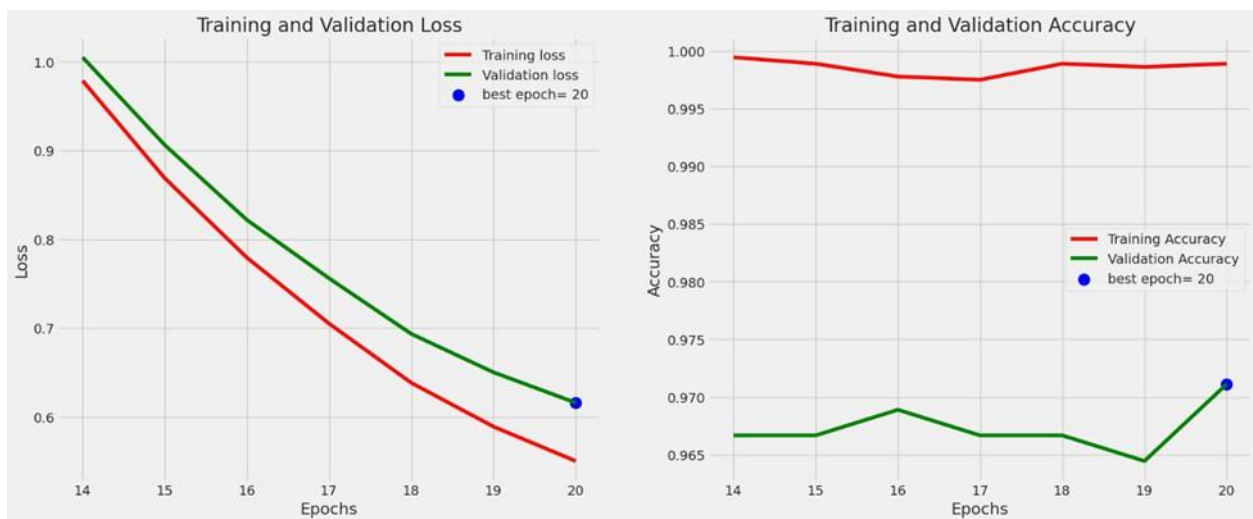


Figure-15: Training loss, validation loss and training accuracy, validation accuracy plot for ResNet152V2

6.5.2. Test Set Error:

Some errors can be observed in the test set of 9 classes using our dataset. We have calculated the error goal for each class. Four errors were found in the Long Horned Grasshopper class. 2 errors

were found in the Rice Bug class. Three errors were found in the Mealy Bug class. 0 errors were found in the Lawn Grubs class. 2 errors were found in the class Heteropterus. 2 errors were found in the class Henosepilachnavigintioctopunctata. 1 error was found in the Cutworm class. Five errors were found in Caterpillar's class. 0 errors were found in the Asota Moth Caterpillar class. A total of 19 errors were found in 9 classes.

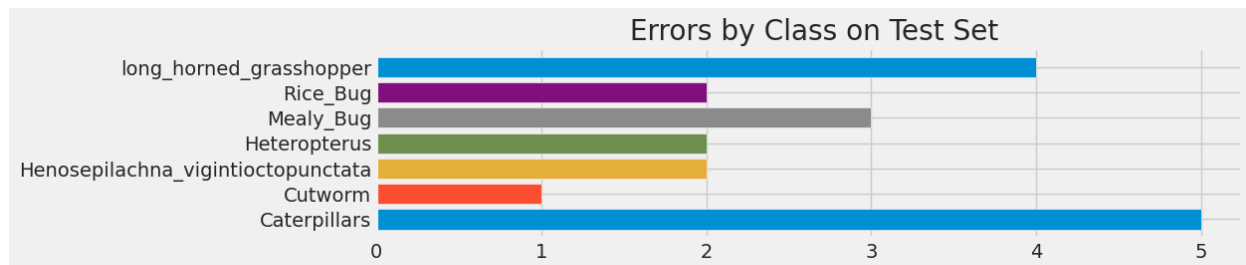


Figure 16: Error by class on the test set

6.5.3. Model Metrics after Training:

After dataset training, the model is divided into two matrices, namely the loss matrix and the Accuracy matrix. The value of the Loss matrix is found to be 0.62925, and the value of the Accuracy matrix is found to be 0.95768. That is, the accuracy of the test dataset is found to be 95.77%.

Table-9: Model metrics of ResNet152V2 Model

Matric	Value
Loss	0.62925
Accuracy	0.95768

6.5.4. Classification Report Model Performance:

Insect image collection – Asota Moth Caterpillar, Caterpillars, Cutworm, Henosepilachnavigintioctopunctata, Heteropterus, Lawn Grubs, Long Horned Grasshopper, Mealy Bug, Rice Bug, by examining the categories, classification report i.e., precision, recall, f1_score, and support indicated that ResNet50v2 Model achieved a 96% Accuracy report.

