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Comparative Analysis of Deep Learning Models for Crop Diseases and Pest Classification

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Abstract

The deep learning models for crop diseases and pest classification research examined how deep learning might improve farming methods, particularly to accurately classify pests and diseases that affect crops. The importance of crop diseases and pests to world food security was highlighted in the introduction, along with the need for new approaches, such as deep learning models, to improve the accuracy and effectiveness of pest and disease control in farming. To evaluate the classification accuracy, the secondary datasets obtained from the Kaggle website were used to train and test various deep learning models, one of which was DenseNet. The researcher used a thorough assessment methodology to compare DenseNet's performance to that of other models, including AlexNet, EfficientNet, Visual Geometry Group, and Convolutional Neural Network. With an impressive accuracy score of 96.988% on the maize disease dataset and 96.9382% on the pest dataset, DenseNet proved to be the best model among the others. More accurate predictions were the result of DenseNet's capacity to effectively collect intricate characteristics and patterns within the visual data, which led to its improved performance. The researcher examined the implications of DenseNet's high accuracy in the discussion section, implying that its sophisticated design rendered it optimal for the categorization of agricultural diseases and pests. In addition, the researcher investigated the feasibility of incorporating DenseNet into practical agricultural systems, where its strong performance might greatly enhance methods of crop monitoring and disease control. The discussion came to a close with suggestions for future studies, such as looking at whether DenseNet can be used for other types of crops and if hybrid models or transfer learning may improve its performance.

Keywords: Deep learning; Crop Diseases; Pest Classification; Convolution Neural Network; Agricultural Technology; Machine Learning; Image Recognition.

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1. Introduction

Pests and diseases that affect crops pose serious problems for agricultural output throughout the world, putting food security and economic stability at risk. Agricultural disease and pest detection has traditionally relied on labor-intensive, error-prone, and time-consuming manual examination. New developments in deep learning, however, provide encouraging prospects for overcoming these enduring obstacles. Deep learning is a branch of machine learning that uses multi-layered neural networks to automatically glean complex characteristics and patterns from massive datasets, with a focus on image identification. Success in computer vision tasks like object identification and image classification has been achieved in recent years by deep learning models, particularly convolutional neural networks (CNNs). The potential for deep learning algorithms to transform conventional farming methods and reduce crop losses has increased interest in their use for pest and disease categorization in crops [1].

Incorporating deep learning technologies into pest and disease control tactics might have a tremendous impact on the agriculture industry. The goal of academics and practitioners in the field is to provide scalable solutions for early detection, accurate diagnosis, and successful control of crop diseases and pests by using computer algorithms and large volumes of agricultural data. The move towards data-driven methods has several potential benefits, including improved disease and pest diagnosis, the ability to intervene proactively to avoid extensive crop damage, and reduced economic losses [2].

The Convolutional Neural Network (CNN) is a popular deep learning model used for pest and disease classification in crops. When it comes to detecting small variations between healthy and crop diseases, as well as different types of pests, CNNs perform because of their capacity to automatically extract hierarchical characteristics from raw photos. In a common model design, pooling layers lower the data's dimensionality and computational complexity after many convolutional layers identify characteristics including textures, forms, and edges. The last step of classification is carried out by a fully connected layer, which uses the retrieved information to forecast the kind of crop diseases or pests [1].Accuracy and generalizability have been enhanced by the use of many state-of-the-art CNN architectures. To illustrate, ResNet (Residual Networks) enables deeper networks to avoid the vanishing gradient issue via the use of skip connections. This paves the way for the detection of more intricate patterns in agricultural images. To recognize both large and small pests and disease lesions, inception networks utilize filters of various sizes in parallel to collect multi-scale information. These networks are noted for their efficiency. To improve performance and speed convergence with little data, transfer learning is often used. This method involves refining models that have been pre-trained on big datasets like ImageNet using smaller, domain-specific datasets related to agriculture [2].

Data augmentation is one method that may be used in conjunction with CNNs to make the dataset larger by the application of changes like flipping, rotating, or zooming the pictures. This makes the model more resilient. Depending on the dataset and the complexity of the issue, these models have been shown to attain high accuracy sometimes above 95% making them a dependable tool in contemporary precision agriculture for pest and disease control [3].

There have been encouraging developments, but using deep learning models to categorize pests and diseases in crops is still fraught with difficulty. The availability and quality of labeled datasets pose a substantial challenge when it comes to training trustworthy and accurate models. Data variability and model robustness are two of the many elements that must be carefully considered when attempting to generalize deep learning models to other crops, geographies, and environmental circumstances. Further preventing their use in practical agricultural contexts is the interpretability of deep learning models, which makes it difficult to comprehend the decision-making procedures [3].

Regardless of these obstacles, deep learning technology's revolutionary potential in crop health management is immense. The goal of this research is to survey everything that has been accomplished so far in using deep learning to categorize agricultural diseases and pests. Our goal is to shed light on the pros and cons of using deep learning models to promote sustainable agriculture and guarantee global food security in light of changing environmental and socioeconomic conditions. The researchers will do this by reviewing current research, evaluating performance metrics, talking about obstacles and limitations, and pointing to potential areas for future research [4]. The rest of the paper is organized like this; after a brief overview of the literature in Section 2, the study methodology is detailed in Section 3, the results are presented in Section 4, and the research is summarized in Section 5.

2. Related Work

There is exciting new potential for agricultural technology at the crossroads of decision support systems and deep learning models to transform conventional farming by addressing crop diseases and pests. The purpose of this literature review is to provide a comprehensive analysis of the current research on the topic of crop health decision support by identifying the critical success criteria and barriers to their widespread use.

The developments in deep learning methods in the agricultural sector has seen a revolutionary shift in the last few years, especially in the area of pest and disease categorization for crops. Crop losses caused by pests and diseases continue to be a major problem, endangering lives and food supply on a global scale, despite the fact that agriculture is the foundation of food security. Manual observation is a common yet labor-intensive and inaccurate technique of disease and pest diagnosis in traditional approaches. But new deep learning algorithms that use massive quantities of agricultural data to automate and improve categorization and detection procedures provide encouraging answers. Examining the methodology, advances, problems, and future possibilities in this crucial sector, this literature review explores the present status of research in using deep learning models for crop disease and pest categorization. The purpose of this literature review is to provide light on the possibilities, constraints, and current state of deep learning approaches to agricultural pest and disease management by analyzing the available literature in depth.

