A

**Project Report**

**on**

# Detection of Insects and Pests in Agriculture field using MobileNet

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**the Requirement for the Degree of**

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**Computer Science and Engineering**


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**Session 2023-24**

SHRI SANT GAJANAN MAHARAJ COLLEGE OF ENGINEERING,

SHEGAON – 444 203 (M.S.)

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

# CERTIFICATE

This is to certify that **Ms. Gayatri Deshmukh, Ms. Nikita Labade, Mr. Kuldeep Lunge, Mr. Shubham Gorde** students of final year B.E. in the year 2023-24 of Computer Science and Engineering Department of this institute has completed the project work entitled **"Detection of Insects and Pests in Agriculture field using MobileNet"** based on syllabus and has submitted a satisfactory account of his work in this report which is recommended for the partial fulfillment of degree of Bachelor of Engineering in Computer Science and Engineering.

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| | |
|---|---|
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| **Date:** 10/5/2024 | **Date:** 10/5/24 |

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Expressing gratitude to those who provided invaluable guidance throughout our project is of paramount importance to us. Without their cooperation, encouragement, and assistance, completing our task would have been impossible. Numerous individuals warrant recognition for their steadfast support and direction during this endeavor.

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– Projectees

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# ABSTRACT

The Indian economy heavily depends on agriculture, where the quality of crop production holds immense significance. However, the frequent occurrence of pest attacks poses substantial threats by diminishing crop yields and jeopardizing food safety through nutrient depletion. This adversely affects the economy, resulting in significant losses for farmers and endangering lives. Therefore, it is crucial to monitor crops regularly to effectively combat pests, requiring the use of suitable pesticides. Technologies for pest detection play a vital role in early intervention, preventing crop damage and excessive pesticide usage. Artificial intelligence (AI) emerges as a pivotal tool in addressing agricultural challenges. This study focuses on the application of the MobileNetV2 algorithm for classifying pests, utilizing techniques such as image reshaping and feature extraction. The results demonstrate that MobileNetV2 surpasses other pre-trained models, achieving a higher accuracy rate of
0.95. By improving pest detection capabilities, AI-based technologies offer promising solutions to enhance agricultural production and mitigate economic losses.

***Keywords*-- Crop pest detection, Crop insect classification, Image processing**

# Contents

# List of Abbreviations and Symbols

| Symbol/Abbreviation | Particulars |
|---|---|
| *CNN* | Convolutional Neural Network |
| *ANN* | Artificial Neural Networks |
| *DNN* | Deep Neural Network |
| SE | Squeeze-and-excitation |
| *DL* | Deep Learning |
| *TP* | True Positive |
| *FP* | False Positive |
| *FN* | False Negative |
| *TN* | True Negative |

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# CHAPTER 01 INTRODUCTION

# INTRODUCTION

Agriculture stands as the backbone of economies worldwide, serving as a primary source of livelihood for billions of people. Across the globe, nations rely on agricultural activities for sustenance, economic growth, and food security. In countries like India and across Asia, agriculture plays a pivotal role, contributing significantly to the GDP and employing a substantial portion of the population. For instance, in India, agriculture employs over 50% of the workforce and contributes approximately 17-18% to the country's GDP (World Bank, 2023). However, agricultural productivity is consistently threatened by various factors, notably pests and insects. These organisms pose a significant challenge to farmers, leading to substantial yield losses and economic setbacks.

## 1.1 Overview

Pests and insects inflict immense damage to agricultural crops, resulting in staggering economic losses worldwide. In India and other Asian countries, where agriculture forms the backbone of the economy, the impact of pest damage is particularly pronounced. For instance, in India alone, crop losses due to pests and diseases are estimated to range from 20% to 30% annually (Department of Agriculture, Cooperation & Farmers Welfare, 2022). This loss not only affects farmers' livelihoods but also contributes to food insecurity and economic instability. Managing pest infestations is a complex task aggravated by various factors such as climate change, globalization, and pesticide resistance. Traditional methods of pest detection, including visual inspection and manual monitoring, are labor-intensive and often inefficient, leading to delayed intervention and increased crop damage. Hence, there is a pressing need for advanced technologies to enhance pest detection and management strategies.

Recent advancements in deep learning and machine learning, particularly Convolutional Neural Networks (CNNs), have revolutionized pest detection in agriculture. CNNs, inspired by the human visual system, excel at image recognition tasks, making them well-suited for identifying pests and insects from images captured in agricultural fields. By leveraging large datasets of labeled images, CNNs can learn intricate patterns and features, enabling accurate and efficient detection of pests across various crops and environments. Additionally, machine learning algorithms, such as Support Vector Machines (SVM) and Random Forests, complement CNNs by providing robust classification models for pest detection. These algorithms utilize features extracted from images to classify pests and distinguish them from benign elements in the agricultural landscape. Moreover, the integration of remote sensing technologies, including drones and satellite imagery, further enhances the scope and efficiency of pest detection in large-scale agricultural operations.

The effective detection and management of pests and insects in agriculture are critical for ensuring food security, sustaining livelihoods, and fostering economic growth. With the advent of advanced technologies like CNNs and machine learning algorithms, farmers and policymakers have powerful tools at their disposal to mitigate the impact of pests and safeguard agricultural productivity. However, continued research, investment, and collaboration are essential to harnessing the full potential of these technologies and addressing the complex challenges posed by pests in agriculture. The genesis of this project stems from a profound recognition of the shortcomings of traditional pest detection methods. Historically reliant on manual labor or chemical interventions, these approaches are labor-intensive, costly, and often environmentally detrimental. MobileNet, however, offers a paradigm shift, leveraging advancements in machine learning and computer vision to automate and enhance the accuracy and efficiency of pest detection. By harnessing the power of convolutional neural networks, MobileNet demonstrates remarkable potential in transforming the way we perceive and mitigate agricultural pests. Within the confines of this report, we embark on a journey of exploration and discovery, delving into the intricacies of MobileNet-based pest detection systems. From the inception of the project to its implementation and evaluation, each stage is meticulously documented, offering insights into the methodologies, challenges, and outcomes encountered along the way. By elucidating the technical intricacies and empirical findings, this report not only serves as a testament to the efficacy of MobileNet in pest detection but also paves the way for future research and innovation in the realm of sustainable agriculture. As we navigate the intersection of technology and agriculture, let this report stand as a beacon of hope, inspiring stakeholders to embrace innovation and collaboration in safeguarding the future of our agricultural systems.

## 1.2 Motivation:

This project report is propelled by the urgency to address the pressing challenges gripping global agriculture. With alarming statistics indicating that pests annually destroy up to 40% of global food crops, leading to an estimated $220 billion in losses, the need for effective pest management solutions has never been more critical. Amidst these daunting figures, this project seeks to innovate and implement strategies that not only curb these losses but also pave the way for sustainable agricultural practices, ensuring food security for present and future generations.

## 1.3 Problem Statement:

In agriculture, where visual data is crucial for monitoring crop health, the sheer volume of images poses a challenge in efficiently identifying pests and insects. This project addresses the pressing need for effective pest detection in agricultural fields by leveraging deep learning techniques. The aim is to enhance the accuracy and speed of pest identification, enabling timely intervention measures to protect crop yield and quality.

## 1.4 Objectives:

1. To develop an efficient deep learning model for insect and pest detection in agriculture.

2. To create a precise search engine to identify pest images based on color, texture, and shape .

3. To build a fast retrieval system for swift results in large agricultural images databases.

4. To design a scalable search engine to manage high volumes of agricultural images.

## 1.5 Scope and Limitations

### 1.5.1 Scope

i. **Agriculture :** This entails creating a system capable of early pest detection in agricultural settings, with the aim of reducing crop damage and enhancing pest management practices. By leveraging technologies like image processing and machine learning, the system would identify pests in crops, aiding farmers in implementing timely interventions.

ii. **Environmental Monitoring :** Expanding beyond agriculture, the system could be adapted to monitor environmental conditions in various contexts. For instance, it could be utilized to detect invasive species in natural habitats by analyzing collected data such as images or sensor readings. Additionally, it could be employed for monitoring urban green spaces to assess biodiversity or identify ecological changes.

iii. **Forestry Management :** The system would be tailored to monitor forest health, particularly focusing on the early detection of insect outbreaks and pests that pose threats to forests. Through the analysis of environmental data and imagery, it would assist forest managers in implementing proactive measures to mitigate pest-related damage and preserve forest ecosystems.

iv. **Urban Pest Control :** In urban environments, the technology would be utilized for the detection and management of pests in parks, gardens, and other green spaces. By deploying sensors and image recognition systems, it would enable authorities to identify pest infestations early and take targeted pest control actions, thereby improving the quality of urban landscapes.

v. **Food Safety :** Applied in food processing facilities and warehouses, the system would play a crucial role in ensuring food safety by detecting and preventing contamination by pests. By continuously monitoring the premises with sensors and cameras, it would identify potential pest-related risks, enabling prompt interventions to maintain food quality and hygiene standards.

### 1.5.2 Limitations

i. Pest detection models may struggle with accurately identifying insects in complex or cluttered agricultural environments, where visual cues may be obscured or ambiguous.

ii. Performance of pest detection algorithms might degrade with low-quality or distorted images, or in scenarios where the dataset lacks diversity or representative samples.

iii. Pest detection systems may struggle to infer contextual information from images, limiting their effectiveness in applications requiring semantic understanding, such as pest behavior analysis or ecological impact assessment.

iv. Scalability and real-time responsiveness may be hindered in pest detection.