Table-10: Classification report of ResNet152V2 Model

	precision	recall	f1-score	support
Asota_Moth_Caterpillar	1.00	1.00	1.00	48
Caterpillars	0.94	0.91	0.92	53
Cutworm	0.93	0.98	0.96	56
Henosepilachna_vigintioctopunctata	1.00	0.96	0.98	53
Heteropterus	0.98	0.96	0.97	45
Lawn_Grubs	1.00	1.00	1.00	64
Mealy_Bug	0.94	0.94	0.94	51
Rice_Bug	0.92	0.96	0.94	51
long_horned_grasshopper	0.91	0.91	0.91	46
Accuracy			0.96	449
Macro avg	0.96	0.96	0.96	449
Weighted avg	0.96	0.96	0.96	449

In the classification report, we can observe that Precision, Recall, F1_Score, and Support are derived for all insect image dataset categories (Asota Moth Caterpillar, Caterpillars, Cutworm, Henosepilachnavigintioctopunctata, Heteropterus, Lawn Grubs, Long Horned Grasshopper, Mealy Bug, Rice Bug). In addition to determining accuracy, macro average and weighted average values were computed. By examining precision, recall, and f1-score, we can conclude that all the categories are adequately classified. The Accuracy of the ResNet152V2 Model is 96%.

6.5.5. Confusion matrix

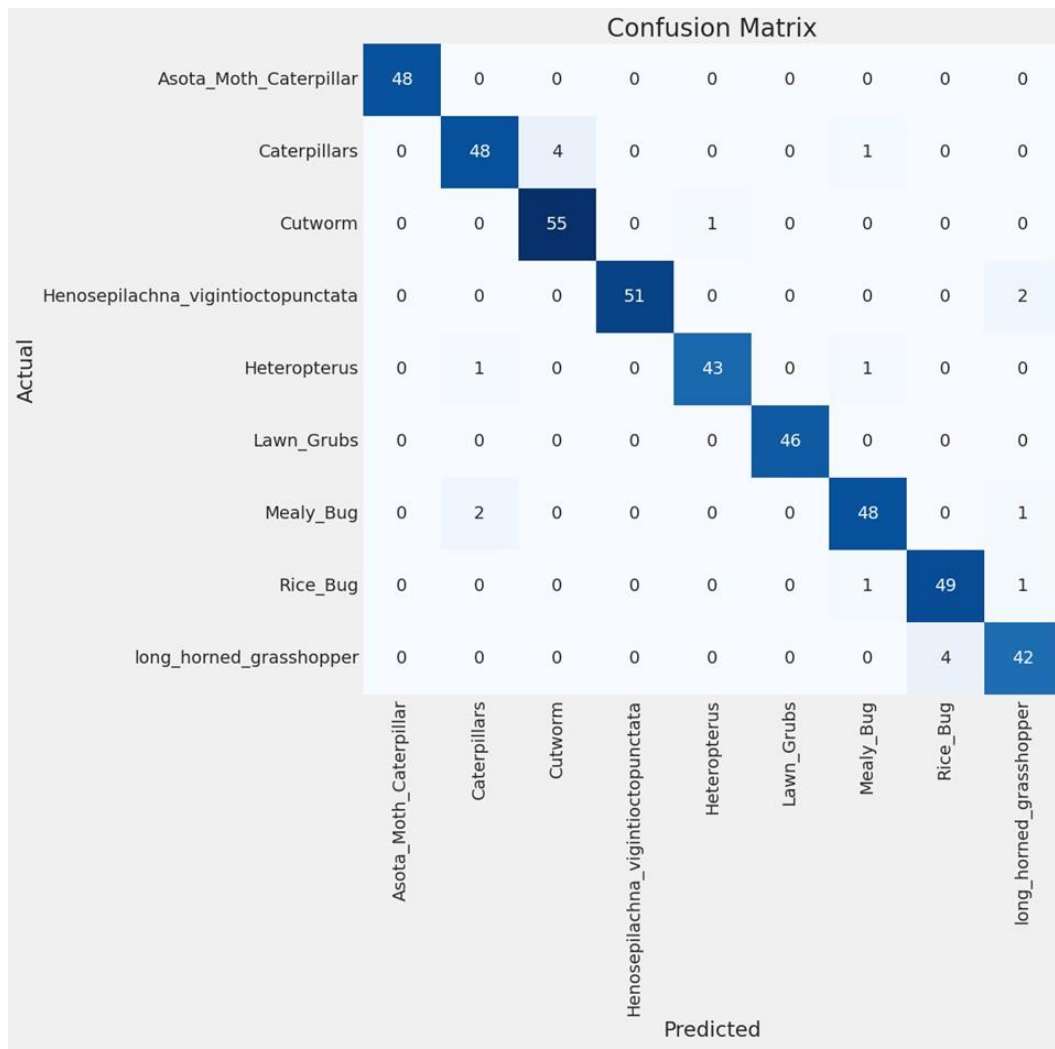


Figure-17: Confusion matrix for ResNet152V2

The confusion matrix offers a clear insight into how many images are accurately categorised in each class and which categories are misinterpreted during classification. In this case, we notice that the real category results in a higher number of incorrectly classified outcomes