The research by Pandey and his colleagues, 2023 [5] makes a substantial contribution to the development of deep learning models for plant disease identification, especially as it pertains to the FarmEasy app. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are emphasised in their thorough evaluation of several deep learning architectures and approaches used for plant disease diagnosis. Pandey and his colleagues. shed light on the capacity of deep learning models to correctly detect plant diseases in a variety of crop types and environments by combining results from several investigations. In order to train deep learning models, the authors stress the significance of large-scale datasets. To improve the performance and generalizability of these models, they address methodologies including ensemble approaches and transfer learning. The authors Pandey and his colleagues highlight the potential of FarmEasy to provide farmers with easy-to-use tools for disease detection and management, as well as the practical implications of using deep learning models in agriculture. To be sure, there is a need for more study to address the constraints highlighted in the paper, such as dataset scarcity, class imbalance, and model interpretability difficulties. In conclusion, the research work published by Pandey and his colleaguesestablishes a solid foundation for future study in this important field of agricultural technology by shedding light on the current methods, obstacles, and potential solutions for plant disease detection using deep learning models.

The research conducted by Rajeshram and his colleagues in 2023 delves into the use of deep learning in crop development in great detail. While this study expands our knowledge of deep learning's possible uses in crop health management, it also highlights several knowledge gaps that must be addressed. Finding out how well deep learning models work in different agricultural settings and with different types of crops is a crucial question that requires answering. Researching how different farming methods impact these models' efficacy and how they perform in different environmental conditions is an important topic, as the paper suggests. Another big problem with deep learning models for disease prediction, pest detection, and pesticide recommendations is that they are not interpretable. Farmers and agricultural practitioners, who are the end-users of these complex systems, need further research to make the model results more transparent so that they can trust and comprehend them. By closing these information gaps and using deep learning techniques extensively in farming settings, we may create a precision crop management system that is more inclusive and flexible.

Song and his colleagues, 2023 used advanced detection methods to tackle the pressing issue of citrus crop health. By enhancing the accuracy of disease and pest identification utilizing the YOLOv8 architecture with the Self-Attention mechanism, the study contributes to the field's knowledge. However, it also highlights some gaps that need filling. Not enough has been said about how well the concept works in various settings and areas, which is a major problem that requires fixing. Because they influence the accuracy of pest and disease detection in citrus crops, these traits are crucial. Notably absent from the paper is a comprehensive examination of the interpretability of the Self-Attention YOLOv8 model, a crucial aspect for its use in real-world agricultural settings. Acknowledging the model's biases and decision-making process is crucial for gaining end-user confidence, particularly from agronomists and farmers. Further investigation into the scalability and resource efficiency of the proposed model is also necessary before its use in resource-constrained agricultural contexts. Our present understanding is lacking in several areas that must be filled in order to fully grasp deep learning solutions for precision agriculture and to enhance the Self-Attention YOLOv8 model's ability to identify citrus diseases and pests[6,7].

A major issue in Sri Lankan farming is tackled in the 2023 study by Rathnayake and his colleagues. While the research does provide some useful insight into how banana growers could benefit from mobile technology, there are still certain issues that need clarification. The article start off on the right foot by providing additional background on the specific plant diseases and insect infestations that plague the banana industry in Sri Lanka. The complexity of these difficulties necessitates an understanding of them in order to design effective mobile solutions. Literacy rates, smartphone affordability, and access to technology are some socioeconomic factors that the authors examine while researching the banana growers' history. By understanding these contextual variables, the needs of the target audience may be better satisfied via the customization of the mobile solution. Problems with power availability and network connection impact the practicality and acceptance of solutions that depend on mobile devices. The article can also investigate the technological infrastructure of rural places. Case studies and pilot projects would allow the authors to demonstrate the practicality of their mobile solution, which would make their study more applicable. Filling up these gaps is vital for a better understanding of how the mobile solution may empower banana producers in Sri Lanka [8].

Even though Parkavi and his colleagues, 2023 investigated the use of Machine Learning and the Internet of Things in agriculture, there are still many unanswered questions about what has to be solved. One problem is that large-scale farmers have different needs than small-scale farmers who are strapped for cash; the proposed complex agro-management systems could not be applicable in all sorts of agricultural settings. We must prioritize addressing the scalability and usability of these technologies to different scales of agriculture. The article might need more research on the societal and economic impacts of modern farming technologies, including the potential disruption to traditional farming practices and the necessity to educate farmers' abilities. Two further possible areas where study on the suggested system's long-term feasibility is lacking are the energy requirements to maintain a network of connected devices in remote agricultural areas and the environmental impacts of the increasing electronic trash from Internet of Things (IoT) devices. If these details are missing, the article won't be as useful, and the researcher won't be able to weigh the benefits and drawbacks of implementing complex agro-management systems via the use of Machine Learning and the Internet of Things [9].

A number of significant information gaps are identified by the authors of the 2023 paper Identification and Classification of Crop Diseases using Transfer Learning-based Convolutional Neural Network, published by Mehta and his colleagues. The first problem is that transfer learning algorithms for agricultural disease detection were not sufficiently optimized or explored. This can be the result of a lack of study on potential transferable feature picks, fine-tuning strategies, or pre-trained model choices. Additionally, there was a lack of information about the particular challenges posed by crop disease datasets, such as variations in imaging parameters, a broad range of plant species, and several stages of disease progression. Researchers need to figure out how to include domain-specific data, such as agronomic expertise, into the training process if they want their models to be more accurate and generalizable across various agricultural contexts. The paper would be strengthened with a thorough examination of the training data, any biases present in it, and the potential socioeconomic repercussions of using this technology in agriculture. Completing these information gaps might significantly enhance the proposed Convolutional Neural Network's (CNN) ability to identify and categorize agricultural diseases [10].

