GROUNDNUT CROP PEST DETECTION AND CLASSIFICATION USING COMPREHENSIVE DEEP-LEARNING MODELS

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Abstract

Pests pose a significant threat to crops, leading to substantial economic losses and decreased food production. Early detection and accurate classification of pests in crops are crucial for effective pest management strategies. In this study, we propose a method for pest detection and classification in groundnut crops using deep learning models. In this research, we compare the performance of three deep learning models, namely Custom CNN [proposed], LeNet-5, and VGG-16, for groundnut pest detection and classification. A comprehensive dataset containing images of diverse groundnut crop pests, including thrips, aphids, armyworms, and wireworms, from the IP102 dataset was utilized for model evaluation. The performance is evaluated using reliability metrics such as accuracy and loss. These findings demonstrate the utility of deep learning models for reliable pest classification of groundnut crops. The Custom CNN [proposed] model demonstrates high training accuracy but potential overfitting, while the VGG-16 model performs well on both training and test data, showcasing its ability to generalize. The models' accuracy in predicting pest species underscores their capability to capture and utilize visual patterns for precise classification. These findings underscore the potential of deep learning models, particularly the VGG-16 model, for pest detection and classification in groundnut crops. The knowledge gained from this study can contribute to the development of practical pest management strategies and aid in maintaining crop health and productivity. Further analysis and comparisons with other models are recommended to comprehensively evaluate the competitiveness and suitability of deep learning models in real-world applications of pest detection and classification in agricultural settings.

Keywords: **Convolutional Neural Networks; Crop Health Monitoring; Deep Learning; Groundnut Crop; Image Analysis; Pest Classification; Pest Detection**

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Introduction

Agriculture has emerged as a vital contributor to the country's economic growth, playing a significant role in its overall expansion. With a substantial contribution to the GDP, agriculture stands as the primary industry in the country. Therefore, any crop damage can have a profound impact on the nation's productivity, resulting in adverse effects on the economy. The leaves, being the most vulnerable part of the plant, often display the initial signs of diseases and these diseases are caused by pests. To address this challenge, it becomes imperative to explore various techniques for efficient crop management. Throughout the crop's lifecycle, from its early stages to the point of harvest, it is crucial to remain vigilant and take necessary measures to prevent and treat any diseases that may affect the plants (Sujatha *et al*., 2021). However, in remote areas, the lack of access to agricultural expertise poses a significant obstacle, making the process time-consuming.

Groundnut crop is one of the commercially important legumes cultivated by farmers across the globe and these crops are susceptible to various pests, including aphids, thrips, armyworms, wireworms, whiteflies, and leaf miners (Agricultural Market Intelligence Centre, [PJTSAU], 2020). These pests can cause significant damage, such as stunted growth, defoliation, reduced seed germination, and transmission of viral diseases (Guthrie and Huber, 2015). Pest detection and classification is the process of identifying and categorizing various types of pests that may be present in an agricultural or environmental setting (Shew, 2020). This process involves using various techniques and technologies to detect the presence of pests and distinguish them from other organisms. Implementing effective pest management strategies is crucial, and early detection and accurate classification of these pests using deep learning models can aid in timely intervention. By utilizing advanced image analysis techniques, deep learning models can identify and classify groundnut pests, enabling farmers to implement targeted control measures, minimize crop damage, and maximize overall yield potential.

The primary objective of this research is to employ Convolutional Neural Networks (CNNs) models for the detection and classification of groundnut crop pests and presents a comprehensive comparison among the models (Mohanty *et al*., 2016). By leveraging these advanced deep learning models, we aim to create a robust and efficient system that can assist farmers and agricultural experts in accurately identifying and managing pests in groundnut crops. The study involves the creation of a comprehensive dataset comprising diverse groundnut pest images, encompassing various species such as aphids, thrips, armyworms, wireworms, and more. The dataset will undergo preprocessing to enhance image quality and ensure optimal input for the CNN model, enabling effective pest detection and classification. This study seeks to investigate the application of deep learning models and deep learning optimizers to overcome the challenge of insufficient data in developing a pest identification model. The specific objective is to collect images of pests that infest peanuts or groundnuts, preprocess the images, train deep learning models using various architectures, optimizers, and learning rates to create effective classifications, and ultimately evaluate the performance of these models.

The key contribution of our research lies in the formation of a novel pest dataset specific to groundnut crops, derived from the IP102 pest dataset, which represents the most prevalent pests affecting groundnut cultivation. Notably, this dataset is the first of its kind dedicated to groundnut crops, marking a significant gap in prior research. This unique groundnut crop pest dataset serves as a distinctive and valuable resource, filling a critical void in the existing literature and offering new insights into pest management strategies tailored specifically for groundnut cultivation. The paper introduces a novel contribution by utilizing deep learning models to identify and categorize pests in groundnut crops. The application of these models is noteworthy as it has the potential to boost agricultural productivity through early and precise pest detection, leading to improved crop management and yields. The study compares a custom CNN [proposed] model with established ones like LeNet-5 and VGG-16, showcasing the effectiveness of advanced AI techniques in agriculture. This research not only highlights the adaptability of these models in practical situations but also marks a significant advancement in integrating state-of-the-art technology with traditional farming practices.

The paper is organized as follows, Section II provides preliminaries and literature related to the detection and classification of groundnut pests. Section III presents the initial work conducted and outlines the proposed methodology. Section IV presents the results and discussions of the proposed techniques. Finally, Section V summarizes the findings, presents the conclusion, and provides recommendations for future research.

Basic Preliminaries and Related Research Work

In this section, we explain the theory behind the introduced concepts that will be applied and investigated. Further, we describe how the concepts are related to the application. One of the most important areas of study in machine vision is the identification and analysis of pests in crops. To diagnose pests, this method uses machine vision equipment to acquire images of the groundnut corps (Patrício and Rieder, 2018). Currently, the agriculture sector has been at the forefront of adopting computer vision-based technology for crop diagnosis and identification. This technology has partially replaced the conventional method of visually examining and classifying pests.

Types of Pests for Groundnut Crops

Groundnut crops are vulnerable to various pests that can cause significant damage if not managed effectively. Here are some common groundnut pests.

1. Aphids: Aphids are small insects that feed on plant sap by piercing the plant's tissues. They reproduce rapidly and can cause stunted growth, yellowing of leaves, and the development of sooty mold. They also secrete honeydew, which attracts ants and can serve as a medium for fungal growth (Agricultural Market Intelligence Centre, [PJTSAU]., 2020; Verma).

2. Thrips: Thrips are tiny, slender insects that feed on groundnut leaves and pods. They scrape the surface of the plant tissues and suck out the sap, leading to the formation of silvery streaks and bronzing on leaves. Thrips infestation can reduce yield and transmit viral diseases (Agricultural Market Intelligence Centre, [PJTSAU]., 2020; Verma).