6.6. Customize CNN

6.6.1. Training Loss, Validation Loss and Training Accuracy, Validation Accuracy:

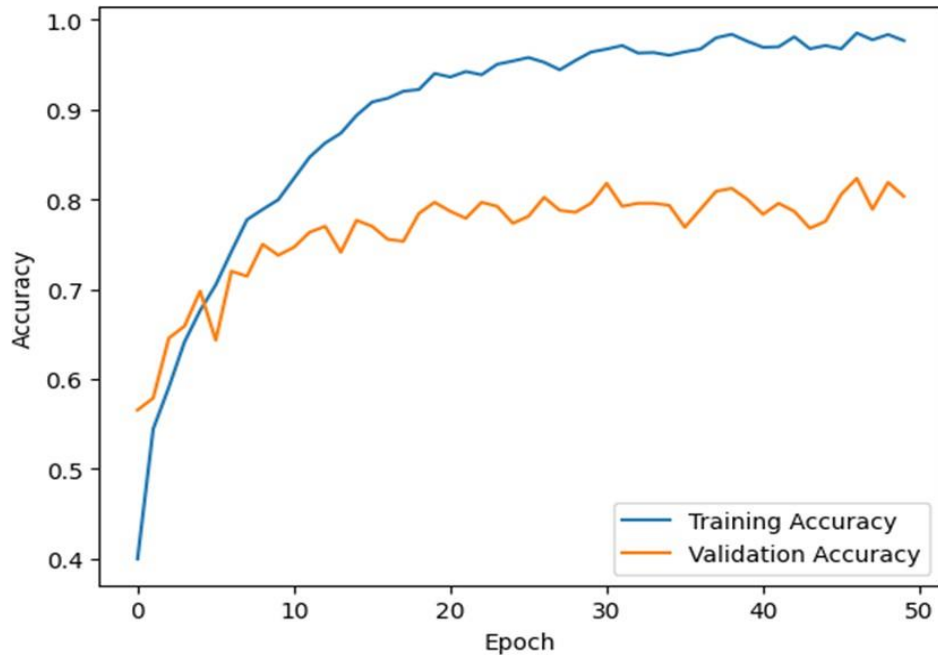


Figure-18: Training loss, validation loss and training accuracy, validation accuracy table for Customize CNN

6.6.2. Model Metrics after Training:

After dataset training, the model is divided into two matrices, namely the loss matrix and the Accuracy matrix. The value of the Loss matrix is found to be 1.3551, and the value of the Accuracy matrix is found to be 0.8033. That is, the accuracy of the test dataset is found to be 80.33%.

Table-11: Model metrics of Customize CNN Algorithm

Matric	Value
Loss	1.3551
Accuracy	0.8033

6.6.3. Classification Report Model Performance:

Insect image dataset - Asota Moth Caterpillar, Caterpillars, Cutworm, Henosepilachnavigintioctopunctata, Heteropterus, Lawn Grubs, Long Horned Grasshopper, Mealy Bug, Rice Bug, by evaluating the categories, classification summary i.e., precision, recall, f1_score, and support indicated that Customize CNN Algorithm achieved 80% Accuracy report.

Table 12: Classification report of Customize CNN Algorithm

	precision	recall	f1-score	support
Asota_Moth_Caterpillar	0.06	0.06	0.06	100
Caterpillars	0.03	0.03	0.03	100
Cutworm	0.07	0.08	0.07	100
Henosepilachna_vigintioctopunctata	0.08	0.09	0.09	100
Heteropterus	0.10	0.12	0.11	100
Lawn_Grubs	0.07	0.06	0.07	100
Mealy_Bug	0.16	0.16	0.16	100
Rice_Bug	0.14	0.12	0.13	100
long_horned_grasshopper	0.11	0.10	0.11	100
Accuracy			0.09	900
Macro avg	0.09	0.09	0.09	900
Weighted avg	0.09	0.09	0.09	900

In the classification report, we can observe that Precision, Recall, F1_Score, and Support are extracted for all Insect image dataset categories (Asota Moth Caterpillar, Caterpillars, Cutworm, Henosepilachnavigintioctopunctata, Heteropterus, Lawn Grubs, Long Horned Grasshopper, Mealy Bug, Rice Bug). Along with determining accuracy, macro average and weighted average values were also computed. By analysing precision, recall, and f1-score, we can conclude that all the classes are adequately categorised. The accuracy of the Customize CNN Algorithm is 80%.