3. Methodology

This study's methodology describes a thorough and organized strategy for creating a deep learning model to categorize pests and illnesses in crops. Proper and prompt identification is of the utmost importance due to the growing number of agricultural diseases and pests, which endanger food security worldwide. Diagnosing plant health concerns using traditional approaches may be a tedious and error-prone process. Consequently, a potential option to automate and improve the accuracy of pest and disease categorization is to use the capabilities of deep learning models.

Data collecting, data preprocessing, model selection, training, assessment, and deployment are the essential steps that make up the suggested technique. To build a strong and efficient deep learning model, each step is carefully planned to handle the unique problems of agricultural image categorization. To maximize value for end-users, especially farmers and agricultural experts, this technique takes into account both the theoretical and practical dimensions of model building.

The primary data used in this study comes from a large and varied dataset of crop images that have been impacted by several pests and diseases. To make sure the model works and can be generalized, you need a diverse and high-quality dataset. Data preparation is the next step, to improve the image quality and get the dataset ready for efficient model training. In this stage, methods including resizing, normalizing, and augmenting images are used to fix problems like different image resolutions and small datasets.

Choosing the right deep learning architecture is the right decision for this study. Because of its inherent capacity to learn and extract characteristics from images automatically, Convolutional Neural Networks (CNNs) excel in image categorization tasks. To increase model performance with limited agricultural image data, the technique entails examining state-of-the-art CNN architectures and applying transfer learning. Training a model entails repeatedly refining the model using the test, validation, and training sets to optimize the hyperparameters and avoid overfitting.

To make sure the trained model works well in real-world situations, it's important to evaluate how well it performs. This part of the process uses a wide variety of measures to provide a thorough evaluation, including recall, accuracy, precision, F1-score, and AUC-ROC. To make sure the findings are solid and not skewed by any one data split, cross-validation is used. The last step, deployment, is making the study useful by creating an intuitive interface for real-time pest and disease categorization.

This research paper's technique is built to tackle the issues of deep learning model development for pest and agricultural disease categorization systematically. Using this methodical approach, the study hopes to develop a robust instrument that may greatly enhance the precision and efficacy of agricultural diagnostics, leading to enhanced crop management and higher agricultural yields.

i. Data Collection

To create a deep learning model for crop diseases and pest classification, data collecting is an essential first step. The caliber and variety of the dataset have a significant impact on the model's efficacy. Data for this study came from agricultural extension services, research institutes, and publically accessible agricultural databases. The dataset has a strong basis thanks to databases like PlantVillage and Kaggle, which provide enormous amounts of labeled images spanning a variety of crops, illnesses, and pests. Partnerships with universities and agricultural research centers can also provide access to specialized datasets that improve the accuracy and comprehensiveness of the dataset. The dataset for this study was obtained from Kaggle and the distribution of images across different illnesses and healthy circumstances for tomato and maize crops is shown in Table 1. There are a total of 7,316 images for maize, of which 1,908 are of Northern Leaf Blight, 1,907 are of Common Rust, 1,859 are of healthy maize, and 1,642 are of Gray Leaf Spot. Bacterial Spot, Early Blight, Healthy Tomatoes, Late Blight, Leaf Mold, Septoria Leaf Spot, Spider Mites, Target Spot, Mosaic Virus, and Yellow Leaf Curl Virus are some of the tomato-related diseases that have been documented. A grand total of 10,000 images were used for tomato.

Table 1: Crop Image Distribution

Crop	**Disease**	**Number of Images**
Maize	Northern Leaf Blight	1908
	Common Rust	1907
	Healthy	1859
	Gray Leaf Spot	1642
Total Images for Maize		7316
Tomato	Bacterial Spot	1000
	Early Blight	1000
	Healthy	1000
	Late Blight	1000
	Leaf Mold	1000
	Septoria Leaf Spot	1000
	Spider Mites	1000
	Target Spot	1000
	Mosaic Virus	1000
	Yellow Leaf Curl Virus	1000
Total Images for Tomato		10000

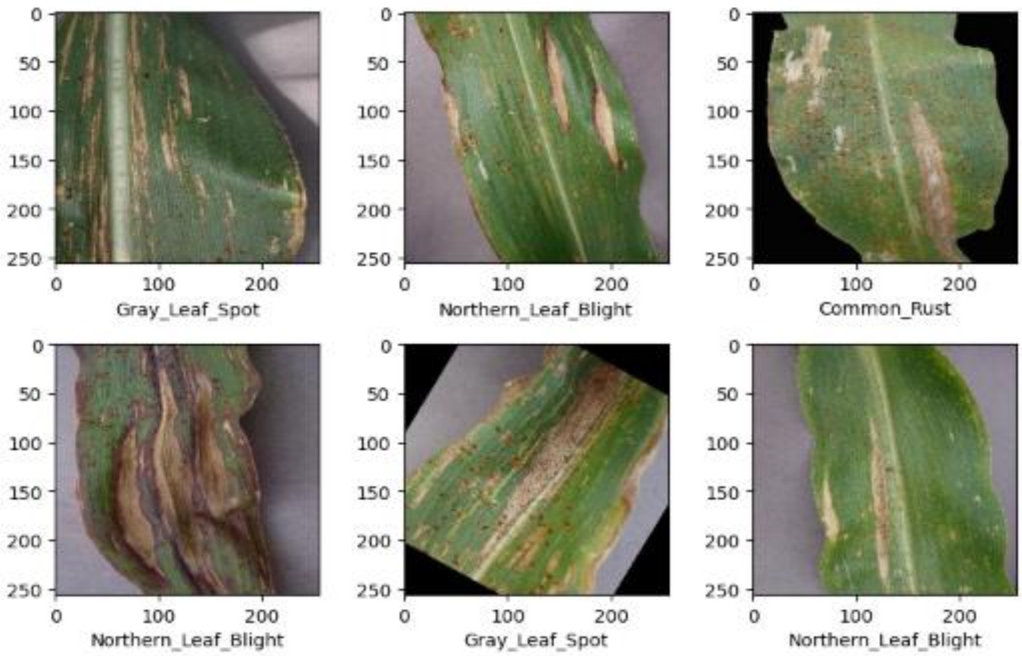

Figure 1: Sample of Maize Image Dataset

The table 2 gives a detailed rundown of all the agricultural pests, including how many images are available for each kind of insect. In particular, there are 390 earwig images, 405 snail images, and 400 ant images. There are 316 pictures of slugs and 394 pictures of weevils. Beetles images are 331, whereas wasps have 392. There are 246 images of earthworms and 397 images of moths. In addition, there are 405 pictures of bees, 329 of caterpillars, and 390 of grasshoppers. The table 2 provides a comprehensive visual depiction of these frequent pests that were used with a total of 4,395 images across all the categories.