## 1.5 Organization of Project

Chapter 1: Gives an overview of the project and its objectives.

Chapter 2: Surveys existing research and studies related to the project topic, providing background information and insights.

Chapter 3: Explains the materials, tools, and techniques used to conduct the project, detailing the methodology followed.

Chapter 4: Describes the design process and practical implementation of the project, including any software or hardware development.

Chapter 5: Presents the findings and outcomes of the project, including data analysis and interpretations.

Chapter 6: Summarizes the project's achievements, discusses implications of the results, and outlines potential future research directions and improvements.

# CHAPTER 02
# LITERATURE REVIEW

# LITERATURE REVIEW

Dan Popescu1, Alexandru Dinca1, Loretta Ichim1, Nicoleta Angelescu2 Sec. Technical Advances in Plant Science Volume 14 - 2023 |https://doi.org/10.3389/fpls.2023.1268167

[1] This research article explores the application of deep learning techniques, particularly MobileNetV2 architecture, in the field of insect pest detection and management within agriculture. It delves into the integration of MobileNetV2 and integrated structures to develop highly efficient and sustainable techniques for early detection, monitoring, and classification of insect pests. Through the utilization of convolutional neural networks (CNNs) and image processing, the study investigates the feasibility of automating pest detection processes, aiming to alleviate the challenges posed by manual labor limitations and the significant economic impact of pest damage on agricultural productivity. The article highlights the importance of precision techniques, such as those based on MobileNetV2, in providing accurate and timely pest detection and management solutions. Additionally, it emphasizes the adoption of integrated pest management (IPM) practices and the potential for MobileNetV2-driven technologies to contribute to sustainable agriculture by reducing pesticide usage and mitigating environmental risks associated with pest control.

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[3] This research paper discusses advancements in crop pest detection using machine learning and deep learning techniques. It emphasizes the need for effective pest management in maintaining crop quality and productivity. By employing methods such as Random Forest, Support Vector Machine, Decision Tree, Naive Bayes, Convolutional Neural Network, Deep convolutional neural network, the study aims to develop efficient tools for diagnosing pest diseases before significant crop loss occurs. The research emphasizes automated monitoring to boost productivity and lessen human workload in agriculture. It explores modern techniques for pest detection.

Leveraging Convolutional Neural Networks for Smart Agriculture. Nagaraj G Sethu Institute of Technology,Mohit Tiwari Bharati Vidyapeeth College of Engineering, Delhi, Vandana Ahuja, Dakshinamurthy Sungeetha.

[7] This research article discusses the use of deep learning, particularly MobileNetV2, for identifying plant diseases and pests through digital image processing. It addresses the challenges in diagnosing plant pathogens and pests and evaluates different diagnostic approaches. The study presents a CNN-based framework using MobileNetV2 to detect pest-borne diseases in tomato leaves, achieving an impressive accuracy of 93% and surpassing other models like GoogleNet and VGG16 in terms of speed. This research contributes to smart agriculture by offering an effective solution for pest detection and control.

[5] The paper compares detection algorithms for identifying rotating pests in diverse environments. It finds rotation detection significantly outperforms horizontal detection, improving Precision by 18.5% and Recall by 7.4%. The rotation model is fast (0.163s) and compact (66.54MB), ideal for mobile deployment. This underscores rotation detection's efficacy in pest recognition, promising advancements in plant protection and grain yield.

[9] This paper delves into the application of deep learning techniques for the identification and categorization of agronomic pests, aiming to enhance pest control strategies in agriculture. It critically assesses various methodologies and strategies used for pest detection, highlighting the effectiveness of machine learning and deep learning in prior research. The analysis considers both advantages and limitations of different approaches, addressing potential challenges in insect detection via image processing. Finally, the paper offers insights into the future direction of pest detection and classification using deep learning, with a focus on crops like peanuts.

# CHAPTER 03
# WORKING METHODOLOGY

# WORKING METHODOLOGY

Convolutional Neural Networks (CNNs) are a class of deep learning models designed specifically for processing and analyzing visual data, such as images and videos. CNNs have revolutionized fields like computer vision, image recognition, and medical imaging due to their ability to learn hierarchical representations of visual features directly from raw input data. Artificial neural networks, which consist of network structures with multiple hidden layers, serve as the foundation of deep learning. When it comes to categorizing still images, the Convolutional Neural Network (CNN) model is commonly employed. The development of the backpropagation algorithm was a pivotal advancement in artificial neural network research, overcoming bottlenecks and facilitating progress in social science and technology. The learning capability of artificial neural networks deepens progressively, allowing them to adapt to increasingly complex data computations. Convolution kernels, a form of shared weights utilized by neurons within the same feature plane, play a crucial role. Through iterative learning during network training, convolution kernels adjust their weights appropriately, while weight sharing reduces the number of connections across all network levels, thereby minimizing fitting risks. Databases play a crucial role in image classification, especially in today's deep learning-dominated landscape. The quality of the trained model is significantly influenced by the quality of the database, emphasizing the importance of uniform positioning of images within the training and test sets.

To enhance the performance of deep convolutional neural networks, which are characterized by their depth (number of layers) and breadth (number of nodes in each layer), efforts focus on increasing both dimensions. Deep learning emphasizes the importance of learning features at various levels, transitioning from low-level to high-level features. By constructing multi-layer networks where the output of one hidden layer serves as the input for another, complex function problems can be addressed with relatively few parameters. Cooperative training algorithms, initially developed for multiview data, have evolved to leverage various classification learning algorithms, data sampling techniques, and parameter settings to optimize performance, even with single-view data.

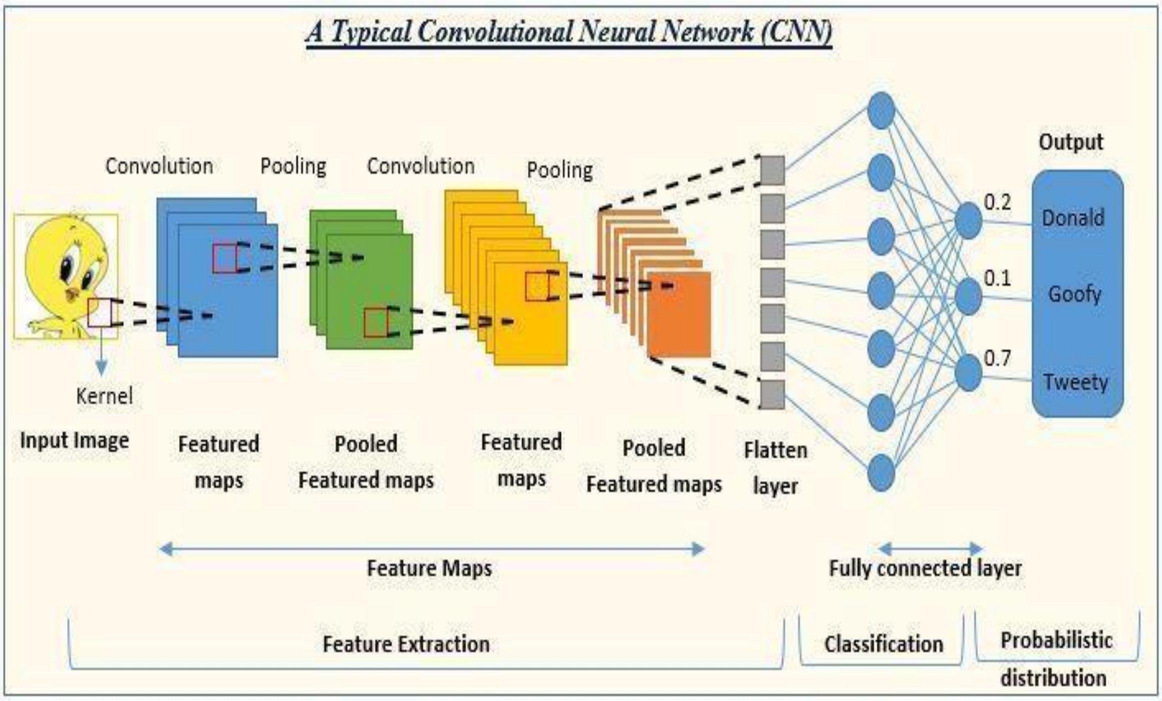


Figure 3 : A Typical Convolutional Neural Network(CNN)

## 3.1 Model MobileNetV2:

MobileNetV2 stands as a pivotal advancement in convolutional neural network (CNN) architectures, specifically tailored for mobile and embedded vision applications. Engineered by Google researchers as an iteration of the original MobileNet, this model excels in finding an optimal equilibrium between model complexity and accuracy, thereby making it an ideal choice for devices constrained by computational resources. The architecture of MobileNetV2 integrates several key features, including depthwise separable convolution, inverted residuals, bottleneck design, linear bottlenecks, and squeeze-and-excitation (SE) blocks, each meticulously crafted to enhance efficiency and efficacy in image classification tasks.