3. Armyworm: Armyworms are caterpillars that can cause extensive damage to groundnut crops by feeding on leaves, stems, and pods. They typically feed in large groups, quickly defoliating the plants. Severe infestations can lead to complete crop loss if not controlled on time (Agricultural Market Intelligence Centre, [PJTSAU]., 2020; Verma).

Figure 1. The sample images of different Groundnut Pests

4. Wireworm: Wireworms are the larval stage of click beetles. These pests reside in the soil and feed on groundnut seeds, causing reduced germination and seedling establishment. Wireworm damage is characterized by hollowed-out or damaged seeds, leading to poor plant stand and yield reduction (Agricultural Market Intelligence Centre, [PJTSAU]., 2020; Verma).

5. Whiteflies: Whiteflies are tiny, winged insects that infest groundnut crops, particularly the undersides of leaves. They suck plant sap and excrete honeydew, leading to the growth of sooty mold. Whitefly feeding weakens plants, reduces photosynthesis, and can transmit viral diseases (Agricultural Market Intelligence Centre, [PJTSAU]., 2020; Guthrie and Huber, 2015).

6. Leaf miners: Leaf miners are the larvae of various fly species that tunnel into groundnut leaves, creating distinctive serpentine mines or trails. These mines interfere with photosynthesis, causing leaf yellowing, reduced plant vigor, and yield loss (Agricultural Market Intelligence Centre, [PJTSAU]., 2020; Guthrie and Huber, 2015).

These are just a few examples of pests in groundnut crops (Verma). Effective pest management strategies involve a combination of cultural practices, biological control methods, and judicious use of pesticides. Early detection and accurate classification of these groundnut pests using deep learning models can play a crucial role in implementing timely and targeted pest control measures to minimize crop damage and maximize yield potential. Figure 1 shows the sample images of groundnut pest types.

Literature Review on Groundnut Crop Pests Detection and Classification

Conventional image processing algorithms or manually developed features and classifiers are typically used in traditional machine-learning approaches for groundnut crop pest identification and detection (Suresh and Seetharaman, 2023). These methods make use of the peculiarities of plant diseases and strategically choose lighting sources and camera angles to create a consistent glow. However, these imaging schemes can be expensive to implement. It is also difficult for standard algorithms to adjust for environmental variables that impact recognition outcomes in natural settings (Saleem *et al.*, 2021). This is because traditional algorithms may not be optimized to deal with the dynamic nature of natural surroundings. The identification and diagnosis of pests in a complex natural ecosystem present numerous challenges. These difficulties encompass factors such as subtle variations in lesion size and type, low contrast, significant variations in lesion characteristics, and a significant amount of noise in lesion images (Shrestha *et al*., 2020). Moreover, when capturing images of crop diseases and insects in environments with natural lighting, there are often numerous distractions. In the present era, conventional methods often prove inadequate, making it challenging to achieve accurate detection outcomes.

Classification, object recognition, and object tracking in films are just a few examples of the many fields that have begun to heavily explore computer vision systems and deep learning-based modelling approaches. These developments have shown promising results when these methods are applied to industries like agriculture, remote sensing, medical imaging, and self-driving vehicles. Especially for vulnerable crops like groundnuts, early detection of pests, classification, and recognition of pests is vital since harvest losses immediately affect their prices (Kumari *et al*., 2019). Through the implementation of cutting-edge image processing solutions and ongoing study, the field of Precision Agriculture has benefited greatly from the application of artificial intelligence methods.

Groundnut disease detection and classification using deep learning models involves applying advanced machine learning techniques to accurately identify and categorize diseases affecting groundnut crops (Vaishnnave *et al*., 2020). Convolutional Neural Networks (CNNs) and other deep learning models have shown promising results in image recognition tasks and are well-suited for analyzing visual patterns in pest-infested groundnut leaves. By leveraging these models, accurate pest detection and classification can be achieved, enabling timely intervention and effective pest management strategies. Several studies have explored the application of deep learning models for groundnut pest detection and classification.

Vaishnnave *et al*. (2019), Compares the classification approaches ANN, k-nearest neighbour, support vector machine (SVM), Naive Bayes (NB), and CNN on datasets with close-up images of insects. The SVM classifier, utilizing nine shape features of the radial basis function (RBF) kernel, reached an accuracy of 79.9% for 5 classes, but the accuracy decreased rapidly to 71.8% when adding 4 more classes. The highest classification accuracy was made with the CNN model scored between 90-91.5% accuracy in the range of 9 to 24 classes. Noteworthy is that different approaches of machine learning algorithms performed best on different types of insects, where SVM gave the most accuracy for winged insects such as fruit flies, and KNN performed better for butterfly species.

Investigates another promising approach for the classification of different insects using auditory features (Liu *et al*., 2020). Utilizing audio recordings for machine learning is an approach that was tested for the classification of wingbeat frequencies to differentiate between pests and pollinators by earlier studies, reaching an accuracy of 99 %, and similar results were obtained when using feature extractions in another study. To enable classification based on wingbeat frequency, the frequency needs to differ from other insects in the vicinity and too great variations might cause difficulties. During experiments, the sound of wingbeats from rape beetles and weevils was very similar, possibly making it hard to differentiate (Liu *et al*., 2020). Collecting microphone-based data could be complicated due to background noise when this approach is applied in the field. A company called FaunaPhotonics takes another approach and uses light detection and ranging (LiDAR) to capture the wingbeat frequency, and LiDAR can also provide information such as relations between the body and wings even at long distances (Liu *et al*., 2020).

It classifies and detects insects (Saleem *et al*., 2021) using the latest machine-learning methods to create an insect identification and detection model for area harvest. This study presents a detection technique that uses IP102 insect datasets for foreground extraction and outline recognition in very complicated backgrounds. KNN, SVM, ANN, NB, and CNN models were used to classify 9 pests. The classification accuracy of the CNN model is 91.5%, and it is 90% for 9 data categories of different insects or pests, respectively. The methods used to extract the image as input bug dataset will undergo image pre-processing by applying filters with image augmentation to extract insect structural features.

Dong *et al*. (2019), proposed a deep-learning approach using CNNs for pest detection in groundnut plants. They collected a diverse dataset of groundnut plant images and trained the CNN model to accurately detect pests by extracting and learning visual features. The research demonstrates the potential of deep learning techniques for early pest identification, offering valuable insights for effective pest management in groundnut cultivation and ultimately improving crop productivity. They achieved promising results in accurately identifying and classifying groundnut pests.

Kishore *et al*. (2005), conducted a study where they utilized deep Convolutional Neural Networks (CNNs) for the detection and classification of pest-induced diseases in groundnut plants. By training their models on a comprehensive dataset of groundnut plant images, they demonstrated the effectiveness of deep CNNs in accurately identifying various diseases caused by pests. Their research showcased the potential of these models in enabling timely intervention and precise management strategies, contributing to improved disease control and increased productivity in groundnut cultivation.