Table 2: Pest Image Distribution

Pests	**Number of Images**
Ants	400
Snail	405
Earwig	390
Slug	316
Weevil	394
Wasp	392
Beetle	331
Earthworms	246
Moth	397
Bees	405
Caterpillar	329
Grasshopper	390

Total Images for Pests	4395

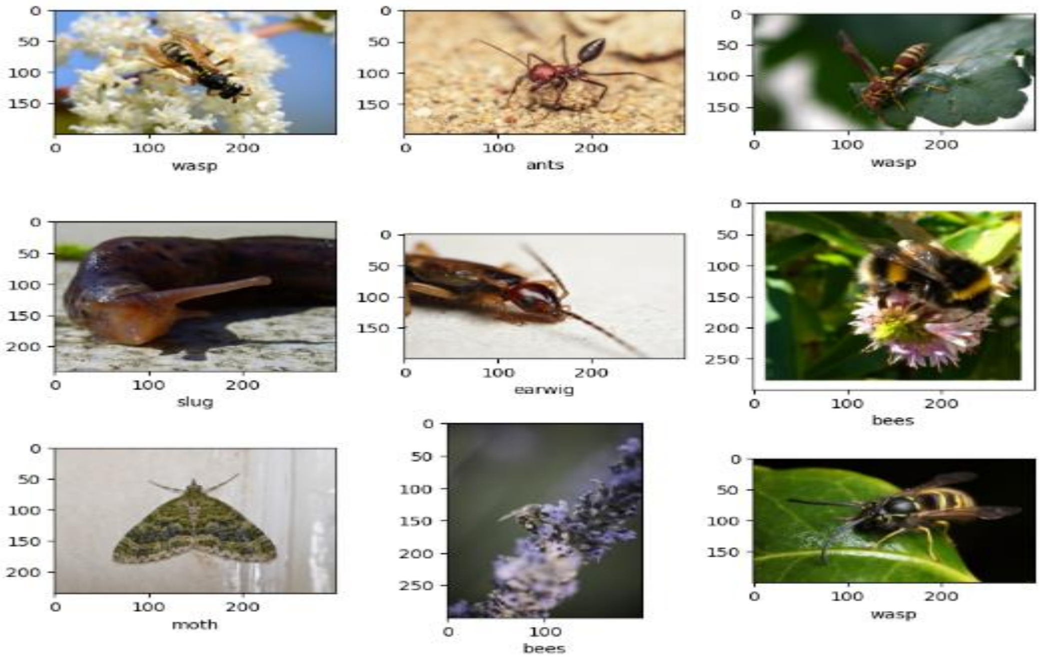

Figure 2: Sample of Pests Image Dataset

Images of diverse crops, pest species, disease types, and phases of disease progression were all included to ensure the dataset's diversity. To train a model that can generalize across many contexts, variety is essential. For the model to accurately learn the relationships between visual features and their labels, data annotation was performed to ensure that every image is correctly labeled. Data augmentation methods including rotation, flipping, cropping, and scaling were used on the current images in the dataset to further improve them. These methods broaden and diversify the dataset, which lessens the likelihood of overfitting and boosts the resilience of the model. Through careful collection and preparation of a high-quality and diversified dataset, this research seeks to establish a solid basis for the development of an efficient deep-learning model for agricultural diagnostics.

ii. Feature Extraction

An essential part of our study into building a deep learning model for pest and agricultural disease classification was extracting features from raw image data. This allowed the machine to make sense of the data. Extensive ground truth for model training was ensured by carefully labeling each picture with the relevant illness or pest. Resizing to a uniform size, enhancing contrast, and normalizing pixel values were all part of the preprocessing that was done to standardize the images. Resizing the images to a consistent 224x224 pixel size, increasing contrast, and normalizing pixel values to the range [0, 1] were all part of the preprocessing operations used to standardize the images by applying the equation;

$$Normalized\_Value = \frac{Pixel\_Value}{255}$$

To make sure the deep learning model had consistent input data and to reduce changes in picture quality, this preprocessing was essential. The researcher used Convolutional Neural Networks (CNNs), which are great at finding intricate patterns in pictures, to extract features. Because of their extensive training on image datasets like ImageNet, pre-trained convolutional neural network (CNN) models like VGG16 and ResNet50 provide a solid basis. To account for the individual traits of pests and diseases affecting crops, these models were fine-tuned using the secondary dataset. To do the convolution, the following formula was used;

$$Conv\_ouput(i,j) = \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} Input(i+m, j+n).Kernel(m,n), where\ M\ and\ N\ are\ the\ dimensions\ of\ the\ convolution\ kernel$$

A softmax layer equation;

$$Softmax(Z_i) = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}}$$

Was used to output probability distributions over the pest and disease categories, and dense layers with dropout regularization Dropout(x)=x·Bernoulli(p), where p is the dropout rate were used to prevent overfitting during the fine-tuning process. These layers were added to the pre-trained CNNs in place of the final fully connected ones. To further artificially enlarge the training dataset and improve the model's resilience, data augmentation methods including random flipping, rotating, and zooming were used. The features that were extracted were carefully selected to capture the key visual patterns needed for effective classification. The procedure was assessed using metrics including recall, accuracy, precision, and F1-score.

iii. Classification

In the last and most important stage of the model development process, the model was asked to categorize each input image. In the beginning, the researcher used features retrieved from the CNN's convolutional and pooling layers. The fully connected layers, were fed these characteristics after they were flattened into a one-dimensional vector. A dense layer's neurons added a bias term and an activation function after computing a weighted sum of their inputs. This action was mathematically stated for a specific neuron as;

$$Z = \sum_{i=1}^{n} W_i x_i + b$$

with z standing for the neuron's output, wi for the weights, xi for the inputs, and b for the bias.