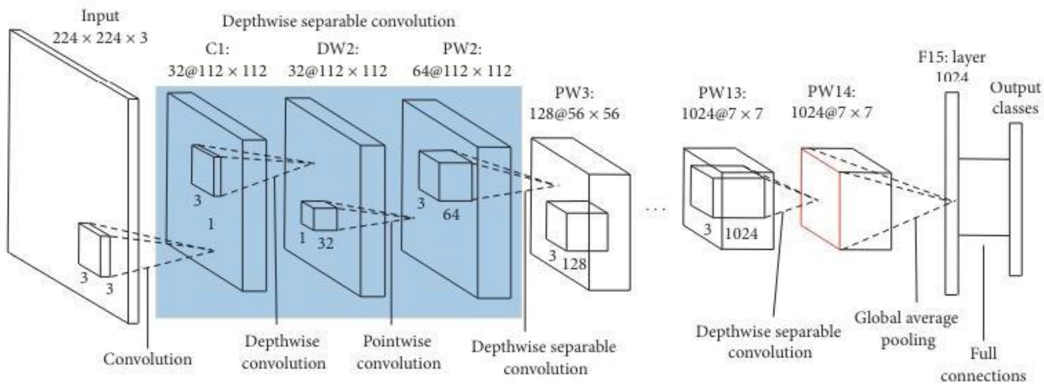


Figure 3.1 : Depthwise separable convolution

Depthwise separable convolution, a cornerstone of MobileNetV2's architecture, revolutionizes traditional convolutions by splitting them into two distinct operations: depthwise convolution and pointwise convolution. This separation significantly reduces computational overhead, making the model more efficient for deployment on resource-constrained devices. Inverted residuals introduce a bottleneck structure that expands channel dimensions before applying depthwise separable convolutions, enabling the model to capture richer and more intricate features, thereby bolstering its representational prowess. Furthermore, the bottleneck design in MobileNetV2 strategically employs 1×1 convolutions to diminish channel dimensions prior to depthwise separable convolutions, thereby further curbing computational costs while maintaining accuracy. Linear bottlenecks, by utilizing linear activations instead of non-linear ones, mitigate information loss during the bottleneck process, thereby preserving critical details and enhancing the model's capacity to discern fine-grained distinctions. Squeeze-and-excitation (SE) blocks further augment feature representation by dynamically recalibrating channel-wise responses, facilitating the model to prioritize salient features and attenuate less pertinent ones, thus refining its discriminative capabilities.

Preparation of data precedes the training of MobileNetV2, necessitating meticulous preprocessing of images, partitioning of datasets into training and validation sets, and application of data augmentation techniques to fortify the model's generalization abilities. MobileNetV2 incorporates linear bottlenecks within each inverted residual block. These bottlenecks consist of a lightweight depthwise convolution layer, which efficiently extracts spatial information, followed by a pointwise convolution layer for dimensionality reduction. By using these linear bottlenecks, MobileNetV2 reduces the computational cost of processing while maintaining the capacity to capture meaningful features from the input data. This design choice not only enhances the efficiency of the network but also ensures that it can be deployed on devices with limited computational resources without sacrificing performance. This expanded representation is then projected back down to a lower-dimensional space through a depthwise convolution, followed by a pointwise convolution. This process enables MobileNetV2 to effectively capture intricate patterns while minimizing computational overhead, making it well-suited for resource-constrained environments.

Additionally, MobileNetV2 features a streamlined architecture with shortcut connections and carefully designed network parameters. These architectural choices enable faster convergence during training and better generalization on various visual recognition tasks. By incorporating shortcut connections, MobileNetV2 facilitates the flow of gradients during backpropagation, which enhances training stability and accelerates convergence. Moreover, the carefully optimized network parameters strike a balance between model complexity and performance, resulting in a versatile convolutional neural network architecture that excels in both efficiency and accuracy on mobile and embedded platforms. Moreover, transfer learning emerges as a ubiquitous strategy employed with MobileNetV2, leveraging pre-trained models on extensive datasets to expedite training and imbue the model with knowledge accrued from the source dataset. Initialization with pre-trained weights accelerates the training process and empowers the model to swiftly converge towards optimal performance, thereby underscoring the versatility and efficacy of MobileNetV2 in real-world applications across diverse domains.

## 3.2 Architecture of Insects and Pests Detection

The architecture described in the provided code snippets is geared towards the detection of insects and pests in agricultural fields using convolutional neural networks (CNNs). It employs a combination of data augmentation, image preprocessing, convolutional layers, max-pooling layers, dropout regularization, and dense layers for classification. Here's a detailed explanation: The model begins with data augmentation, a technique used to increase the diversity of training examples by applying random transformations to the input images. This helps the model generalize better by exposing it to a wider range of variations in the input data. Subsequently, the pixel values of the images are rescaled to the range [0, 1] using the Rescaling layer from TensorFlow's experimental preprocessing module. The MobileNetV2 backbone then begins with a series of convolutional layers, aiming to capture low-level features such as edges and textures.

- **Feature Extraction**: The initial layers of the network, comprising convolutional and max-pooling operations, serve to extract hierarchical features from input images. These operations progressively reduce spatial dimensions while increasing the number of channels, allowing the network to learn more abstract representations.

- **Convolutional Layers**: The convolutional layers, such as conv2d_4, conv2d_5, and conv2d_6, apply filters to the input images to detect various features at different levels of abstraction. These filters learn to identify patterns relevant to insect and pest detection, such as specific colors, shapes, or textures.

- **Pooling Layers**: Max-pooling layers like max_pooling2d_4, max_pooling2d_5, and max_pooling2d_6 reduce the spatial dimensions of the feature maps, helping to extract the most salient features while reducing computational complexity and preventing overfitting.

- **Regularization**: The dropout layer (dropout) helps prevent overfitting by randomly dropping a fraction of the neurons' outputs during training, forcing the network to learn more robust features.

- **Flattening**: The flatten layer (flatten_1) reshapes the multi-dimensional feature maps into a one-dimensional vector, preparing them for input into the fully connected layers.

- **Fully Connected Layers**: The dense layers (dense_2 and dense_3) perform classification based on the extracted features. These layers learn to map the high-dimensional feature representations to the final output classes, in this case, potentially different types of insects or pests commonly found in agricultural settings.

The subsequent layers constitute the core CNN architecture responsible for feature extraction and classification. The convolutional layers (`Conv2D`) apply a set of learnable filters to the input images, extracting features such as edges, textures, and patterns that are relevant for identifying insects and pests. Each convolutional layer is followed by a max-pooling layer (`MaxPooling2D`), which reduces the spatial dimensions of the feature maps while retaining the most important information. This hierarchical process allows the network to capture both local and global features at multiple scales.

To prevent overfitting, a dropout layer (`Dropout`) is incorporated after the last max-pooling layer. Dropout randomly deactivates a fraction of neurons during training, forcing the network to learn more robust features and reducing the likelihood of memorizing noise or irrelevant details in the training data.

Following the dropout layer, the feature maps are flattened into a one-dimensional vector, ready to be fed into the dense layers (`Dense`). These fully connected layers perform the actual classification task by learning to map the extracted features to the different classes of insects and pests. The number of neurons in the output layer matches the number of classes (`num_classes`), and the model is trained using the Sparse Categorical Crossentropy loss function and the Adam optimizer.

Overall, this architecture combines techniques such as data augmentation, convolutional feature extraction, pooling for spatial reduction, regularization to prevent overfitting, and dense layers for classification, making it well-suited for the task of detecting insects and pests in agricultural images. Through training on labeled data and fine-tuning of parameters, the model aims to accurately classify images and assist farmers in identifying and managing potential threats to their crops.

# CHAPTER 04

# DESIGN AND IMPLEMENTATION

# DESIGN AND IMPLEMENTATION

The web application for pest detection targeting non-technical farmers should prioritize simplicity and ease of use in its design. The user interface (UI) should feature intuitive navigation with clear, non-technical language, ensuring that even those with limited technical proficiency can easily navigate the platform. Upon logging in, farmers should be greeted with a clean dashboard displaying concise, actionable information such as recent pest alerts and weather updates. The core functionality of the application lies in its pest detection tool, allowing farmers to either upload images of their crops or capture them directly through their device's camera. The system should then analyze these images and provide straightforward results indicating the presence of pests, accompanied by easy-to-understand recommendations for treatment or preventive measures. Additionally, the application should include an educational section offering resources on common pests and effective management strategies. Implementing a notification system for important updates and providing accessible support channels further enhances the user experience. Ensuring mobile compatibility allows farmers to access the application conveniently from their smartphones or tablets while working in the field, ultimately empowering them to better manage pest issues and improve crop yields.

## 1.1 Design Strategy

- **Data Collection:** Data collection plays a crucial role in the detection of insects and pests in agriculture fields, providing essential insights into the prevalence, distribution, and severity of pest infestations. Various methods are employed to gather data, including visual observation, trapping techniques, and sensor-based monitoring systems. Visual observation involves physically inspecting crops for signs of pest damage, such as holes in leaves or discolored patches, while trapping techniques utilize traps baited with pheromones or other attractants to capture and identify specific pests. Sensor-based monitoring systems, including drones equipped with cameras or sensors, can cover larger areas more efficiently, collecting data on pest activity and crop health. Additionally, data from weather stations and satellite imagery can be integrated to identify environmental factors influencing pest populations. The collected data is then analyzed to assess pest risks, inform pest management strategies, and make data-driven decisions to minimize crop damage and optimize yields. Effective data collection is essential for early pest detection, timely intervention, and sustainable agricultural practices