6.6.4. Confusion matrix

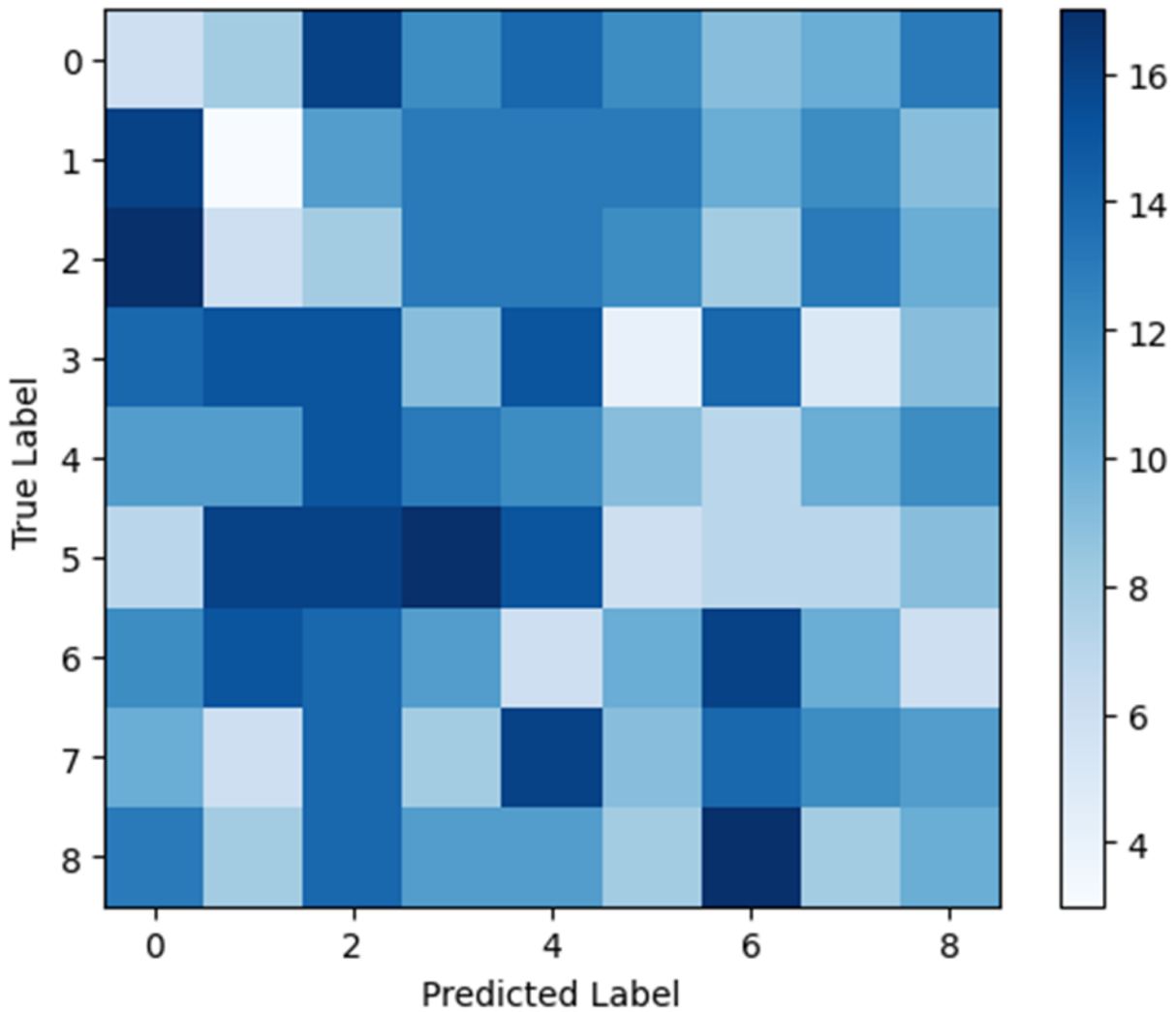


Figure-19: Confusion matrix for Customized CNN

The confusion matrix offers a clear understanding of how many images are accurately categorised in each class and which categories are confused during the classification process. Here, we observe that the real category results in a higher number of incorrectly classified outcomes.

6.6.5. Testing Customized_CNN algorithm with our own image

The Customized_CNN algorithm is tested with dummy images to see how well this algorithm predicts. Here, a Rice_Bug is taken as a sample image, and after prediction, it is found that it predicts Rice_Bug. That is, it made the correct guess.