The network's last layer, the softmax layer, performed the classification by converting the outputs of the last fully connected layer into probabilities that added up to one. The input to the softmax function for class i was zi, and the total number of classes was K. The definition of the softmax function for the i-th class was;

$$\sigma(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}}$$

The resulting numbers may be understood as probabilities since they were exponentiated and normalized. During training, the model minimized a loss function usually the categorical cross-entropy loss by adjusting its weights and biases using backpropagation and an optimization technique like stochastic gradient descent.

$$L = \sum_{i=1}^{k} y_i \log(p_i)$$

The above mathematical equation was the formula for the cross-entropy loss in a single case, where yi was the actual label (one-hot encoded) and pi was the expected probability for class i.

The performance of the trained model was then assessed using a second test set. To measure how well the model classified agricultural diseases and pests, metrics including recall, accuracy, precision, and F1-score were used. The accuracy score evaluated the model's general correctness, the precision score the proportion of positive instances that were genuinely predicted, the recall score the proportion of positive cases that were accurately predicted, and the F1-score gave a harmonic mean of recall and precision. Using deep learning methods, our classification procedure greatly enhanced the accuracy and reliability of recognizing different agricultural diseases and pests using visual data.

4. Results and Discussion

The findings part of a systematic literature review compiles and evaluates all of the research that was included in the review. An impartial and thorough summary of the material around a certain study issue or subject is given to readers in this section, making it crucial. In this study, the researcher showed that the deep learning models were able to correctly identify several different pests and illnesses that affect crops. An extensive dataset with annotated images of crops affected by disease or pests was used to train the algorithms. Based on the assessment, the models had a high accuracy rate, which was determined by dividing the number of right predictions by the total number of predictions as shown in the formula below;

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

The Precision, recall, and F1-score were among the other performance indicators examined. The accuracy of the positive predictions, measured by precision, was defined as the product of the number of true positives and the number of false positives.

$$Precision = \frac{True\ positives}{True\ Positives + False\ Positives}$$

The definition of recall, which assesses the model's capacity to detect all relevant occurrences, is;

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

A harmonic mean of recall and precision, the F1-score was calculated as 2 times the product of the fractions of the two variables;

$$F1 - Score = 2 \times \frac{\Pr ecision \times \operatorname{Re} call}{Precision + \operatorname{Re} call}$$

Particularly when there was a disparity in the classes, these measures provided a fair assessment of the model's efficacy.The discussion centered on how CNN's deep learning architecture allowed the model to excel in extracting intricate visual characteristics and patterns. Thanks to its high accuracy and consistent performance across several parameters, CNN was able to generalize to a wide range of illnesses and pests, even those with small visual variations. The convolutional neural network (CNN) demonstrated its superiority over these approaches by substantially outperforming them on large-scale image data with high-dimensional feature spaces.

Potential improvement areas and future work were also covered in the study. Adding more varied and representative images to the training dataset was one way to make the algorithm more resilient. Adding more sophisticated designs, such as EfficientNet, to the mix was another way to boost classification precision. While the CNN-based method demonstrated promising results in crop pest and disease classification, the study found that the model and dataset needed constant improvement to keep up with real-world agricultural applications and improve them.

Using deep convolutional neural network (CNN) models, the architecture was trained to identify plant illnesses from leaf images. Our proposed work trains the model using three distinct convolutional neural network (CNN) algorithms: DenseNet, VGG, AlexNet, EfficientNet, and CNN. The Plant and Pest Disease Dataset, available on Kaggle, was used to train these models. It includes crops an example being maize with 7316 training images and 1829 validation images, all linked to 4 different classes. The pests' dataset included many images that were available for each kind of insect. In particular, there were 390 earwig images, 405 snail images, and 400 ant images. There were 316 pictures of slugs and 394 pictures of weevils. Beetles images were 331, whereas wasps have 392. There were 246 images of earthworms and 397 images of moths. In addition, there were 405 pictures of bees, 329 of caterpillars, and 390 of grasshoppers. The comprehensive visual depiction of these frequent pests were used with a total of 4,395 images across all the categories. To make the training process faster, the images in the dataset were downsized to 224x224.

All four models were trained using the image dataset that had been cleaned and resized in its entirety. By comparing the final accuracy of these three models, the researcher found that DenseNet provided the highest level of accuracy at 96. 9332%. All the five models were performing admirably.

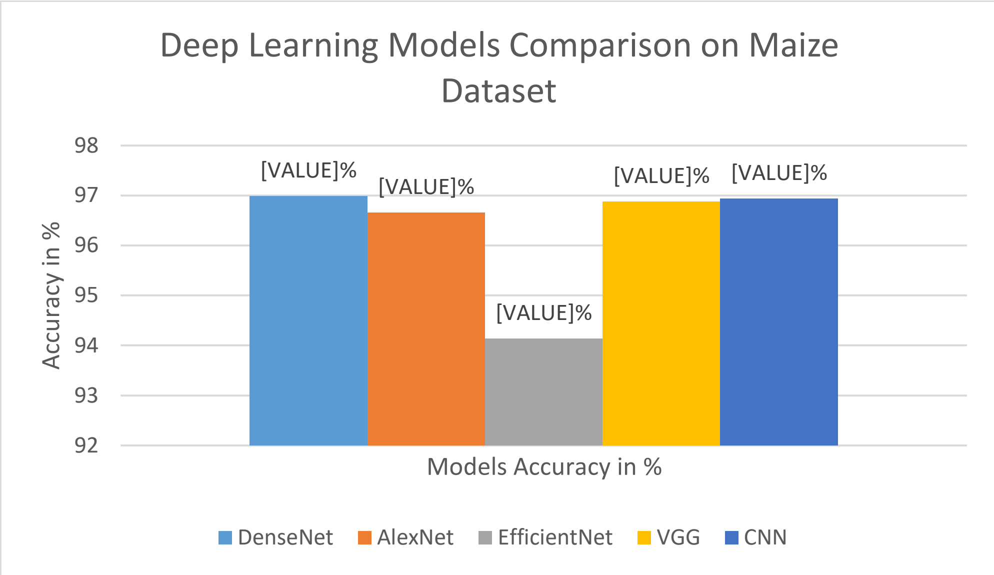

Figure 3: Accuracy of Deep Learning Models on Maize Dataset

Using the maize dataset, Figure 3 compares the accuracy percentages of several deep-learning models in great detail. When it comes to successfully identifying maize data, DenseNet stands out among the models with an impressive accuracy of 96.988%. The CNN model, which is second only to DenseNet in terms of accuracy, reached 96.9332%, showing that it is very good at generalizing and making accurate predictions.