Devi *et al*. (2020), utilised deep learning methods for groundnut pest identification and classification, with a particular emphasis on the application of CNNs. Their study aimed to explore the potential of CNNs in pest detection and showcase their effectiveness in accurately identifying and categorizing groundnut pests. The researchers collected a dataset comprising diverse groundnut pest images and trained their CNN models to learn the visual patterns and features associated with different pest species. Through their experiments and evaluations, have demonstrated the potential of CNNs as a powerful tool for pest detection in groundnut crops, highlighting the capability of these models to accurately classify groundnut pests based on their visual characteristics. Their findings contribute to the development of advanced pest management strategies, facilitating timely interventions and improving the overall health and productivity of groundnut crops.

In their study, Türkoğlu and Hanbay, (2019), investigated the application of deep Convolutional Neural Networks (CNNs) for identifying and classifying groundnut plant diseases, including those caused by pests. Their research focused on leveraging the power of deep learning models to accurately classify various groundnut pests. By collecting a comprehensive dataset of groundnut plant images encompassing different disease classes, the researchers trained their deep CNN models to extract and analyze intricate visual patterns associated with groundnut pest diseases. Through their experiments and evaluations, have demonstrated the efficacy of deep CNNs in accurately classifying groundnut pests, showcasing the potential of these models in supporting pest management efforts in groundnut cultivation. Their findings contribute to the development of effective disease identification and management strategies, ultimately improving the health and productivity of groundnut crops.

To address these challenges, Vaishnnave *et al*. (2019), have utilized Convolutional Neural Networks (CNN) in the agricultural domain to extract and classify relevant features. Their research introduces an advanced CNN model that leverages popular architectures such as GoogleNet, AlexNet, ResNet, and LeNet to extract features from publicly available insect datasets (Rosebrock, 2021). To mitigate overfitting issues, the authors employed data augmentation techniques. The proposed model achieved high accuracy rates on the selected datasets. It’s important to note that while the experiments focused on common insects in general crops, the findings may not be specific to peanut crop infections.

In the existing literature, innovative approaches to crop pest and disease identification are explored. The authors of (Yang *et al*., 2021) propose a convolutional rebalancing network for rice pests, achieving 92.58% accuracy through instance-balanced and reversed sampling. The authors of (Zhan *et al*., 2023) introduce an IterationVIT model for tea disease diagnosis that demonstrates a superior 91% classification accuracy by combining convolution and iterative transformers to address complex image challenges. Anwar and Masood (2023), employs CNN-based transfer learning ensembles, achieving 82.5% accuracy in crop insect classification on the IP102 dataset, surpassing recent models. Additionally, Pramudhita *et al*. (2023), present a lightweight CNN algorithm for strawberry plant disease detection, achieving 92.14% accuracy and suitability for resource-restricted devices. Amin *et al*. (2023) introduce a novel method that addresses pest-related damage, combining YOLOv5 for localization and a quantum machine learning model. YOLOv5, trained optimally, exhibits enhanced localization accuracy (0.91 F1 score), while the quantum model achieves 99.9% classification accuracy in distinguishing Paddy with pest and Paddy without pest. Comparison with recent methods underscores the proposed approach’s superiority, indicating its potential to advance pest management in agriculture.

Conventional methods for groundnut pest identification, relying on image processing and manual feature-based classifiers, face challenges in adapting to dynamic natural environments, resulting in suboptimal outcomes due to factors such as subtle variations, low contrast, and environmental variables. The rise of computer vision and deep learning, particularly Convolutional Neural Networks (CNNs), has shown promise in precision farming and agriculture, enabling accurate and early detection of pests in vulnerable crops like groundnuts. A comparative study (Vaishnnave *et al*., 2019) highlighted the superiority of CNNs over traditional machine learning approaches, achieving an accuracy of 90-91.5% and emphasizing the need for tailored algorithms for specific insect types. Innovative approaches explored the use of auditory features for insect classification based on wingbeat frequencies, with challenges addressed through solutions like LiDAR by FaunaPhotonics. Saleem *et al*. (2021) machine learning models (KNN, SVM, ANN, NB, CNN) were applied to insect identification in harvest areas, with CNN achieving an accuracy of 91.5%, and image preprocessing playing a crucial role in feature extraction. Multiple studies (Kishore *et al*., 2005; Dong *et al*., 2019; Türkoğlu and Hanbay, 2019; Devi *et al*., 2020) underscored the effectiveness of CNNs in pest detection and classification for groundnut plants, contributing to improved crop health and productivity.

To address challenges and mitigate overfitting, a recent work (Vaishnnave *et al*., 2019) proposed an advanced CNN model utilizing popular architectures, achieving high accuracy rates on selected datasets through the employment of data augmentation techniques. The reviewed literature collectively underscores the shift towards leveraging deep learning, particularly CNNs, for accurate and automated pest identification in groundnut crops. The studies highlight the potential of these models in enabling timely interventions and improved crop management practices. However, there remains a need for further research to address specific challenges such as environmental variations, noise in images, and scalability to diverse insect types. Additionally, the generalization of findings to peanut crop infections needs careful consideration. Future work should focus on refining models, incorporating multi-modal data sources, and addressing practical challenges in real-world agricultural systems.

Deep Learning Models for Groundnut Crop Pests Detection and Classification

Groundnut crop pest Detection and Classification involves a collection of pest images, pre-processing, image processing, and classification. This section elaborates on the implementation of CNN models for Groundnut Pest Detection and Classification.

To identify and categorize groundnut pests, deep learning methods have been extensively researched in the literature. However, these methods come with several complications, including the potential for misdiagnosis due to variations in pests, varieties, and environmental factors. Early identification and treatment of groundnut pests are crucial, but the process can be time-consuming and hindered by the lack of agricultural expertise in rural areas. With autonomous feature selection and reduced reliance on labor-intensive picture pre-processing, convolutional neural networks (CNNs) have proven effective in image-based recognition tasks (Balasubramaniyan and Navaneethan, 2022a; Balasubramaniyan and Navaneethan, 2022b). However, one of the challenges is the availability of large and diverse datasets to train these models effectively. Acquiring such datasets remains a difficult task. Figure 2 represents the Flowchart for the CNN models for Groundnut pest detection and classification.