Table 13: Test Customized CNN algorithm using dummy image

Sample Image	Predicted Class
Predicted Class: Rice_Bug 	Rice_Bug

6.7. Experimental Results and Analysis

In this study, three transfer learning models—VGG19, MobileNetV2, and ResNet152v2—and one deep learning model, Customize CNN, were employed to detect crop-harming insects. The performance evaluation of these models reveals that the transfer learning model ResNet152v2 achieved the highest accuracy of 96%, followed by VGG19 with 94% and MobileNetV2 with 90%. On the other hand, the Customize CNN model, developed using deep learning techniques, attained an accuracy of 80%. The superior accuracy of the ResNet152v2 model highlights its effectiveness in leveraging pre-trained weights for identifying pests with greater precision. While the Customize CNN model performed relatively well, it fell short compared to the transfer learning

models, indicating the significant advantage of transfer learning in achieving higher accuracy. Overall, the findings demonstrate that transfer learning, particularly the ResNet152v2 model, is a highly reliable approach for detecting and classifying harmful insects in agricultural settings. Table 1414: Classifiers' accuracy, recall and precision

Algorithm techniques	Accuracy %	Recall %	Precision %	Support
VGG19	0.94	0.94	0.94	449
MobileNetV2	0.90	0.90	0.90	449
ResNet152v2	0.96	0.96	0.96	449
Customise CNN	0.80	0.80	0.80	900

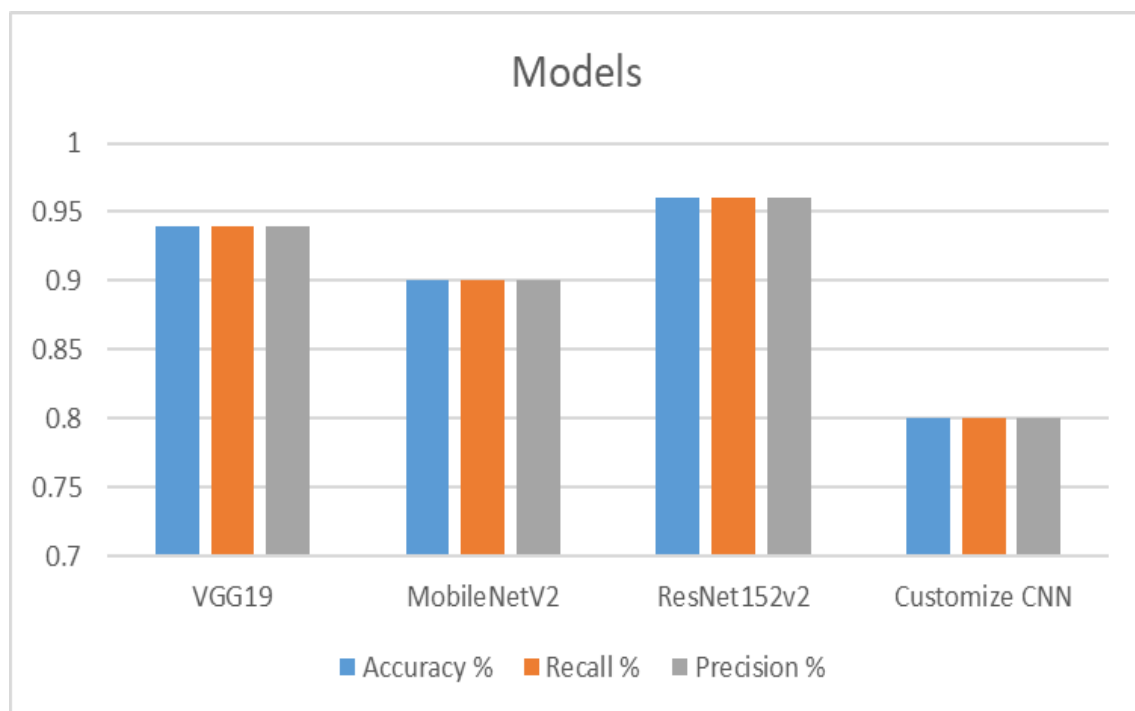


Figure 20: Summary of all Models

6.8. Conclusion

The project effectively addresses the challenge of detecting crop-harming insects using AI and transfer learning techniques, offering an innovative solution to protect agriculture. By applying image processing and computer vision methodologies, the study identified nine specific insect types and their harmful impact on various crops. The models were developed and evaluated through training, testing, and validation processes, ensuring high accuracy in pest identification. Among the four models used—VGG19, MobileNetV2, ResNet152v2, and Customize CNN—ResNet152v2 achieved the highest accuracy of 96%, followed by VGG19 with 94% and MobileNetV2 with 90%.

The Customize CNN model, built using deep learning techniques, attained 80% accuracy. The superior performance of ResNet152v2 underscores the effectiveness of transfer learning in enhancing pest detection. This approach not only enables proactive pest management and reduces crop damage but also demonstrates the transformative potential of AI in modernising agricultural practices and fostering future advancements in crop protection.