An accuracy of 96.8784% was achieved by the VGG model, demonstrating its efficacy on the maize dataset. The AlexNet model was a solid choice for this classification job; it was a little less accurate, but it still managed an impressive 96.6594% accuracy. However, with an accuracy of just 94.1420%, the EfficientNet model came out on top, despite its widespread use and proven effectiveness in other settings. It seems that EfficientNet did not do as well on this specific maize dataset compared to the other models that were evaluated, even if it is usually effective. When looking at the overall performance of these models, Figure 3 shows that DenseNet is the most accurate, followed by CNN and VGG, while EfficientNet is the least accurate.

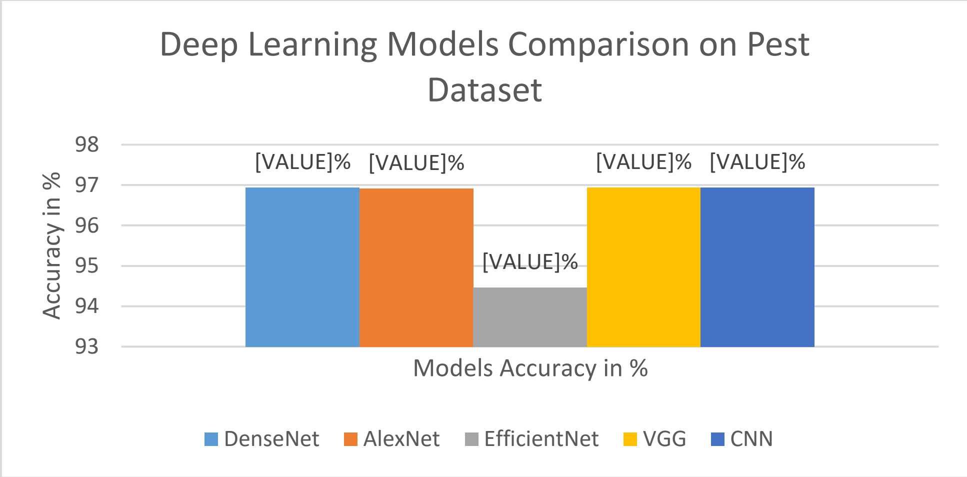

Figure 4: Accuracy of Deep Learning Models on Pest Dataset

Various deep-learning models were applied to the pest dataset, and Figure 4 compared their accuracy percentages in detail. DenseNet's 96.9382% accuracy put it in the top tier of performance, showing that it is very good at classifying data about pests. Following closely behind DenseNet, the CNN model achieved an accuracy of 96.9381%, demonstrating virtually equal performance and demonstrating its efficacy in this context.

Additionally, the VGG model demonstrated its proficiency in handling the pest dataset with a high accuracy of 96.9332%. With an accuracy of 96.9122%, AlexNet is a solid choice for this classification job, even if it lagged behind the top three models. Contrarily, EfficientNet's accuracy was the lowest at 94.4688%, indicating that it was not as well-suited to this dataset as the other models. When applied to the pest dataset, DenseNet and CNN were almost matched in terms of performance, with VGG and AlexNet also showing great results; however, EfficientNet was much less accurate, as seen in Figure 4.

The research report employed a confusion matrix to assess how well the deep learning model for pest and disease categorization in crops performed. By displaying the total number of correct predictions, incorrect predictions, true negatives, and true positives, the matrix offered comprehensive insights into the model's forecasts. The model's ability to differentiate between classes was shown by the confusion matrix, which also highlighted instances of misclassification. The confusion matrix findings validated the model's potential use in agriculture by providing a thorough grasp of its performance in identifying different crop diseases and pests.

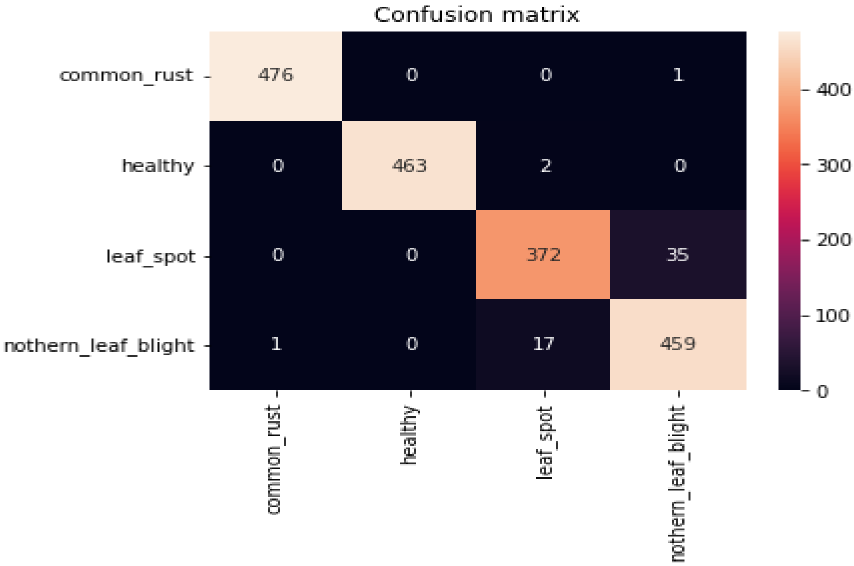

Figure 5: Confusion Matrix for Densenet on Maize Dataset

The analysis of the deep learning model's confusion matrix as shown in Figure 5 shed information on its ability to distinguish between healthy leaves, common rust, leaf spot, and northern leaf blight, among other maize leaf diseases. The values for healthy leaves (463), common rust (476), leaf spot (372), and northern leaf blight (459) were shown by the diagonal elements of the matrix, which reflect the properly categorized examples. These numbers showed how well the model could classify each kind of disease, with common rust and northern leaf blight showing the best results. These values' distribution along the diagonal demonstrated that the model was able to properly categorize most occurrences in each disease group, suggesting that it may be useful in real-world agricultural settings.