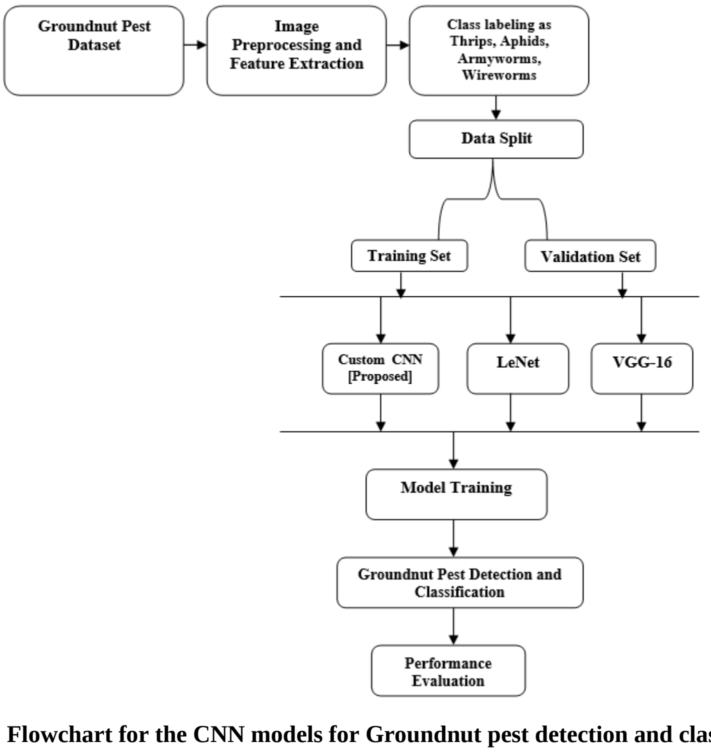

Figure 2. Flowchart for the CNN models for Groundnut pest detection and classification

Dataset Description

A collection of high-quality images of diverse groundnut pests is collected from IP102 Dataset (Verma). The collected images include Thrips, Aphids, armyworms, and wireworms. This research work gathered four various bug data set types. Aphids, containing 2456 pest images from 42 aggravation types from field crops, is the most important bug dataset affecting groundnut (Verma). The next severe risk groundnut is Armyworm which contains 642 pest images. The class of Wireworm insects is the next to be examined containing 532 pest images for model training and testing and the last groundnut pest used is Thrips which contains 527 pest images (Verma). The dataset contains complete 4157 pest images of groundnut crops with 4 classes. The ratio between training, validation, and testing is 80:20. Figure 3 displays the variety of pest images from each of the 4 categories.

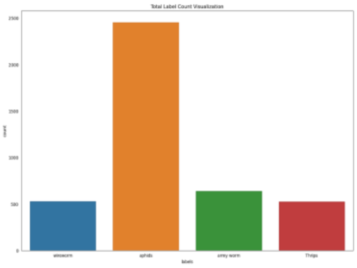

Figure 3. Distribution of Groundnut Pest images among 4 classes

Image Processing

The performance of the insect recognition task is enhanced by employing image preprocessing techniques to separate the insects from the background information in the images before inputting them into the deep learning models. This preprocessing step helps in isolating the insects and improving the accuracy of the recognition process. Image processing plays a crucial role in effective groundnut pest detection deep learning. By applying various image processing techniques, the raw pest images can be preprocessed and enhanced to enhance deep learning model accuracy (Mishra and Srivastava, 2019).

Image compression techniques can be applied to reduce the size of pest images without significant loss of important information. This can help in the efficient storage and transmission of images, as well as faster processing in pest identification systems. In our proposed work we have used Lossless compression and Hybrid compression to attain low-resolution images for effective deep-learning applications.

1. Lossless Compression: Huffman and Run-Length Encoding are lossless compression methods. (RLE), preserve all the original information of the image while reducing the file size (Hernández-Cabronero *et al*., 2020). These methods exploit redundancy in the image data to achieve compression without sacrificing any details. Lossless compression is suitable when an exact representation of the image is required for accurate pest identification.

2. Hybrid Compression: Hybrid compression techniques combine the strengths of both lossless and lossy-compression methods. They employ a lossless compression algorithm for preserving critical image information, such as pest-specific features, while applying lossy compression to less important image components. This approach strikes a balance between compression efficiency and image fidelity (Yao *et al*., 2020).

$$NewPixelValue(x', y') = PixelValue\big(round(x), round(y)\big) \tag{1}$$

$$NewWidth = ScaleFactor \times OriginalWidth \tag{2}$$

$$NewHeight = ScaleFactor \times OriginalHeight \tag{3}$$

Insect images captured in RGB. Edge of Caution to recognize the edges in an insect image and alleviate the irritation, unambiguous evidence is utilized. The external design in pest images are found to be equal in how they are perceived from the edge. When the upper shape is taken as (p,q), the breadth and the level are (r,s), and the bobbing is not settled by these four centres. Each member of the upright hopping square is still a work in progress. The premium (return on investment) region of the insect is removed using the primary RGB insect image's coordinates (p+r, q+s). Finally, the dreaded insect symbol may be put to rest.

Scaling, conveying, turning, and flipping were used, along with other mathematical transformation techniques, to increase the number of insect experiments included in the datasets. In reality, this method of image generation is both commonplace and computationally cheap, requiring only a few key learning models to get started. By incorporating image processing techniques into the pipeline of deep learning for groundnut pest detection, the models can benefit from enhanced image quality, improved feature representation, and better generalization capabilities, leading to more effective and accurate pest classification.

Groundnut pest detection and classification using Deep Learning models

The literature on deep learning approaches has many issues, such as misdiagnosis of pest identification, variety in pests, and environmental influences. Early identification and treatment of such pests are therefore useful. However, doing such is a challenging and time-consuming process; agricultural expert knowledge is unavailable in rural locations. Convolutional neural networks have recently achieved significant advancements in picture-based recognition with the elimination of requirements for image pre-processing and enabling built-in feature selection (Guthrie and Huber, 2015). Finding huge datasets for such challenges is another issue, which is quite challenging.

Convolutional Neural Network (CNN) Model

To handle data having a grid-like structure, like images, CNNs were developed (Gandhi *et al.*, 2018). The pixels in an image are arranged in a grid, and the value of each pixel determines its hue and luminance. Likewise, each neuron in a CNN processes information within its receptive field. Similar to how the human brain processes visual information, CNN layers detect simpler patterns first, then more complex patterns as the layer progresses. Convolutional neural networks have input, hidden, and output layers. Convolution, normalization, pooling, and fully connected layers lie between the output and input layers (Gandhi *et al.*, 2018). Classification feature maps are created by the convolutional layer's filters. Image processing uses ReLU (Liu and Wang, 2021).

An enhanced fine-grained robust CNN model is proposed for the classification of pests in this study. At the first level, preprocessing techniques are used to reduce the size of the pest image. To detect pests from images, a CNN learning model has been created at the second level utilizing a convolutional neural network (Gandhi *et al.*, 2018). Figure 4 shows how the Custom CNN [proposed] model for groundnut pest detection and classification is implemented.

CNN models have numerous convolutional layers, pooling layers, and fully linked layers. Because of its high degree of complexity, a neural network can develop hierarchical representations of the input data, which are crucial for achieving precise categorization. Table 1 presents a detailed pseudo code for the deep learning models for groundnut pest detection and classification. The Convolutional Neural Network (CNN) model consists of multiple layers, including Conv2D, Batch Normalization, Max Pooling, and Activation functions (Gurucharan, 2020). Here is a description of the model architecture.