CHAPTER 7

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

7.1. Introduction

This project tackles the critical challenge of safeguarding agriculture by detecting crop-harming insects using Artificial Intelligence (AI) and transfer learning techniques. Leveraging image processing and computer vision, the study identified nine specific insect types and their impact on various crops. By employing advanced AI models like ResNet152v2, VGG19, MobileNetV2, and Customized CNN, the system achieved high accuracy in pest detection, with ResNet152v2 attaining 96%. This innovative approach enables early identification and management of harmful insects, offering farmers an efficient and scalable tool for proactive pest control. By minimising the need for excessive pesticide use, the project not only ensures agricultural productivity but also promotes sustainable farming practices.

7.2. Impact on Society

The project "Insect Detection Using Transfer Learning Model" holds significant potential for impacting society in various ways, especially in fields related to agriculture, biodiversity, and public health.

- **Agricultural Benefits:** One of the primary societal impacts of this project is its potential to revolutionise pest management in agriculture. By accurately detecting and classifying insect species, farmers can better manage pest infestations, leading to more efficient and targeted pesticide usage. This reduces the overuse of harmful chemicals, which not only cuts costs but also minimises the ecological footprint of agriculture. In turn, this supports sustainable farming practices and food security by protecting crops from both harmful pests and excessive pesticide residues.
- **Biodiversity and Environmental Conservation:** Insects play a crucial role in ecosystems, acting as pollinators, decomposers, and a food source for other animals. By accurately identifying different insect species, this project contributes to biodiversity monitoring,

helping researchers and conservationists track insect populations and assess the health of ecosystems. In the face of climate change, understanding insect distribution and behaviour can inform conservation efforts, ensuring that vital ecological processes continue to thrive.

- **Public Health and Disease Control:** Insects, particularly mosquitoes, are vectors for diseases such as malaria, dengue, and Zika virus. By providing tools to monitor and identify potential disease-carrying insects, the project could aid in public health efforts, particularly in regions prone to insect-borne diseases. Early detection systems based on this technology could help in proactive interventions, reducing the spread of diseases and improving public health outcomes.
- **Educational and Research Opportunities:** The project promotes AI and data science literacy, opening up new educational opportunities for individuals interested in technology and environmental science. It can be used as a learning tool for students and researchers to explore the intersection of AI, ecology, and conservation, fostering innovation in other sectors as well.

In summary, this project has the potential to bring about positive changes in various sectors by enhancing our ability to monitor, protect, and sustainably manage insect populations for the benefit of society.

7.3. Impact on Environment

The Insect Detection Using Transfer Learning Model project has the potential to positively impact the environment in several significant ways. The primary focus of the project is to enhance insect identification through artificial intelligence, which can contribute to more effective environmental monitoring, biodiversity preservation, and sustainable agricultural practices.

- **Biodiversity Monitoring:** Insects play a critical role in maintaining ecological balance, as they are involved in pollination decomposition and serve as a food source for other wildlife. By using AI for accurate and efficient insect detection, this project helps monitor insect populations and identify species that might be endangered or in decline. This information

can inform conservation efforts and support the preservation of biodiversity, which is crucial for ecosystem health.

- **Sustainable Agriculture:** The detection of beneficial insects, such as pollinators or pest-controlling species, can support sustainable farming practices. The project's model can be used to differentiate between beneficial insects and pests in agricultural settings, allowing farmers to implement more targeted and eco-friendly pest control measures. This minimises the use of harmful chemical pesticides, reducing their negative impact on the environment, wildlife, and human health.
- **Ecological Health Monitoring:** With accurate insect detection, the model can also contribute to monitoring changes in ecological health. For instance, a sudden decline in certain insect populations may indicate an environmental disturbance, such as pollution or habitat destruction. By detecting these patterns early, corrective actions can be taken to address environmental threats and prevent further damage.
- **Reducing Environmental Footprint:** The use of AI for insect identification reduces the need for manual surveys, which can be labour-intensive and require extensive resources. This technology-driven approach is more resource-efficient and minimizes human intervention in natural habitats, helping preserve delicate ecosystems.

In summary, the project not only advances technological solutions for insect detection but also contributes to environmental conservation by supporting biodiversity, sustainable farming, and ecological monitoring efforts.

7.4. Ethical Aspects

In the Insect Detection Using Transfer Learning Model project, ethical considerations play an important role, particularly when dealing with image data and artificial intelligence. The following ethical aspects are carefully addressed:

- **Data Privacy and Consent:** Ensuring that the image data used for training and testing is collected from reliable, open-access sources or with explicit consent is crucial. Any use of

data from private entities or individuals must comply with relevant data privacy regulations and ethical standards.