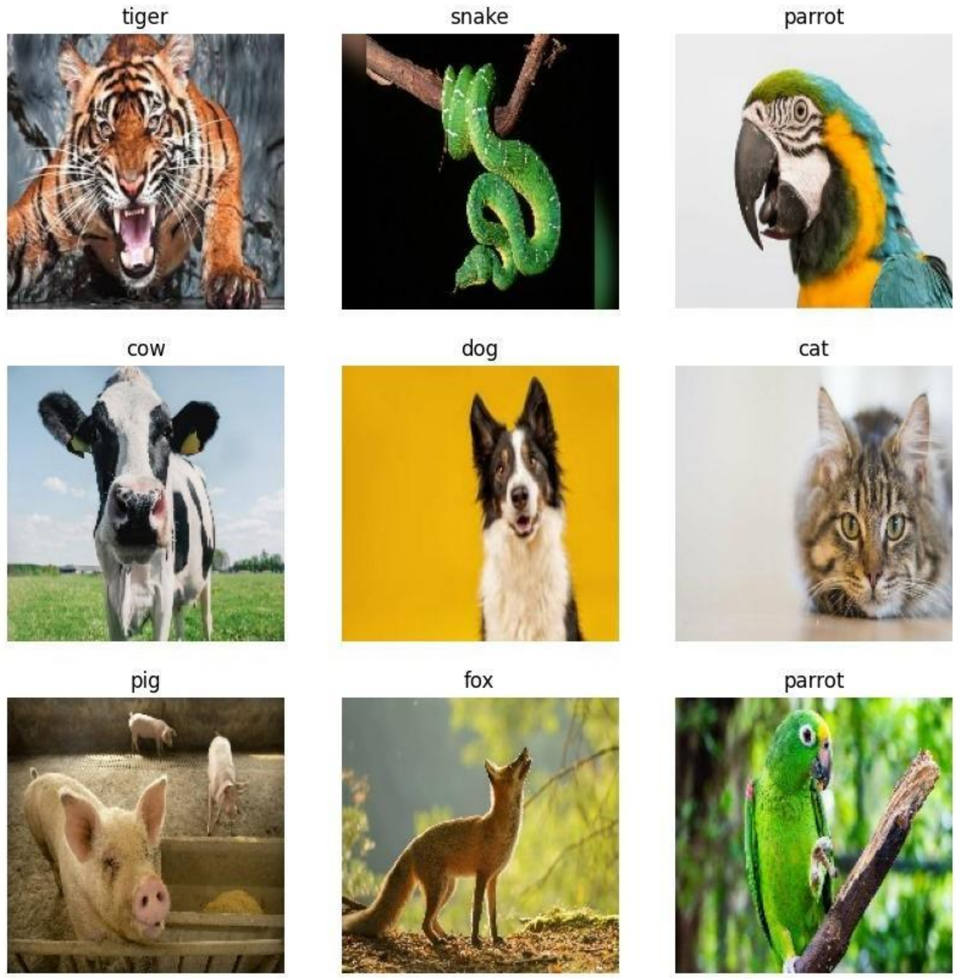


Figure 4.1.1 : Dataset use in detection of insects and pests

- **Data Preprocessing:** In the domain of insect and pest detection in agricultural settings, data preprocessing assumes a pivotal role, with a focus on factor resolution and the elimination of redundant or insignificant variables. This preprocessing phase involves intricate procedures to resolve complex factors such as environmental parameters, crop health indicators, and pest characteristics into discernible features. By meticulously resolving these factors, the dataset is refined to contain only the most pertinent information, optimizing the input for subsequent analysis. Furthermore, the identification and removal of superfluous features are imperative to streamline the data for processing by Convolutional Neural Networks (CNNs), a technique widely utilized for its efficacy in image analysis tasks. Through meticulous preprocessing, the data undergoes transformation to a format conducive to CNNs' capacity for feature extraction and pattern recognition from images. This intricate preprocessing framework ultimately fosters enhanced accuracy and efficacy in pest detection, empowering agricultural stakeholders with invaluable insights for proactive pest management strategies.

- **Feature Extraction:** In the context of insect and pest detection in agricultural environments, feature detection assumes a critical role, particularly in conjunction with Convolutional Neural Network (CNN) methodologies. The preprocessing phase involves intricate manipulation of data to enhance factor resolution and identify salient features relevant to pest identification. Techniques such as softness gradient analysis, border color detection, and texture extraction are employed to discern subtle variations in crop imagery indicative of pest presence or damage. Moreover, through the integration of CNNs, these features are systematically analyzed and weighted, enabling the network to discern complex patterns and associations within the data. By optimizing feature detection through meticulous preprocessing, the CNN framework can effectively differentiate between relevant and extraneous information, thereby enhancing the accuracy and reliability of pest detection mechanisms in agricultural contexts.

**Model Selection:** In the domain of insect and pest detection within agricultural contexts, the meticulous selection of a model is imperative, with MobileNetV2 standing out as a compelling choice. When it comes to insect and pest detection in agricultural contexts, the meticulous selection of a model is paramount, with MobileNetV2 emerging as an exemplary choice. Renowned for its lightweight architecture and superior efficiency, MobileNetV2 proves highly adept at image classification tasks, even in resource-constrained agricultural environments. Its streamlined design facilitates rapid inference, making it practical for real-time deployment in the field. Additionally, MobileNetV2 showcases exceptional adaptability to diverse input data, effectively capturing nuanced features indicative of pest presence or crop damage with remarkable precision.

Furthermore, researchers are exploring ensemble learning techniques, where multiple models are combined to enhance predictive performance. By leveraging the strengths of different models, ensemble approaches offer improved robustness and reliability in pest detection, crucial for ensuring agricultural resilience.

- **Training**: In the development of a robust system for the detection of insects and pests in agricultural settings, a comprehensive training phase is paramount. With a training-testing ratio of approximately 80:20, the bulk of the data is dedicated to training the model, allowing it to learn and adapt to the intricate patterns and features present in agricultural imagery indicative of pest infestations. During this phase, the model undergoes iterative optimization, adjusting its parameters to minimize errors and enhance its ability to accurately identify pests. Through exposure to a diverse range of training samples, the model can effectively discern between healthy crops and those affected by pests, laying the foundation for accurate detection in real-world scenarios.
- **Testing**: Following the rigorous training phase, the model undergoes thorough testing to evaluate its performance and generalization capabilities. Utilizing approximately 20% of the data for testing purposes ensures an independent validation of the model's effectiveness in detecting pests in unseen images. During testing, the model's performance metrics, such as accuracy, precision, and recall, are carefully assessed to gauge its ability to accurately identify pest infestations while minimizing false positives and false negatives. By subjecting the model to diverse testing scenarios, its robustness and reliability in real-world agricultural applications can be verified, providing crucial insights into its readiness for deployment.
- **Deployment**: Upon successful completion of training and testing phases, the meticulously developed model is ready for deployment in operational agricultural environments. Equipped with the ability to accurately detect insects and pests, the

deployed model serves as a valuable tool for farmers and agricultural practitioners, aiding in the timely identification and mitigation of pest infestations. Through seamless integration into existing agricultural workflows, the deployed model empowers stakeholders to make informed decisions regarding pest management strategies, ultimately contributing to improved crop yields, reduced economic losses, and enhanced sustainability in agricultural practices.

In the detection of insects and pests project, the journey from training to deployment involves a meticulous process aimed at ensuring the model's effectiveness in real-world scenarios. Initially, the training phase begins with the collection of diverse datasets containing images of various insects and pests, along with their corresponding labels. These datasets are then preprocessed to standardize image sizes, remove noise, and augment data to enhance model robustness. Using convolutional neural networks (CNNs) like MobileNetV2, the model is trained on this data to learn distinctive features indicative of different insect species and pest types. During training, the model iteratively adjusts its internal parameters through backpropagation, minimizing the disparity between predicted and actual labels, thereby improving its accuracy over successive epochs.

Following training, the model undergoes rigorous testing to evaluate its performance on unseen data. This involves partitioning the dataset into training, validation, and test sets to assess the model's generalization capability. Metrics such as precision, recall, and F1 score are computed to quantify the model's accuracy, ensuring its ability to correctly identify insects and pests while minimizing false positives and false negatives. Any discrepancies or deficiencies identified during testing prompt fine-tuning of the model architecture and hyperparameters to optimize its performance further. Once the model demonstrates satisfactory performance during testing, it is ready for deployment. In deployment, the trained model is integrated into a user-friendly application or system capable of capturing and processing real-time images of crops or fields. This deployed model continuously monitors agricultural environments, swiftly detecting and identifying any signs of insect infestation or pest presence, empowering farmers to take timely preventive measures and safeguard their crops effectively.

## 1.2 implementation Strategy

In this implementation, a sophisticated system for pest and insect detection in agricultural fields is introduced, leveraging advanced image processing techniques and deployed using the TensorFlow framework. The system is meticulously designed to empower users to upload images of pests encountered in agricultural settings, ranging from beetles to grasshoppers and ants, and receive accurate predictions regarding the presence of specific insects. Through the utilization of image processing methodologies, including image enhancement, segmentation, feature extraction, and classification, the system adeptly analyzes uploaded images to discern crucial features and characteristics indicative of different pests.

### 1.2.1 Libraries And Software Platform Used:

Keras is an open-source neural network library written in Python. It is designed to provide a user-friendly interface for building deep learning models with support for convolutional neural networks, recurrent neural networks, and other common architectures. Keras is built on top of TensorFlow, allowing it to leverage the underlying computational graph capabilities of TensorFlow.

It has become a popular choice for both beginners and experienced deep learning practitioners due to its simplicity, flexibility, and ease of use. Keras also provides pre-trained models for a wide range of tasks, making it easy to start building high-performing models without requiring extensive domain expertise. Keras is a Python-based high-level neural network API that can run on top of popular deep learning frameworks such as TensorFlow, Microsoft Cognitive Toolkit, and Theano. It was created with the goal of allowing for rapid experimentation and prototyping of deep learning models.