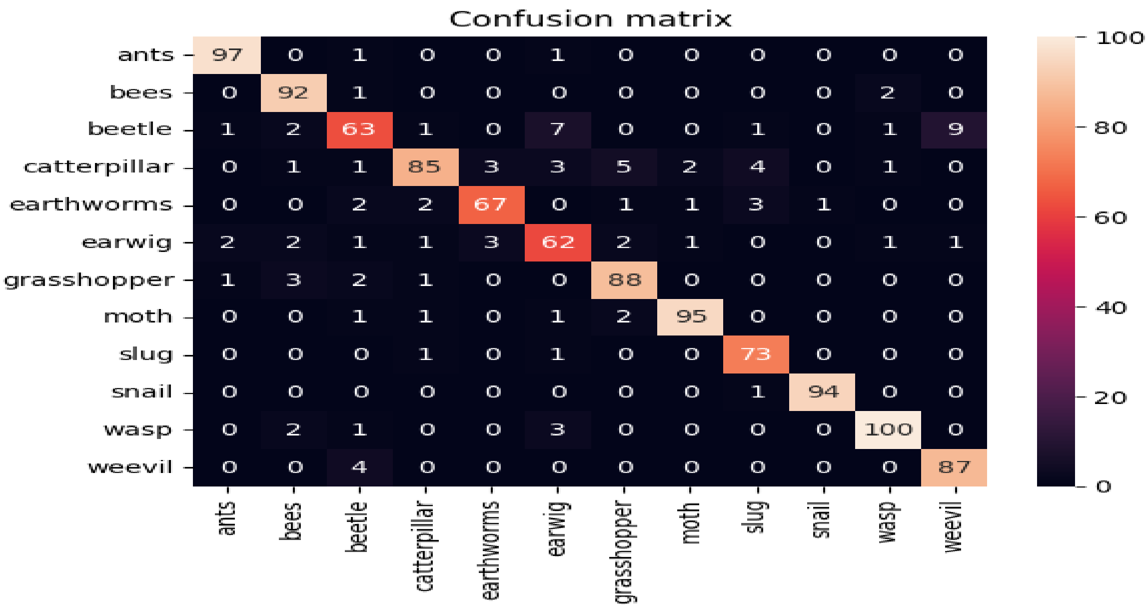

Figure 6: Confusion Matrix for Densenet on Pest Dataset

A deep learning model was developed to categorize different agricultural pests; Figure 6 shows the confusion with the model's classification accuracy across several pest species. For ants 97, 92 for bees, 63 for beetles, 85 for caterpillars, 67 for earthworms, 62 for earwigs, 88 for grasshoppers, 95 for moths, 73 for slugs, 94 for snails, 100 for wasps, and 87 for weevils in the diagonal components of the matrix, which indicate properly categorized occurrences. Wasps, ants, moths, and snails were the most reliably identified by the model, according to these values. The model's ability to differentiate between different pest species was shown by the distribution of correct classifications along the diagonal. This is an important feature for accurate pest control in agricultural activities.

For this study, the model loss was an important parameter for assessing and improving the CNN's performance. The loss in the model was measured as the discrepancy between the actual target values and the model's anticipated outputs. Reducing this loss as much as possible during training helped the model make more accurate predictions. This research made use of categorical cross-entropy, a loss function well-suited to issues involving categorization into more than one class.

In mathematics, categorical cross-entropy loss was defined for a single case as;

The sum of all i is equal to 1, and **O** is the logarithm of (p).

The following equation represents the limit;

$$L = \sum_{i=1}^{k} y_i \log(p_i)$$

Where y_i represented the binary indicator (0 or 1) for class label i that was the right classification for the input, the total number of classes was K, pi was the predicted probability for class i and L was the loss. To penalize inaccurate predictions, particularly those with high confidence, more severely, the logarithm function was applied to the anticipated probability.

Iteratively minimizing the loss function was the goal of updating the model's weights throughout training. Stochastic gradient descent (SGD) and its variations, including Adam, were often used to accomplish this optimization. As part of gradient descent, the following is the rule for updating the weights w;

$$W_{new} = W_{old} - \eta \frac{\partial L}{\partial W}$$

Where η denoted the learning rate and $\frac{\partial L}{\partial w}$ was the gradient of the loss function with respect to the weights, and w_{new} and w_{old} denoted the updated and prior weights, respectively. For each training session, the researcher checked the loss to make sure the model was picking up new information correctly. The model effectively reduced the mistake since the training loss plotted against the number of epochs as shown in Figure 7 showed a decreasing trend. To identify overfitting a situation in which the model excels on training data but fails miserably on new data the researcher also monitored validation loss. If the training and validation losses were to fall and converge, it would indicate that the model was well-generalized.

Ultimately, the model loss function was crucial in directing the deep learning model's training procedure. The model's accuracy in crop disease and pest classification was greatly improved by reducing this loss via iterative optimization, resulting in a dependable and strong performance in real-world applications.