1. Conv2D layers: As mentioned above, the convolutional operation is what distinguishes a CNN from other neural networks. The basic form of convolution consists of two functions that take real numbers as arguments. To explain convolution, we can pretend that it is possible to keep track of where a car is using a laser that gives an output: x(t), where x is the position of the car in time step t. To reduce possible noise that arises during the measurements, several measurements can be taken and an average value of them used as the measurement value. Later measurements have greater value than the older ones. Therefore, a weight function, w(a), is used, where a represents how old a measurement is. The weight function w must be a valid density function. If these weighted average measurements are performed every time step, it can be described with a function, s known as the Convolution function.

$$S(t) = \int x(a)w(t-a)da \tag{4}$$

In CNN terminology, the first argument in the convolution function is called the input and the second is called the kernel, what is returned is called the feature map.

$$s(t) = (x * w)(t) \tag{5}$$

For the example with the car above to be realistic, the data cannot be collected in each time step when the amount had become too large, but in regular intervals, for example, every second or minute. In

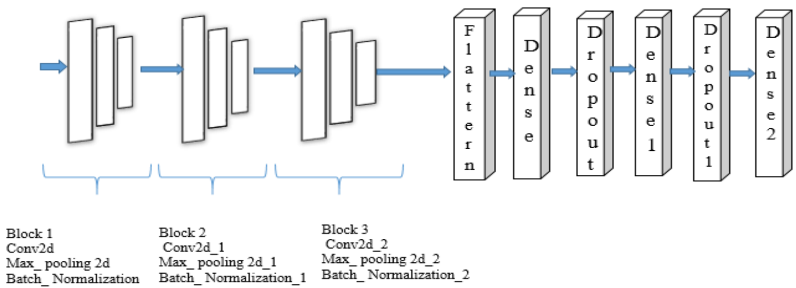

Figure 4. The architecture of the Custom CNN [proposed] model for groundnut pest detection and classification

Table 1. Algorithm of deep learning models for Groundnut pest detection and classification

Input:	Groundnut Pest (IP102) Dataset
Output:	Pest Detection and classification
Step1:	Acquire the Groundnut Pest images with Aphids, Armyworms, Thrips, and Wireworms.
Step2:	Loading the data (X_train,y_train) , (X_test,y_test)=Pest.load_data().
Step 3:	Image- Preprocessing • Reshaping the data X_train = X_train.reshape((X_train.shape[0], X_train.shape[1], X_train.shape[2], 1)) X_test = X_test.reshape((X_test.shape[0],X_test.shape[1],X_test.shape[2],1)) • Normalizing the pixel values X_train=X_train/255 X_test=X_test/255
Step 4:	Put the correct labels on the pictures of the pests.
Step 5:	Sort photos into categories using the available class labels from both the training and testing datasets.
Step 6:	Initialize the parameters image size, epochs, batch size, and train and test image labels.
Step 7:	Initialize Custom CNN [proposed] model architectures with parameters, conv, pooling, flatten, and FC layers • Train the model using the labelled groundnut pest dataset, specifying the batch size and the number of epochs. • Evaluate the trained model using a separate testing dataset. • Calculate the test loss and accuracy of the model.
Step 8:	Initialize the LeNet-5 model. conv, pooling, FC, Dense layers. • Train the model using the labelled groundnut pest dataset, specifying the batch size and the number of epochs. • Evaluate the trained model using a separate testing dataset. • Calculate the test loss and accuracy of the model.
Step 9:	Initialize the VGG-16 model., conv, max pooling, FC, and Dense. • Train the model using the labelled groundnut pest dataset, specifying the batch size and the number of epochs. • Evaluate the trained model using a separate testing dataset. • Calculate the test loss and accuracy of the model.
Step 10:	Check the accuracy of the proposed models, and see how they stack up against the rest of the CNN models out there. Make predictions on new data predictions = model.predict(new_images).

such a case, the time variable t would only be of integer type, likewise, the variables x and w, then the mathematical discrete convolution can be defined as.

$$s(t) = (x * w)(t) = \sum_{a=0}^{\infty} x(a)w(t-a) \quad (6)$$

The model includes 5 Conv2D layers. Conv2D performs convolution operations on the input image to extract features. Each Conv2D layer consists of a set of learnable filters that scan the input image and produce feature maps. These filters capture different patterns and features at different scales.

2. Batch Normalization layers: The batch normalized activation is

$$x_i = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}} \quad (7)$$

Where $\mu_B = \frac{1}{m}\sum_{i=1}^{m} xi$ is the batch mean and $\sigma^2_B = \frac{1}{m}\sum_{i=1}^{m}(xi - \mu B)^2$ is the batch variance. Batch Normalization is applied after each Conv2D layer. It helps in normalizing the output of the previous layer by adjusting the mean and variance. This helps in stabilizing the training process and improving the overall performance of the model.

3. Max Pooling layers: Max Pooling is performed after each Conv2D layer. It reduces the spatial dimensions of the feature maps by selecting the maximum value within a defined pool size. Max Pooling helps in down-sampling the feature maps and extracting the most important features while reducing computational complexity.

$$h_{xy}^{1} = max_{i=0\ldots s\ j=0\ldots s}\ h^{l-1}\ (x+i)(y+i) \quad (8)$$

4. Activation functions: The model utilizes 7 activation functions throughout its layers. Activation functions introduce non-linearity to the model, enabling it to learn complex patterns and make nonlinear decisions. *ReLU*, *sigmoid*, and *tanh* activation functions are frequently employed in CNNs. The output of the layer before it is fed into the next activation function, element by element.

$$ReLU(xi) = \max(0, xi) \quad (9)$$

The combination of Conv2D layers, Batch Normalization, Max Pooling, and Activation functions help the CNN model to effectively extract and learn intricate features from the input data. This allows the model to capture the relevant information needed for accurate classification or detection tasks.

Lenet-5

The LeNet-5 model is a classic convolutional neural network architecture (LeCun, Y.). It consists of seven layers, including three convolutional layers and two fully connected layers. Here's a detailed description of implementing LeNet-5 for groundnut pests' detection and classification, specifically for thrips, aphids, armyworms, and wireworms. Figure 5 represents the architecture of the LeNet-5 for groundnut pest detection and classification.

To implement LeNet-5 for groundnut pest detection and classification, start by collecting a labelled dataset of groundnut crop images containing thrips, aphids, armyworms, and wireworms. Preprocess the dataset by resizing the images and normalizing pixel values. Train the model on the dataset using an optimization algorithm such as stochastic gradient descent, monitoring performance with evaluation metrics. Evaluate the trained model on a separate testing dataset to assess its generalization. Experiment with hyperparameter settings and fine-tune the architecture to optimize performance. Analyze the results to understand the model's effectiveness in detecting and classifying groundnut pests.

During the training phase of implementing LeNet-5 for groundnut pest detection and classification, the labelled dataset is used to optimize the model's parameters through iterative batch processing. The optimization algorithm, such as stochastic gradient descent, adjusts the parameters based on these gradients to minimize the loss. Training continues for multiple epochs, with periodic evaluation on a validation set to monitor progress and prevent overfitting. Techniques like dropout regularization and data augmentation can be applied to improve performance and generalization. Hyperparameters are fine-tuned through experimentation, and the training phase concludes when the model demonstrates satisfactory performance. The final trained model can then be evaluated on a separate testing dataset to assess its effectiveness in detecting and classifying groundnut pests accurately.