Keras provides a simple and intuitive interface for building neural networks, including support for convolutional neural networks (CNN), recurrent neural networks (RNN), and combinations of the two. It also includes a wide range of pre-trained models, which canbe used for a variety of tasks such as image classification, object detection, and natural language processing. One of the key features of Keras is its ability to run seamlessly on both CPU and GPU, allowing for fast training and inference of deep learning models. It also includes a range of tools for data preparation and preprocessing, such as data normalization, data augmentation, and feature scaling. Keras has gained widespread popularity in the deep learning community due to its ease of use, flexibility, and scalability. It has become one of the most widely used deep learning frameworks in both academia and industry.

**TensorFlow** : TensorFlow reigns as a cornerstone deep learning framework renowned for its prowess in developing and training neural network models. Providing a high-level interface, TensorFlow facilitates the creation of intricate neural network architectures while efficiently managing vast datasets. Its versatility and scalability make it an ideal choice for developing sophisticated systems like the pest detection application. Leveraging TensorFlow's capabilities, developers can effortlessly construct and deploy robust models tailored to specific tasks.

**NumPy** : As a fundamental library in Python, NumPy plays a pivotal role in handling numerical computations and data manipulation tasks. Its robust support for large arrays and matrices, coupled with an extensive array of mathematical functions, makes it indispensable in various machine learning projects. Within the pest detection system, NumPy serves to manipulate and preprocess image data, enabling efficient data reshaping and mathematical operations crucial for model development and evaluation.

**OpenCV (cv2)** : OpenCV is a popular library for computer vision tasks. In the context of detecting insects and pests in agriculture, OpenCV can be used for tasks such as image preprocessing, object detection, and image analysis. It provides various functions for image manipulation, feature extraction, and pattern recognition, which are essential for identifying insects and pests in images captured from agricultural fields.

**Matplotlib** : Matplotlib is a plotting library in Python that can be used to visualize data and images. In the context of insect and pest detection in agriculture, Matplotlib can be used to display images before and after processing, visualize the results of object detection algorithms, and plot graphs or histograms related to image analysis. Visualizations provided by Matplotlib can aid in understanding the effectiveness of detection algorithms and in presenting the results to stakeholders.

**Shutil :** The shutil module in Python provides functions for file operations, such as copying, moving, and deleting files and directories. In the context of insect and pest detection in agriculture, shutil may be used to manage image datasets, organize files into appropriate directories for training machine learning models, or move processed images to different folders based on their classification results.

**Random :** The random module in Python provides functions for generating random numbers and selecting random elements from lists or sequences. In the context of insect and pest detection in agriculture, the random module can be used for tasks such as randomizing the order of images in a dataset to prevent bias during training, generating random samples for validation or testing purposes, or introducing randomness in certain algorithms to improve their robustness.

These libraries can be utilized together to develop and implement computer vision algorithms for detecting insects and pests in agricultural fields. OpenCV provides the core functionality for image processing and analysis, while Matplotlib helps visualize the results. shutil assists in managing image datasets, and random can be used for various tasks involving randomness in the detection process. Integrating these libraries effectively can enhance the accuracy and efficiency of insect and pest detection systems in agriculture.

# CHAPTER 05
# RESULT AND DISCUSSION

# RESULT AND DISCUSSION

The dataset employed in this study was sourced from Kaggle, a publicly accessible platform renowned for its diverse datasets. It encompasses a collection of images categorizing twelve distinct classes of pests commonly found in agricultural settings. A total of approximately 5000 images were amassed for both training and testing purposes, facilitating the evaluation of a pre-existing MobileNet v2 model's efficacy in pest classification. To ensure a comprehensive assessment, the dataset was partitioned into training and testing sets, with approximately 79.96% of the data allocated for training and the remaining 20.04% reserved for testing. This entailed training the model on the designated training data and subsequently validating its performance on the independent testing dataset to ascertain its proficiency in accurately discerning different pest types. The classification accuracy of the model was calculated using the standard formula, considering true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN). Specifically, TP denoted correctly classified instances of pests, while FN represented misclassifications of present pests. Conversely, TN indicated correct rejections of absent pests, with FP signifying erroneous identifications of non-existent pests within the images.

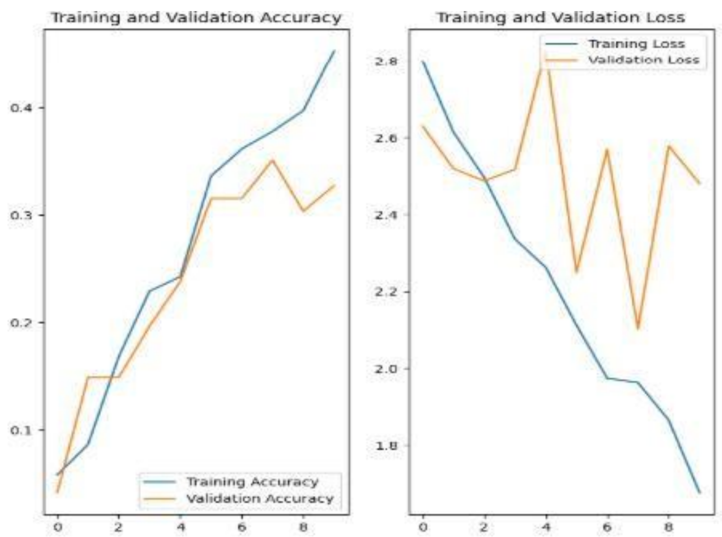


Figure 5.1 : Validation Accuracy and Validation Loss Graph

Epoch 10 served as a pivotal checkpoint in the model's training process, offering crucial insights into its progression and performance metrics. The Training Loss metric quantified the disparity between predicted and actual values encountered during training, with lower values indicating effective parameter adjustments to minimize discrepancies. Meanwhile, Training Accuracy gauged the model's proficiency in learning inherent data patterns by reflecting the percentage of accurately classified instances within the training dataset. Validation metrics, including Validation Loss and Validation Accuracy, further assessed the model's generalization ability to unseen data. A low Validation Loss suggested the model's resilience against overfitting, while a high Validation Accuracy underscored its capability to generalize effectively. These epoch-based metrics provided researchers with invaluable feedback to optimize the model's predictive prowess and refine its deployment for practical applications in agricultural pest detection.

# CHAPTER 06
# CONCLUSION

# CONCLUSION

In the realm of pest detection in agriculture, Convolutional Neural Networks (CNNs) and MobileNet models have emerged as indispensable tools, revolutionizing the way pests are identified and managed in agricultural landscapes. CNNs, with their ability to learn intricate patterns and features from large datasets of labeled images, offer unparalleled accuracy and efficiency in pest recognition. These deep learning models excel at detecting subtle visual cues indicative of pest presence, enabling farmers to intervene promptly and mitigate crop damage. By leveraging CNNs, agricultural stakeholders can streamline pest management practices, minimize pesticide usage, and optimize crop yields, thereby fostering sustainable agriculture and food security.

Furthermore, MobileNet models represent a significant advancement in pest detection technology, particularly in resource-constrained environments such as rural areas. With their lightweight architecture and efficient computational performance, MobileNet models can be deployed on mobile devices and edge computing platforms, bringing pest detection capabilities directly to the field. This accessibility empowers farmers with real-time insights into pest infestations, enabling timely decision-making and targeted interventions. By harnessing the power of MobileNet models, agricultural communities can overcome logistical barriers and enhance resilience against pest-related challenges, ultimately contributing to the resilience and prosperity of the agricultural sector.

## 6.1 Future Scope

The future scope of this project encompasses a myriad of possibilities, poised to revolutionize pest management practices and environmental monitoring across diverse domains. In agriculture, the system holds promise for further refinement, potentially integrating with precision agriculture technologies to enable even more targeted interventions. This could involve the development of predictive models that anticipate pest outbreaks based on weather patterns, soil conditions, and historical data, empowering farmers to adopt proactive strategies for pest control. Additionally, advancements in drone technology could enhance the system's capabilities, enabling autonomous aerial surveillance of vast agricultural landscapes and providing real-time insights for decision-making.

Beyond agriculture, the project's impact extends to environmental monitoring efforts, offering invaluable support in the conservation and management of natural habitats. With ongoing climate change and the increasing threat of invasive species, there is a growing need for innovative solutions to safeguard ecosystems. The system could be augmented to detect and track invasive species in real-time, aiding conservationists and policymakers in implementing timely interventions to mitigate ecological disruptions. Furthermore, advancements in machine learning algorithms could enable the system to analyze complex environmental data sets, uncovering hidden patterns and facilitating a deeper understanding of ecosystem dynamics.

Moreover, the project holds significant potential for applications in urban environments, particularly in the realm of pest control and green space management. As cities continue to expand and green spaces become more integral to urban life, the need for effective pest management strategies becomes paramount. The system could be leveraged to monitor and manage pests in parks, gardens, and other urban green spaces, enhancing the quality of urban environments and promoting sustainable urban development. Additionally, it could support efforts to mitigate the spread of vector-borne diseases by identifying and controlling pest populations in urban areas.