- **Bias and Fairness:** AI models can sometimes learn biases from the data on which they are trained. We ensure that the dataset used for insect detection represents diverse insect species across different environments. This reduces the risk of the model being biased toward certain species, ensuring fairness in identification.
- **Environmental Impact:** AI and deep learning models can require significant computational resources, which can contribute to carbon emissions. Efforts are made to optimise models for efficiency, reducing unnecessary computational load and its environmental footprint.
- **Transparency and Accountability:** The project ensures that the process behind model decisions is transparent. Providing users with an explanation of how the model works and ensuring that the decisions made by the AI are explainable is essential for ethical AI deployment.

These ethical aspects are critical to ensuring that the project contributes positively to society and the environment while adhering to responsible AI practices.

7.5. Sustainability Plan

The sustainability of the "Insect Detection Using Transfer Learning Model" project is fundamental to its long-term impact and real-world applications. The following strategies are proposed to ensure the sustainability of the project:

- **Scalability and Adaptability:** The developed model can be continuously improved with new datasets, ensuring adaptability to different environments, regions, and insect species. Future collaborations with agricultural organizations and environmental agencies will allow for the expansion of the dataset, enabling more accurate and diverse insect identification.
- **Resource Efficiency:** To ensure sustainable use of resources, the model will be optimised for low-resource devices and edge computing. This will allow real-time insect detection in

remote areas, reducing the need for expensive infrastructure and enabling the application of the model in diverse ecological settings.

- **Open-Source Contributions:** The project will be made available as an open-source resource, encouraging collaboration within the global research community. By providing access to the model and data, other researchers can contribute improvements and further innovations, ensuring the project's long-term development.
- **Environmental Impact:** The project's focus on identifying and managing insect populations contributes to more sustainable agricultural practices by helping farmers control pest populations, reduce pesticide usage, and enhance biodiversity conservation.

By prioritising these sustainability strategies, the project will remain valuable and adaptable in the future.

7.6. Conclusion

The project demonstrates the transformative potential of AI in agriculture, reducing crop damage, ensuring food security, and fostering sustainable pest management. Its societal impact includes alleviating food shortages, improving farmers' livelihoods, and enhancing agricultural efficiency. Environmentally, the reduction in pesticide usage preserves soil fertility and supports ecological balance. Through this innovative application of AI, the project offers a scalable and sustainable solution to modern agricultural challenges, paving the way for a more resilient farming future.

CHAPTER 8

SUMMARY AND CONCLUSION

8.1. Conclusions

In conclusion, this study successfully demonstrates the efficacy of transfer learning models in detecting crop-harming insects, with the ResNet152v2 model outperforming others by achieving the highest accuracy of 96%. The results indicate that transfer learning techniques, especially when leveraging pre-trained models like ResNet152v2, significantly enhance pest detection accuracy compared to traditional deep learning models, such as the Customized CNN, which achieved 80% accuracy. The performance of VGG19 and MobileNetV2 further underscores the strength of transfer learning in improving model precision. These findings highlight the potential of AI-driven solutions in agriculture, providing a reliable, scalable, and efficient method for early pest detection and pest management. By accurately identifying harmful insects, this approach can help farmers protect crops, reduce pesticide usage, and improve overall agricultural productivity, contributing to sustainable farming practices and food security.

8.2. Further Suggested Work

- **Expansion of Dataset:** Future work can focus on expanding the dataset by collecting more diverse insect images across various environments and conditions, which will help improve the model's generalization capability.
- **Model Optimization:** Further studies can explore different transfer learning models and architectures to optimize performance, such as experimenting with advanced models like EfficientNet or incorporating ensemble learning techniques.
- **Real-Time Insect Detection:** Implementing real-time insect detection systems in field applications, such as mobile apps or edge computing devices, could offer practical benefits for farmers and researchers.
- **Addressing Imbalanced Data:** Future research could explore methods to handle class imbalance in insect species, such as data augmentation, oversampling, or using synthetic data generation techniques.