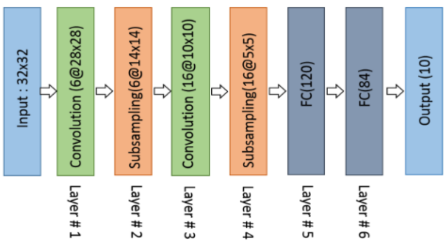

Figure 5. Architecture of LeNet-5

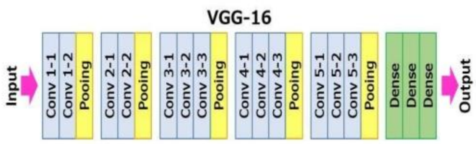

Figure 6. The architecture of the VGG-16 model for groundnut pests detection and classification

VGG-16

There are a total of 16 layers in the VGG16 model, 13 of which are convolutional layers and 3 of which are completely linked, making it a deep convolutional neural network design (Rosebrock, 2021). Commonly, people will utilize it to classify images. For implementing groundnut pests detection and classification using VGG16, the first step is to collect a labelled dataset of groundnut crop images containing thrips, aphids, armyworms, and wireworms. The dataset is then preprocessed, including resizing the images and normalizing pixel values. The VGG16 model is then built and fine-tuned using transfer learning (Jiang *et al*., 2020), where the pre-trained weights from the ImageNet dataset are utilized (Veeragandham and Santhi, 2022). The model is trained on the prepared dataset, optimizing the classification loss using an optimization algorithm. Finally, the trained model is evaluated on a testing dataset, and the results are analyzed to assess its performance in detecting and classifying groundnut pests. Hyperparameter tuning and experimentation can be performed to optimize the model's performance. Figure 6 represents the architecture of the VGG-16 for groundnut pest detection and classification (Ananda and Vandana, 2022).

During the training phase of implementing the VGG-16 model for groundnut pest detection and classification, the labelled dataset is utilized to optimize the model's parameters. Batches of data are processed through the network, with forward propagation computing output probabilities and backward propagation calculating gradients for parameter updates. An optimization algorithm, typically stochastic gradient descent, is used to minimize the loss. Training involves multiple epochs, with periodic evaluation on a validation set to monitor progress and prevent overfitting. Techniques such as dropout regularization and data augmentation can be employed to improve performance and generalization. Hyperparameters, including learning rate and batch size, can be tuned through experimentation. The training phase concludes when the model achieves satisfactory performance, and the final trained VGG-16 model can be evaluated on a separate testing dataset to assess its effectiveness in detecting and classifying groundnut pests accurately.

Training, Validation, and Testing Description

The dataset was divided into training and test sets. The test dataset tested the proposed model's performance, whereas the training dataset fine-tuned CNN models. As a result, we segmented the datasets into three categories i.e. training, validation, and testing into equal halves of 80%, 10%, and 10%, respectively. In the event of an incorrect forecast, back-propagation was carried out in the opposite direction. As a result, the back-propagation technique was used in the current research to appropriately update the model weights for a better forecast. One epoch was the collective term for forwarding and backpropagation. For the investigation, the model made use of the Adam optimizing algorithm. The training images for the current investigation were obtained while retaining the 80% image. Each dataset was examined using the remaining 20% of unaltered photos (Arnal Barbedo, 2019).

Performance Measure

Multiple metrics are used to evaluate the success of a network (Powers, 2020). Using different metrics for different tasks is useful to represent the network's ability to solve a given problem.

The reason for using accuracy and loss as performance evaluation metrics in their deep learning models for pest detection in groundnut crops. These metrics play a crucial role in assessing the models' effectiveness and reliability in classifying various pest types. Accuracy reflects the precision of the model in correct classifications, while loss gauges how well the model learns from the training data, both vital for practical agricultural applications. The evaluation metrics can use true positive (TP), false positive (FP), true negative (TN), and false negative (FN).

***Classification Accuracy*:** This is determined by the ratio of correct prediction to total predictions (Powers, 2020).

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ number\ of\ Predictions} \tag{10}$$

Precision: Precision (Powers, 2020) determines with what precision the network places images in the positive category. Precision is calculated as follows:

$$Precision = \frac{TP}{TP+FP} \tag{11}$$

Recall: Recall (Powers, 2020) indicates how many positive images the network recorded. The recall is calculated as:

$$Recall\ \frac{TP}{TP+FN} \tag{12}$$

F-measure: F-measure (Powers, 2020) is a combination of Precision and Recall. The calculation is as follows:

$$F1 - Score = 2 * \frac{Precision*Recall}{Precision+Recall} \tag{13}$$

Results and Discussion

Python libraries are used to implement the proposed research and TensorFlow (Gulli and Pal, 2017), and Keras is for the CNN models experiments proposed. It employed the Adam optimizer for training, which possessed a learning rate and a built-in loss function. The experimental analysis is carried out on a GPU-enabled server with an i5 processor and 8GB RAM.

Dataset Description

In this research work, a diverse collection of high-quality images of groundnut pests is obtained from the IP102 Dataset. The dataset consists of four classes of insect pests: Aphids, Armyworms, wireworms, and Thrips. The Aphids class is the most significant as it contains 2456 pest images from 42 different aggravation types found in field crops. The Armyworm class consists of 642 pest images, while the Wireworm class, extracted from the IP102 Dataset, comprises 532 pest images used for both model training and testing. The Thrips class includes 527 pest images. Overall, the dataset encompasses 4157 pest images of groundnut crops, distributed across the four classes. The dataset is divided into training, validation, and testing sets with 80:20 ratios.

Pre-Processing The Data

The objective is to learn how to pre-process images for Convolutional Neural Networks. Tensors can be thought of as multi-dimensional arrays simply because they are meant to hold knowledge rather than actual data. Load the dataset after importing the required libraries. Every data analysis procedure must include this step. Images come in a variety of sizes and shapes (Jayamala and Raj, 2017). Data pre-processing starts with uniformly sizing all of the images. With the help of ImageDataGenerator in Keras (Gurucharan, 2020), several enhancing techniques are used to the collected photos, resulting in the creation of new images with a resolution of 400×400 pixels. Figure 7 represents the pre-processed image with a resolution of 400×400.