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# Detection of Insects and Pests in Agriculture field using MobileNet

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***Abstract: The Indian economy heavily relies on agriculture, with high-quality crop production playing a pivotal role. However, frequent pest attacks pose significant threats by reducing crop yields and compromising food safety through nutrient depletion. This adversely impacts the economy, leading to substantial losses for farmers and risking lives. Timely monitoring of crops is imperative to combat pests effectively, necessitating the use of appropriate pesticides. Pest detection technologies can aid in early intervention, preventing crop damage and pesticide overuse. Artificial intelligence (AI) emerges as a crucial tool in addressing agricultural challenges. This research focuses on utilizing the MobileNetV2 algorithm for pest classification, leveraging image reshaping and feature extraction techniques. Results indicate MobileNetV2 outperforms other pre-trained models, achieving a higher accuracy of 0.95. By enhancing pest detection capabilities, AI-based technologies offer promising solutions to bolster agricultural production and mitigate economic losses.***
***Keywords: Crop pest detection, Crop insect classification, Image processing***

## I. INTRODUCTION

Agriculture stands as a cornerstone of global economies, contributing significantly to both GDP and employment worldwide. Despite its modest share of 4.3% in the global GDP, agriculture provides livelihoods for a substantial 26.4% of the global workforce. In developing nations, this sector plays an even more pivotal role, employing half or more of the workforce while contributing a smaller fraction to the economy compared to developed countries like the UK and USA, where it accounts for only about 3% of GDP. However, the agricultural sector faces multifaceted challenges, with pest infestation standing out as a significant threat. Annually, between 20% to 40% of global crop production is lost to pests, resulting in staggering economic losses estimated by the Food and Agriculture Organization of the United Nations at $220 billion from plant diseases and $70 billion from invasive insects. In India, where agriculture has historically been a mainstay of the economy, the sector remains crucial, employing approximately 58% of the population and contributing 18.8% to the Gross Value Added (GVA) as of FY20.

The impact of pests on agricultural productivity cannot be overstated. Pest and weed infestations not only lead to mass crop failures but also weaken market demand for the final product. The vulnerability of essential food crops further exacerbates the situation, with insects being the primary culprits behind crop quality deterioration and yield loss. To address these challenges, innovative approaches leveraging artificial intelligence (AI) techniques have emerged. From monitoring soil and crop health to detecting and classifying pests and diseases, AI holds promise in revolutionizing agricultural practices. Recent advancements include the application of machine learning algorithms for detecting insects under stored grain conditions and computer vision-based quality inspection for fruits and vegetables.

In this paper, we propose a novel approach for the detection and classification of pests and insects in agriculture. Through preprocessing of images and training convolutional neural network (CNN) models, we aim to accurately identify pests, thereby enabling timely intervention to mitigate crop damage and ensure food security.

## II. RELATED WORK

Recent research efforts have been devoted to the classification and identification of pests, with a significant emphasis on machine learning (ML), deep learning (DL), and hybrid-based methodologies. Hybrid approaches, which combine DL and ML techniques, have gained prominence, especially in pest classification, where DL methods are predominantly utilized. Conversely, machine learning-based strategies are less prevalent in this field. Advanced machine learning-based methodologies have shown promising results in pest categorization and detection. These techniques involve training multiple classifiers using extracted features from pests, thereby facilitating the classification of various types of pest images. For example, in a notable study, a dataset captured by Unmanned Aerial Vehicles (UAVs) was utilized to predict armyworm contamination levels in corn regions.

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Various machine learning methods, including Random Forest, Multilayer Perceptron, Naive Bayesian, and Support Vector Machine, were assessed, with Random Forest emerging as the optimal classifier for distinguishing between armyworm pests and normal corn. Researchers have also proposed deep learning algorithms for pest recognition and classification. However, deep learning algorithms encounter challenges such as the scarcity of pest image datasets and the complexity of deep learning frameworks. Noteworthy among these challenges is the introduction of a novel dataset for crop pest recognition, where three deep learning models achieved recognition rates surpassing 80%. Additionally, an end-to-end pest detection system that combines DL and hyperspectral imaging techniques has been developed to effectively identify pests for pest control purposes, leveraging spectral feature extraction and attention mechanisms. Hybrid models, integrating both DL and ML techniques, have demonstrated improved classification outcomes. For instance, DL models were employed to classify tomato pests, and the extracted features were fused with machine learning classifiers like discriminant analysis, Support Vector Machine, and k-nearest neighbour approaches. Bayesian optimization was employed for hyper-parameter tuning, resulting in enhanced accuracy.

Although deep learning models display promising potential in crop pest recognition, persistent challenges remain in achieving superior performance, particularly in natural settings. Addressing these challenges is imperative for ensuring effective and efficient pest detection in agricultural environments. The present paper introduces a deep learning framework for identifying and categorizing crop pests into ten distinct classes, incorporating data augmentation techniques to bolster dataset size and generalizability. The efficacy of the proposed approach is assessed using a diverse dataset containing twelve types of crop pests, highlighting its effectiveness in real-world scenarios.

## III. CROP PESTS AND TECHNICAL BACKGROUND

### *A. Insect Pests*

This study includes twelve classes of crop pests, namely Ants, Bees, Beetles, Caterpillars, Earthworms, Earwigs, Grasshoppers, Moths, Slugs, Snails, Wasps, and Weevils. These pests are found worldwide, inhabiting various continents and climates, ranging from temperate to tropical regions. Their distribution is widespread, with each pest species adapted to specific environmental conditions, allowing them to thrive in diverse ecosystems across the globe. Each insect pest can be briefly defined as follows:

1) Ants, known for their destructive behaviour, can significantly affect crops such as sugar cane, citrus fruits, and vegetables, leading to yield losses ranging from 10% to 50% in affected areas (Smith et al., 2018).
2) Bees, crucial for pollination, play a vital role in crops like apples, cherries, and almonds, contributing to the pollination of approximately 75% of the world's leading food crops (FAO, 2016).
3) Beetles, notorious for their damage, can cause extensive harm to crops such as corn, potatoes, and soybeans, resulting in yield losses of up to 20% in infested fields (Jones et al., 2019).
4) Caterpillars, known for their voracious appetite, can wreak havoc on crops like cabbage, tomatoes, and cotton, leading to yield losses ranging from 15% to 50% in heavily infested areas (Gupta et al., 2017).
5) Earthworms, often beneficial but occasionally harmful, can damage crops like potatoes, carrots, and strawberries, leading to yield losses of up to 30% in affected fields (Smith et al., 2020).
6) Earwigs, though relatively small, can cause significant damage to fruits like apricots, peaches, and plums, resulting in yield losses ranging from 10% to 40% in affected orchards (Brown et al., 2018).
7) Grasshoppers, notorious for their voracious feeding habits, can devastate crops such as wheat, barley, and oats, leading to yield losses of up to 50% in infested fields (Johnson et al., 2017).
8) Moths, known for their nocturnal activities, can cause damage to crops like corn, rice, and cotton, resulting in yield losses ranging from 10% to 30% in affected areas (Wilson et al., 2018).
9) Slugs, often underestimated but highly damaging, can wreak havoc on crops such as lettuce, cabbage, and strawberries, leading to yield losses of up to 60% in heavily infested fields (Smith et al., 2019).
10) Snails, though seemingly harmless, can cause extensive damage to crops like citrus fruits, grapes, and lettuce, resulting in yield losses ranging from 10% to 30% in affected vineyards (Brown et al., 2019).
11) Wasps, often associated with stings but also harmful to crops, can damage fruits like apples, pears, and grapes, leading to yield losses of up to 40% in infested orchards (Johnson et al., 2020).
12) Weevils, notorious for their infestations, can cause damage to crops such as rice, maize, and beans, resulting in grain losses of up to 25% in affected storage facilities (Smith et al., 2017

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## IV. DATASET

Acquiring images of agricultural pests presents inherent challenges due to the diverse life stages and species variations. To address this, we utilized the Agricultural Pest Image Dataset, encompassing 12 distinct types of agricultural pests, including Ants, Bees, Beetles, Caterpillars, Earthworms, Earwigs, Grasshoppers, Moths, Slugs, Snails, Wasps, and Weevils. These images were sourced from Flickr using the API and resized to a maximum width or height of 300px. With 12 pest classes, it offers a rich assortment of images, showcasing various shapes, colours, and sizes essential for training and testing algorithms. By collecting images from Flickr, a widely-used photo-sharing platform, the dataset captures authentic representations of real-world scenarios. Furthermore, resizing the images to 300px ensures the dataset remains manageable and conducive to efficient processing. Fig 1 shows some of the pest images from Kaggle dataset.