REFERENCE

- [1] W. Li, T. Zheng, Z. Yang, M. Li, C. Sun, and X. Yang, "Classification and detection of insects from field images using deep learning for smart pest management: A systematic review," *Ecological Informatics*, vol. 66, p. 101460, Dec. 2021, doi: <https://doi.org/10.1016/j.ecoinf.2021.101460>.
- [2] Z. Anwar and S. Masood, "Exploring Deep Ensemble Model for Insect and Pest Detection from Images," *Procedia Computer Science*, vol. 218, pp. 2328–2337, Jan. 2023, doi: <https://doi.org/10.1016/j.procs.2023.01.208>.
- [3] N. E. M. KHALIFA, M. LOEY, and M. H. N. TAHA, "INSECT PESTS RECOGNITION BASED ON DEEP TRANSFER LEARNING MODELS," *Journal of Theoretical and Applied Information Technology*, vol. 98, no. 01, pp. 60–68, Jan. 2020.
- [4] M. K. Khan and M. O. Ullah, "Deep Transfer Learning Inspired Automatic Insect Pest Recognition," 3rd International Conference on Computational Sciences and Technologies.
- [5] Y. Liu, X. Zhang, Y. Gao, T. Qu, and Y. Shi, "Improved CNN Method for Crop Pest Identification Based on Transfer Learning," *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1–8, Mar. 2022.
- [6] W. Li, T. Zhu, X. Li, J. Dong, and J. Liu, "Recommending Advanced Deep Learning Models for Efficient Insect Pest Detection," *Agriculture*, vol. 12, no. 7, p. 1065, Jul. 2022.
- [7] Ana Cláudia Teixeira, J. Ribeiro, R. Morais, J. J. Sousa, and A. José, "A Systematic Review on Automatic Insect Detection Using Deep Learning," *Agriculture*, vol. 13, no. 3, pp. 713–713, Mar. 2023.
- [8] Gonçalves, J., Silva, E., Faria, P., Nogueira, T., Ferreira, A., Carlos, C., Rosado, L. Edge-Compatible Deep Learning Models for Detection of Pest Outbreaks in Viticulture. *Agronomy* 2022, 12, 3052.
- [9] Tsai, M.-F., Lan, C.-Y., Wang, N.-C., Chen, L.-W. Time Series Feature Extraction Using Transfer Learning Technology for Crop Pest Prediction. *Agronomy* 2023, 13, 792.
- [10] Li, C., Zhen, T., Li, Z. Image Classification of Pests with Residual Neural Network Based on Transfer Learning. *Applied Sciences*. 2022, 12, 4356.
- [11] Ahmad, I., Yang, Y., Yue, Y., Ye, C., Hassan, M., Cheng, X., Wu, Y., Zhang, Y. Deep Learning Based Detector YOLOv5 for Identifying Insect Pests. *Applied Sciences*. 2022, 12, 10167.
- [12] X. Cao, Z. Wei, Y. Gao, and Y. Huo, "Recognition of Common Insect in Field Based on Deep Learning," *Journal of Physics: Conference Series*, vol. 1634, no. 1, p. 012034, Sep. 2020.

- [13] T. Nguyen, Q.-T. Vien, and H. Sellahewa, "An Efficient Pest Classification In Smart Agriculture Using Transfer Learning," *EAI Endorsed Transactions on Industrial Networks and Intelligent Systems*, vol. 8, no. 26, p. 168227, Apr. 2021.
- [14] C. M. Little, T. W. Chapman, and N. K. Hillier, "Considerations for Insect Learning in Integrated Pest Management," *Journal of Insect Science*, vol. 19, no. 4, Jul. 2019.
- [15] Bjerger K, Alison J, Dyrmann M, Frigaard CE, Mann HMR, Høye TT (2023) Accurate detection and identification of insects from camera trap images with deep learning. *PLOS Sustainability And Transform* 2(3): e0000051.
- [16] E. Önlü, "REAL TIME PEST DETECTION USING YOLOv5," *International Journal of Agricultural and Natural Sciences*, vol. 14(3), no. 2651–3617, pp. 232–246, 2021.
- [17] M. G. Selvaraj et al., "AI-powered banana diseases and pest detection," *Plant Methods*, vol. 15, no. 1, Aug. 2019.
- [18] Marković, D.; Vujić, D.; Tanasković, S.; Đorđević, B.; Ranđić, S.; Stamenković, Z. Prediction of Pest Insect Appearance Using Sensors and Machine Learning. *Sensors* 2021, 21, 4846.
- [19] N. Moses-Gonzales and M. J. Brewer, "A Special Collection: Drones to Improve Insect Pest Management," *Journal of Economic Entomology*, vol. 114, no. 5, pp. 1853–1856, Jun. 2021.
- [20] L. Yang, L. Yu, S. Tao, Z. Yang, W. Gao, and Y. Ren, "Identification of Tomato Pests and Diseases Based on Transfer Learning," *Journal of Physics: Conference Series*, vol. 2025, no. 1, pp. 012076–012076, Sep. 2021.

ORIGINALITY REPORT

13%	10%	6%	6%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	assets-eu.researchsquare.com Internet Source	3%
2	Submitted to Daffodil International University Student Paper	2%
3	dspace.daffodilvarsity.edu.bd:8080 Internet Source	2%
4	pubmed.ncbi.nlm.nih.gov Internet Source	1%
5	"Data Engineering and Applications", Springer Science and Business Media LLC, 2024 Publication	<1%
6	dlibrary.univ-boumerdes.dz:8080 Internet Source	<1%
7	V. Sharmila, S. Kannadhasan, A. Rajiv Kannan, P. Sivakumar, V. Vennila. "Challenges in Information, Communication and Computing Technology", CRC Press, 2024 Publication	<1%
8	www.researchsquare.com Internet Source	<1%