Table 2. Parameters used in the Deep CNN model

S.No	Parameter used	Value
1	Training Epochs	5 or 10
2	Optimizer	Adam
3	Learning Rate	0.0001 to 0.000001
4	Batch Size	32 or 64
5	Drop out	0.2
7	Image size	256x256
8	Image Depth	3

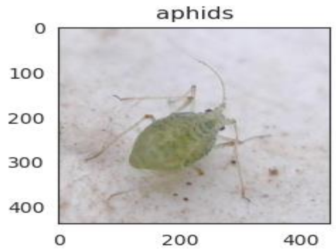

Figure 7. Represents the pre-processed image with a resolution of 400×400

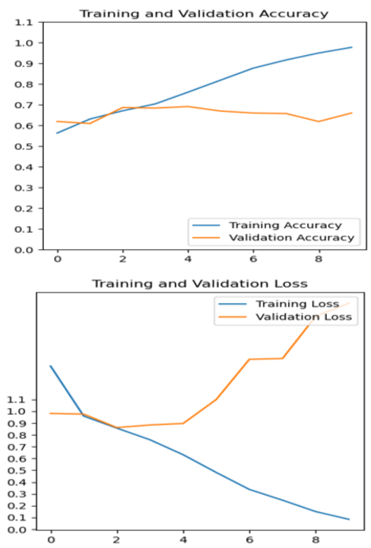

Figure 8. The Accuracy of a Custom CNN [proposed] model Groundnut pests dataset

Performance of The Custom CNN [proposed] Model on Dataset

The performance measures, such as accuracy and loss, of Custom CNN [proposed] models trained on the groundnut pests Dataset may be examined with the number of epochs used in the training process. groundnut pests detection Custom CNN [proposed] model parameters are shown in Table 2. During the training process, the Deep CNN model is exposed to the dataset and iteratively updates its internal parameters to improve its performance. As the training progresses through multiple epochs, the model learns to extract relevant features and make accurate predictions for the given task of classifying pests. Monitoring the accuracy and loss values at each epoch provides insights into the model's performance. Accuracy measures the percentage of correctly classified instances, while loss quantifies the dissimilarity between the predicted outputs and the actual labels. Figure 8, 9, and 10 represents the accuracy of the Custom CNN [proposed], LeNet-5, and VGG-16 architectures on groundnut pest detection and classification.

From Figure 8, it is noted that the training accuracy of a Custom CNN [proposed] model on the Pest Dataset for 10 epochs is reported to be 93.34%, while the validation accuracy of a Custom CNN [proposed] model is 66.02%. These accuracy values provide insights into the performance of the model in correctly classifying the pest images. The reported training accuracy of 93.34% indicates that the proposed CNN model can correctly classify the majority of instances in the groundnut pest Dataset. However, in Figure 8, the training accuracy is gradually increasing and validation accuracy is decreasing it is due to the model's likely overfitting. This is due to the model having memorized the training data too well, but it struggles to generalize to new, unseen data as the images contain watermarking and some textual features in the feature extraction. The loss function shows the effect of the model training, which is due to noise in the image.

This high accuracy suggests that the model has effectively learned the distinguishing features and characteristics of different pests, allowing it to make accurate predictions.

Performance of The Lenet-5 Model on Dataset

The LeNet-5 model demonstrates promising performance on the pest dataset for groundnut pest detection and classification shown in Figure 9. The model is trained for 10 epochs, with a training accuracy of 64.06%, the model effectively learns and accurately classifies groundnut pests during training, while the test accuracy of 63.37% shows its capability to make accurate predictions on an independent testing dataset. These results suggest that the LeNet-5 model is capable of accurately classifying groundnut pests, indicating its potential for practical application in real-world scenarios. However, as the images contain watermarking and some textual features in the feature extraction, the model is likely to overfit, as the training and validation accuracies are crossing each other for each epoch. Hence further analysis and comparison with other models would be beneficial to fully evaluate its competitiveness in this domain. While the accuracy achieved by the LeNet-5 model on groundnut pest detection and classification is decent, further optimization or exploration of other deep-learning architectures might potentially improve the accuracy even further.

Performance of The Vgg-16 Model on Dataset

The VGG-16 model demonstrates strong performance on the pest dataset for groundnut pest detection and classification shown in Figure 10. The model is trained for 10 epochs, with a training accuracy of 74.62%, the model effectively learns and accurately classifies groundnut pests during training. The validation accuracy of 72.44% indicates its ability to generalize well to unseen data. However, the training accuracy is lower than the validation accuracy during a 3 epoch, which indicates that the model is likely overfitting. This is due to the model having memorized the training data too well, but it struggles to generalize to new, unseen data as the images contain watermarking and some textual features in the feature extraction. Further analysis and comparison with other models would be beneficial to fully evaluate its competitiveness and suitability for groundnut pest detection and classification.

Deep Learning Models Performance On Correctly Predicted Images

Custom CNN [proposed] Model

The Custom CNN [proposed] model also exhibits strong performance on correctly predicted images, highlighting its accuracy in classifying groundnut pests. The Custom CNN [proposed] model prediction on correctly classified images is shown in Figure 11. Analyzing these correctly predicted images provides valuable insights into the model's ability to identify and classify different pest species, such as thrips, aphids, armyworms, and wireworms. This indicates that the Custom CNN [proposed] model effectively captures the visual patterns and features specific to each pest class, allowing for accurate classification. The high accuracy of correctly predicted images suggests that the model successfully distinguishes between groundnut pests with a high level of precision. By examining these images, researchers can gain a

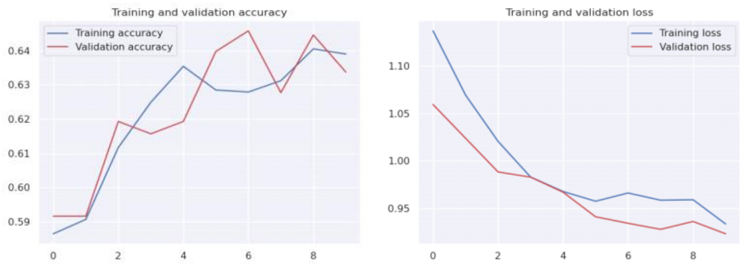

Figure 9. The Accuracy of a LeNet-5 model Groundnut pest dataset

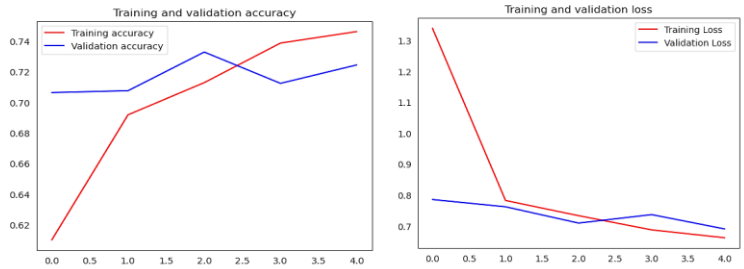

Figure 10. The Accuracy of a VGG-16 model Groundnut pest dataset

deeper understanding of the distinguishing characteristics utilized by the Custom CNN [proposed] model for accurate classification. This knowledge can contribute to further research efforts and the development of effective pest management strategies. Overall, the Custom CNN [proposed] model's performance on correctly predicted images underscores its capability in accurately classifying groundnut pests and highlights its potential for practical implementation in pest detection and classification systems.