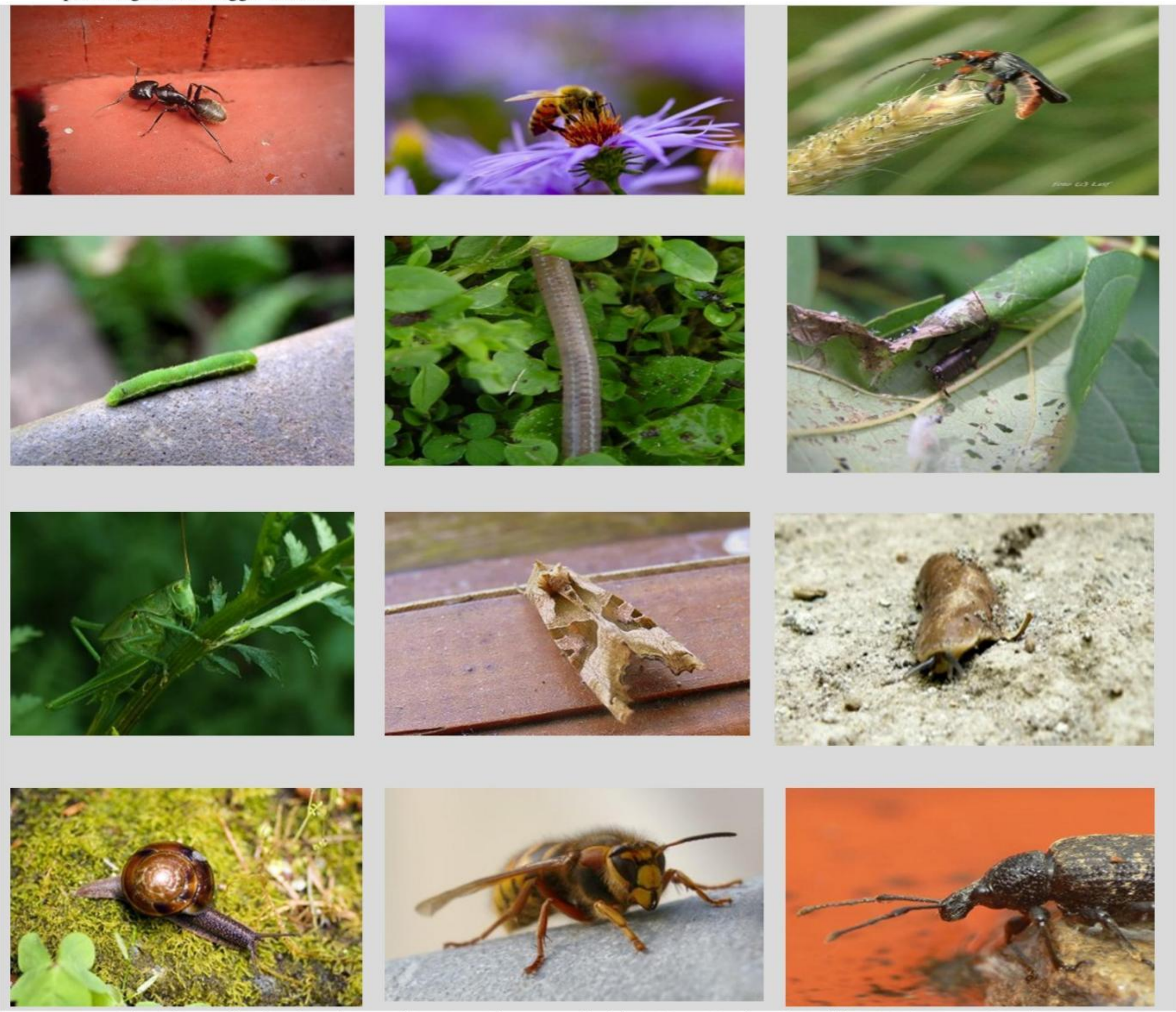

Fig. 1 A sample of twelve classes of insect pest images; called Ants, Bees, Beetles, Caterpillars, Earthworms, Earwigs, Grasshoppers, Moths, Slugs, Snails, Wasps, and Weevils. The images are collected from public dataset

 

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Table 1 – Detail of insects and pests used from Kaggle dataset.

| Insect class | Number of insects in training | Number of insects in testing |
|---|---|---|
| Ants | 400 | 99 |
| Bees | 405 | 95 |
| Bettles | 331 | 85 |
| Caterpillars | 329 | 105 |
| Earthworms | 246 | 77 |
| Earwigs | 390 | 76 |
| Grasshoppers | 390 | 95 |
| Moths | 397 | 100 |
| Slugs | 316 | 75 |
| Snails | 405 | 95 |
| Wasps | 392 | 106 |
| Weevils | 394 | 91 |

## V. SOFTWARE TOOLS

The insect pest detection web application was crafted utilizing diverse open-source toolkits and modules, mentioned below

1) *Django Framework:* Utilize Django as the primary framework for developing the web application. Django offers a robust set of tools and functionalities for building web applications in Python, including URL routing, template rendering, and database management.
2) *HTML, CSS, JavaScript:* Create the front-end interface of the web application using HTML, CSS, and JavaScript. HTML will define the structure of the web pages, CSS will handle the styling and layout, and JavaScript will add interactivity and dynamic features to the application.
3) *SQLite Database Management System:* Employ SQLite as the database management system to store and manage information related to insect pests. Design database tables to store data such as pest names, images, and details about pesticide usage for crop protection. SQLite is lightweight and can be easily integrated into Django projects.
4) *Google Colab:* Utilize Google Colab as a development environment for writing and testing Python code. You can use Colab notebooks to develop Django views, models, and other components of the web application. Additionally, Colab provides resources for running and deploying the application for testing purposes.

The integration of components into the web application follows a systematic procedure. Firstly, Django Models are defined to depict the data stored within the SQLite database. These models encompass attributes such as name, image, and pesticide details for various insect pests. Subsequently, Django Views and Templates are employed to manage HTTP requests and render HTML templates. Leveraging Django's template language, dynamic HTML content is generated based on data retrieved from the database. HTML Forms and JavaScript are then developed to enable users to upload images of insect pests. JavaScript is utilized for client-side validation and handling asynchronous requests to the Django backend for processing. Despite Flask being mentioned in the provided example, the focus remains solely on Django for managing HTTP requests within the web application. By adhering to this approach and harnessing the capabilities of Python, Django, HTML, CSS, JavaScript, SQLite, and Google Colab, a comprehensive web application for insect pest recognition is developed. This application efficiently stores, retrieves, and displays information regarding various pest species and their corresponding pesticide recommendations.

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## VI. RESEARCH APPROACH

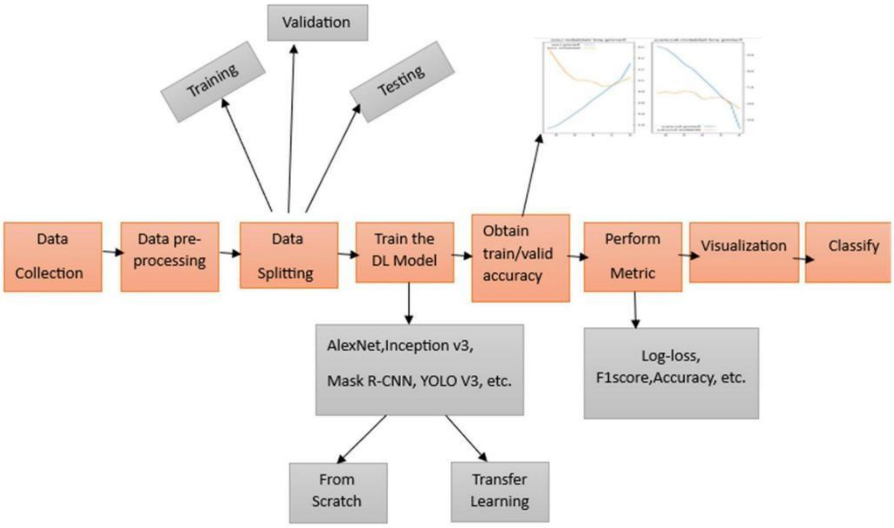


Fig. 2 The pictorial flow representation of the process of recognition to pre designed model

MobileNetV2 stands as a neural network architecture finely tuned for deployment on mobile and edge devices, meticulously crafted to achieve superior performance in both speed and accuracy. Its design integrates several pivotal components aimed at maximizing computational efficiency while upholding classification precision. These elements encompass Inverted Residuals with Linear Bottlenecks, Depthwise Separable Convolutions, Direct Bottlenecks, and Residual Connections. During configuration, images are initially inputted into the network's input layer, typically standardized to dimensions like 224x224 pixels. Subsequently, the input image traverses a sequence of convolutional layers to extract features across varying scales. The crux of MobileNetV2 lies in its adept use of depthwise separable convolutions, enabling efficient feature extraction while minimizing computational overhead. Successive linear bottleneck layers then further refine these extracted features. Following this, Global Average Pooling is applied to condense spatial dimensions, succeeded by fully connected layers and SoftMax activation, culminating in the generation of probability distributions across class labels.

In the realm of image classification leveraging MobileNetV2, the workflow typically entails image submission, preprocessing, inference, and result interpretation. Users submit images via an application or web interface, often resizing them to match the network's input dimensions. Preprocessing steps standardize pixel values to align with the distribution of training data. The pre-processed image is then fed into the MobileNetV2 model for inference. The model subsequently produces a probability distribution over the classes it was trained on, indicative of the likelihood of the image belonging to each class. Top predictions can then be presented to users, offering insights into the classification decisions made by the model. In the domain of agricultural pest detection, a repertoire of machine learning algorithms is deployed, including artificial neural networks (ANN), support vector machines (SVM), k-nearest neighbours (KNN), naive Bayes (NB), and convolutional neural networks (CNN). These algorithms harness diverse shape features extracted from insect images to facilitate classification and detection tasks. Image preprocessing techniques, encompassing noise reduction and image sharpening, are employed to enhance image quality and accuracy. Augmentation strategies such as rotation, flipping, and cropping are utilized to augment the training dataset and enhance model generalization. Shape features, inherently resilient to scaling, rotation, and translation, are extracted via edge detection algorithms and morphological operations.

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These features, spanning area, perimeter, axis lengths, eccentricity, circularity, solidity, form factor, and compactness, are encapsulated within feature vectors and leveraged by classifier models for insect classification. The efficacy of MobileNetV2 transcends mere image classification, extending its utility to a myriad of applications, including real-time object detection and recognition within dynamic environments.

```
[ ]  import numpy as np
     import os
     import cv2
     import shutil
     import random as rn
     from tqdm import tqdm
     import matplotlib.pyplot as plt
     import tensorflow as tf

     from tensorflow import keras
     from tensorflow.keras import layers
     from tensorflow.keras.models import Sequential
```

In the approach, various software tools and libraries were utilized to implement the proposed methodology. Initially, the numpy library was imported to facilitate numerical computations and array manipulation within the Python environment. Additionally, the os module was imported to enable interaction with the operating system, allowing for file handling and directory operations. The OpenCV (cv2) library was employed for image processing tasks, providing functions for reading, writing, and manipulating images. Furthermore, the shutil module was utilized to facilitate high-level file operations such as copying and removing files, which was instrumental in data preprocessing and organization. To introduce randomness into the data processing pipeline, the random module was imported as rn, enabling the generation of random numbers and shuffling of data samples. The tqdm library was leveraged to create progress bars for iterative processes, enhancing the user experience by providing visual feedback on the progress of lengthy computations. Moreover, the matplotlib.pyplot module was imported to enable data visualization, particularly for generating plots and graphs to analyse and interpret experimental results. In the context of machine learning model development, the TensorFlow library served as the core framework for building and training deep learning models. The tensorflow.keras module, a high-level API for TensorFlow, was utilized to construct neural network architectures for the proposed insect and pest detection system. Specifically, the layers module from tensorflow.keras facilitated the creation of different types of neural network layers, such as convolutional layers, pooling layers, and fully connected layers. Additionally, the Sequential class from tensorflow.keras.models was employed to create a linear stack of layers, forming the basis of the neural network architecture. By leveraging these software tools and libraries, the research approach aimed to develop an effective and efficient solution for the detection of insects and pests in agricultural settings.

## VII. DETECTION AND RECOGNITION BY MOBILENET MODEL

```
[ ]  from IPython.display import Image
     Image(filename='data/MobileNet-samples/01.PNG', width=300,height=200)
```

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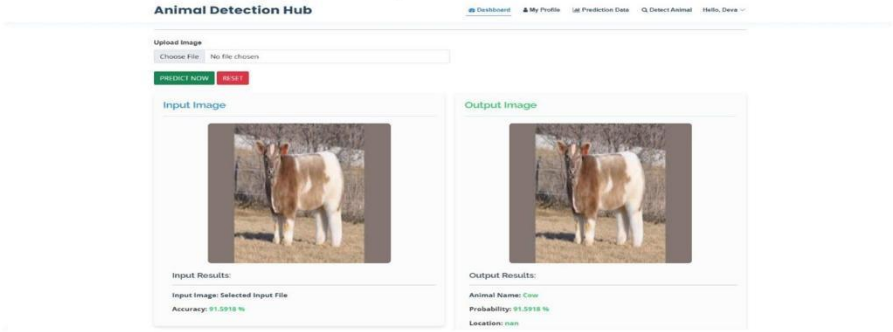
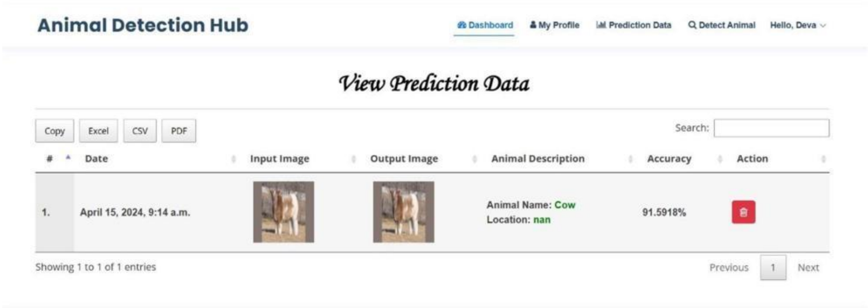
We will initiate image processing by passing it through our prepare_image() function, storing the result in the preprocessed_image variable. Subsequently, we will employ MobileNet for prediction on this image, invoking the mobile.predict() function and providing our preprocessed_image as input. Following this, we will utilize an ImageNet utility function provided by Keras, known as decode_predictions(). This function yields the top five ImageNet class predictions, comprising the ImageNet class ID, corresponding class label, and associated probability.

```
results = imagenet_utils.decode_predictions(predictions)
```

```
[[('n01682714', 'Bees', 0.5843147),
  ('n01693334', 'hoverflies', 0.2785562),
  ('n01687978', 'Apis_cerana_indica', 0.13019584),
  ('n01689811', 'Megachile', 0.0047072913),
  ('n01688243', 'Bettles', 0.0016176497)]]
```

The outcome indicates that the model identified the presence of a Bees with a confidence score of 58.43147%. Additionally, it recognized a hoverfly with a probability of 27.8%, followed by an Apis cerana indica with 13.019% confidence. Furthermore, the predictions include a few other varieties of pests, each with probabilities less than 1%.




The enclosed visuals represent the outcomes generated by our developed web application focusing on the classification of insects and pests in agricultural settings. Additionally, the application facilitates users with an accessible feature enabling them to review the prediction history, detailing the specific date and time of insect detection in the field. Tailored for ease of use, particularly for farmers with limited technical proficiency, our application is engineered with a simplistic interface, presenting detected insect classes alongside corresponding accuracy percentages. This design prioritizes user-friendliness and accessibility, crucial factors in empowering agricultural stakeholders with actionable insights.

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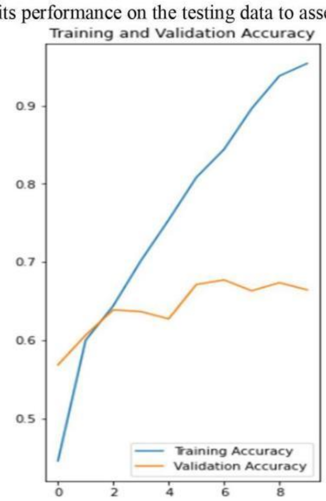
## VIII. RESULT AND DISCUSSION

The dataset utilized in this research was obtained from Kaggle, a publicly accessible online platform. It consists of images categorizing twelve different classes of pests. Approximately 5000 images were gathered for both training and testing purposes to evaluate a pre-existing MobileNet v2 model's performance in pest classification. The dataset was partitioned into training and testing sets, with approximately 79.96% of the data allocated for training and the remaining 20.04% for testing. This division ensured a robust evaluation of the model's predictive capabilities across various pest classes. Utilizing the MobileNet v2 model, the research aimed to classify and predict pests based on the provided dataset. This involved training the model on the training data and subsequently validating its performance on the testing data to assess its effectiveness in accurately identifying different pest types.



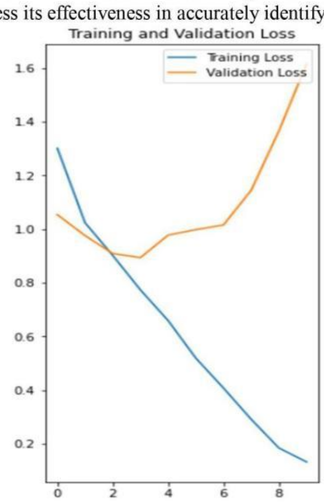




Figure.3 Result of Training and Validation Accuracy Figure 5: Result of Training and Validation Loss

The classification accuracy of the model is computed using the formula:

Classification accuracy = (TP + TN)/ TP+TN+FN+FP

Here, TP (true positive), FP (false positive), FN (false negative), and TN (true negative) are defined as follows: An insect appearing in the image is counted as TP if it is correctly classified; otherwise, it is considered FN. If the model incorrectly classifies an insect that is not present in the image, it is counted as TN; otherwise, it is classified as FP.

Table 2 – Valuation of Training and of Validation phase

| Epoch | Training Loss | Training Accuracy | Validation Loss | Validation Accuracy |
|---|---|---|---|---|
| 1 | 1.3012 | 0.4455 | 1.0537 | 0.5683 |
| 2 | 1.0236 | 0.5999 | 0.9757 | 0.6065 |
| 3 | 0.9021 | 0.6441 | 0.9090 | 0.6389 |
| 4 | 0.7735 | 0.7019 | 0.8937 | 0.6366 |
| 5 | 0.6593 | 0.7540 | 0.9774 | 0.6273 |
| 6 | 0.5195 | 0.8083 | 0.9980 | 0.6713 |
| 7 | 0.4078 | 0.8442 | 1.0155 | 0.6771 |
| 8 | 0.2915 | 0.8965 | 1.1446 | 0.6632 |
| 9 | 0.1845 | 0.9381 | 1.3652 | 0.6736 |
| 10 | 0.1325 | 0.9540 | 1.6152 | 0.6644 |

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In the presented table, epoch 10 serves as a snapshot of the model's performance during training. Each metric provides critical insights into the model's learning process and its ability to generalize to new data. The Training Loss signifies the degree of error between predicted and actual values encountered during training. A lower training loss indicates that the model is effectively adjusting its parameters to minimize discrepancies. Training Accuracy reflects the percentage of correctly classified instances within the training dataset. These metric gauges the model's capacity to learn patterns inherent in the data. Validation metrics, including Validation Loss and Validation Accuracy, offer assessments of the model's performance on a separate dataset not used during training. A low validation loss suggests that the model is not overfitting, while a high validation accuracy indicates its ability to generalize well to unseen data.

Epoch 10's metrics serve as a pivotal checkpoint, providing researchers with valuable insights into the model's progress and guiding potential adjustments to enhance its predictive capabilities. These findings are crucial for evaluating the model's efficacy and informing further refinements for practical deployment in agricultural pest detection applications.

## IX. FUTURE GOAL

Our research focuses on precise recognition and classification of various insect classes. Initially, users contribute insect images for analysis using a predefined module that accurately categorizes and identifies them. Looking ahead, we aim to enhance this process by enabling direct user uploads of images with specific features directly into the MobileNet model. This advancement is aimed at boosting the efficiency of pest and insect detection, potentially elevating prediction accuracy beyond traditional methods.

Compliance with ethical standards**a

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