VGG-16 Model

The VGG-16 model demonstrates strong performance on correctly predicted images, indicating its accuracy in classifying groundnut pests. The VGG-16 model prediction on correctly classified images is shown in Figure 12. By analyzing these correctly predicted images, the model's ability to accurately identify and classify different pest species, including thrips, aphids, armyworms, and wireworms, becomes evident. This showcases the model's effectiveness in discerning visual patterns and features specific to each pest class. The high accuracy of correctly predicted images suggests that the VGG-16 model successfully captures the distinctive characteristics of each pest class and utilizes them for accurate classification. This performance not only demonstrates the model's ability to differentiate between groundnut pests with precision but also provides valuable insights into the visual cues and features used by the model for classification. Understanding these distinguishing characteristics can contribute to further research and the development of effective pest management strategies. Overall, the VGG-16 model's performance on correctly predicted images showcases its proficiency in accurately classifying groundnut pests and underscores its potential for practical implementation in pest detection and classification systems.

Performance Measures on Individual Pests Detection and Classification

When evaluating the performance of prediction and classification models for individual pests of Groundnut, the efficacy and precision of the VGG-16 Model can be measured by its Precision, Recall, and F1-score. These performance measures provide insights into the prediction and classification accuracy of individual groundnut

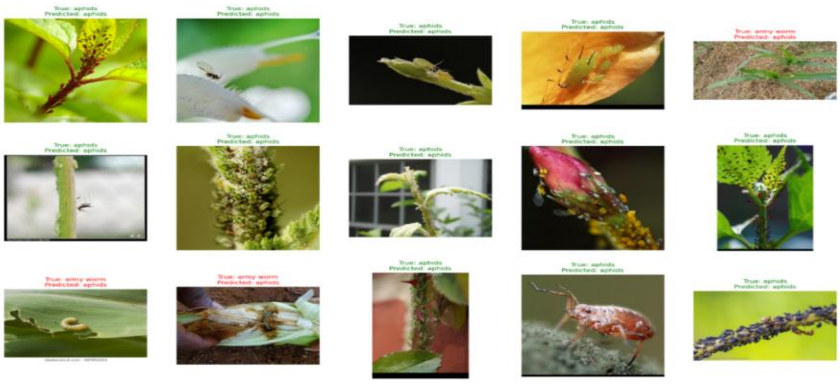

Figure 11. Custom CNN [proposed] model performance on correctly predicted images

Figure 12. VGG-16 model performance on correctly predicted images

pests. Depending on the specific goals and requirements of the study, different measures may be prioritized. It's important to consider these metrics collectively to gain a comprehensive understanding of the model's performance. Table 3 shows the performance measures of individual pest classes on groundnut pests. From Table 3, it is observed that a few pest types Thrips are not predicted accurately due to Out-of-distribution data, Lack of representative training data, Noisy or ambiguous input, and Overfitting. The remaining pests are predicted more accurately with the VGG-16 model.

Discussion

Table 4 presents the performance metrics of different models, Custom CNN [proposed], LeNet-5, and VGG-16, used for groundnut pest detection and classification. The Custom CNN [proposed] model achieved a high training accuracy of 93.34%, indicating successful learning and accurate classification during training. However, it exhibited a lower test accuracy of 66.02%, suggesting possible overfitting. The LeNet-5 model demonstrated similar training and test accuracies of 64.06% and 63.37% respectively, indicating consistent performance and balanced generalization. The VGG-16 model achieved a training accuracy of 74.62% and a test accuracy of 72.44%, demonstrating effective learning and generalization. Overall, while the Custom CNN [proposed] model showed the highest training accuracy, the VGG-16 model exhibited a good balance between training and test accuracies. A more all-encompassing evaluation of the models' performance could be achieved by taking into account precision, recall, and F1-score. The best model to use will be determined by the needs of the intended application and the desired balance between precision and ease of implementation. The proposed system in the paper, employing deep learning models for pest detection in groundnut crops, faces several limitations, notably the risk of overfitting in the Custom CNN [proposed] model. Despite achieving high training accuracy, the observed significant drop in test accuracy suggests a lack of generalization to new, unseen data, raising concerns about the model's practical effectiveness in diverse agricultural settings. Furthermore, the system's performance is susceptible to variations in the quality of input images, with factors such as watermarking impacting feature extraction and, consequently, pest classification accuracy. Acknowledging the necessity for further analysis and comparative assessments with alternative models like VGG-16, the study underscores the imperative for ongoing refinement and development to address these limitations and enhance the proposed system's reliability and applicability in real-world scenarios of agricultural pest management.

Conclusion

The study conducted training and evaluation of Custom CNN [proposed] models on a groundnut pest dataset for pest detection and classification. The Custom CNN [proposed] model achieved a high training accuracy of 93.34%, indicating its ability to correctly classify the majority of instances in the dataset. However, its validation accuracy of 66.02% suggests potential overfitting. On the other hand, the LeNet-5 model exhibited balanced performance with similar accuracies for both the training (64.06%) and testing (63.37%) datasets, indicating its capability to generalize well to unseen data. The VGG-16 model showcased strong performance with

Table 3. Performance measures of individual Pest classes

S.No	Pest class	Precision (%)	Recall(%)	F1-Score(%)
1	Thrips	56.00	22.00	32.00
2	Aphids	81.00	88.00	85.00
3	Armyworm	52.00	65.00	58.00
4	Wireworm	78.00	66.00	72.00

Table 4. Analysis of Deep learning models on groundnut pest Performance

Model	Training Acc(%)	Test Acc(%)	Epochs	Loss
Custom CNN [Propsoed]	93.34	66.02	10	0.0847
MobileNet [39]	90.71	87.2	30	0.223
ResNet [38]	82.50	82.44	100	0.9899
VGG19 [38]	82.50	84.62	100	0.7899
VggNet [37]	80.4	73.37	100	1.230
CRN [36]	70.42	76.22	500	0.1688
VGG-16	74.62	72.44	10	0.6899

a training accuracy of 74.62% and a test accuracy of 72.44%, indicating its effectiveness in accurately classifying groundnut pests. These results highlight the potential of the VGG-16 model for practical implementation in real-world scenarios.

Analyzing correctly predicted images further demonstrated the accuracy of both the Custom CNN [proposed] and VGG-16 models in classifying various pest species within the groundnut pest dataset. The models successfully captured the distinct visual patterns and features specific to each pest class, enabling precise classification. This insight into the distinguishing characteristics utilized by the models provides valuable knowledge for developing effective pest management strategies. Overall, the VGG-16 model's strong performance and accurate classification of groundnut pests make it a promising choice for pest detection and classification systems, though further analysis and comparisons with other models are necessary to fully assess its competitiveness and suitability in real-world applications.

As future work, the study can be extended to investigate the impact of transfer learning models on groundnut pest detection and classification. Comparative studies can be conducted to evaluate the performance of different models and techniques, considering metrics such as accuracy, precision, recall, and F1-score. Additionally, optimization techniques can be applied to enhance the trained models, including the exploration of different optimization algorithms, hyperparameter tuning, and regularization methods for groundnut pest detection and classification using deep learning models, leading to improved pest management strategies and enhanced agricultural practices.

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