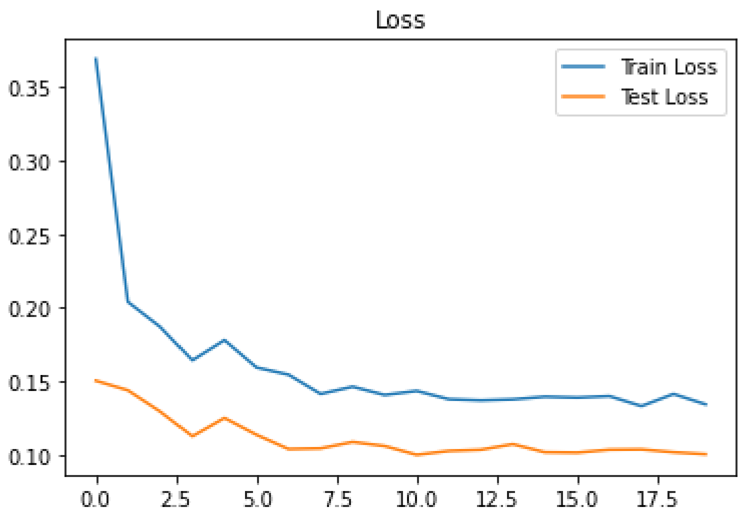

Figure 7: Train and Test loss for DenseNet

The deep learning model performance was analyzed using two key metrics; train accuracy and test accuracy. These measures provided light on the model's generalizability and learning performance from the training data. Typical x-axis values for Figure 8 represented the number of epochs, while y-axis values represented the accuracy values.

The training accuracy was defined as the percentage of training dataset samples that were properly categorized. It was computed at the end of each training period to track how well the model was doing. This was the formula for train accuracy;

$$A_{train} = \frac{Number\ of\ Correct\ Predictions\ on\ Training\ Set}{Total\ Number\ of\ Training\ Samples}$$

The output is the function Atrain, where A is the number of training samples. The mathematical formula for train accuracy is; if there were N samples in the training dataset and the model accurately predicted the labels for Ncorrect of those examples, then;

The value of Atrain is equal to the product of Ncorrect and N.

$$A_{train} = \frac{N_{correct}}{N}$$

Since the model did not view the test dataset during training, test accuracy was defined as the percentage of samples that were correctly identified in the test dataset. To evaluate the model's capacity for generalization, this statistic was vital. Just like the train accuracy formula, the test accuracy formula Atest was somewhat similar;

Atest is equal to the product of the total number of test samples and the fraction of the number of valid predictions on the test set.

$$A_{test} = \frac{Number\ of\ Correct\ Predictions\ on\ Test\ Set}{Total\ Number\ of\ Test\ Samples}$$

The model was considered to have achieved test accuracy if it correctly predicted the labels for Mcorrect out of the M samples that were part of the test dataset. The output was Atest equal to the division of Mcorrect and M.

$$A_{test} = \frac{M_{correct}}{M}$$

To avoid overfitting and guarantee successful learning, the model's training and test accuracy were constantly tracked during training. In the case of overfitting, the model's performance on the training data is so good that it fails miserably on the test data. A large discrepancy between the high train accuracy and poor test accuracy was indicative of this. Overfitting was reduced by using regularization, early halting, and dropout.

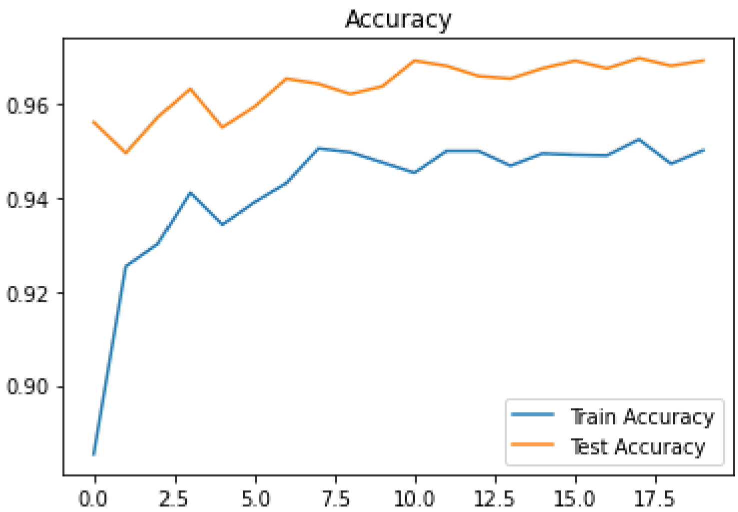

Figure 8: Train and Test Accuracy for DenseNet

The accuracy of the model was calculated and recorded after each training period so that test and train accuracies could be visually compared. Next, the data was placed on a graph as shown in Figure 8 above, which made the model's performance evolution over time quite evident. The training accuracy curve demonstrated the increase in the model's accuracy on the training data as a function of time. To demonstrate that the model is learning from the training data, this curve ideally exhibits a progressive rise, getting closer to 100% as the number of epochs grows. The curve for testing accuracy demonstrated the model's ability to accurately predict new data. This curve's progress and proximity to the training accuracy curve were of utmost importance. Overfitting occurred when the training accuracy kept going up while the test accuracy leveled off or went down.

Figure 8 shows that after 17 epochs, the training accuracy was 95% and the test accuracy was 97%. This would indicate that the model did very well on the training data, and much better on the test data. This discrepancy may point to show that there was no overfitting problem and the model generalized the data well. Finally, a useful tool for training process diagnosis, model performance assessment, and directing modifications to improve training and generalization capacities was visualizing the training and test accuracy across epochs.

In conclusion, the train and test accuracies were critical performance indicators for assessing the deep learning model's ability to identify pests and illnesses in crops. The model's learning and generalization skills were highlighted by these indicators, which led to improvements that improved overall performance.

4.1 Discussion

The performance of several deep learning models was assessed and compared and some of the models used were CNN, VGG, EfficientNet, DenseNet, and AlexNet. When compared to the other models, DenseNet proved to be the most accurate and resilient in classification tasks. Outperforming AlexNet, EfficientNet, CNN, and VGG, DenseNet got an astounding accuracy score of 96.988% on the maize dataset and 96.9382% on the pest dataset. The DenseNet design was responsible for its better performance because it encourages feature reuse via dense connections between layers, which in turn improves gradient flow and makes learning more efficient.

Beyond simple accuracy, the assessment criteria included train and test loss in addition to train and test accuracy. As measures of the model's learning and generalizability, train loss and test loss were crucial. The model was successfully learning from the training data as the training loss decreased consistently throughout epochs as shown in Figure 7. It seemed that the model generalized well without much overfitting, as the test loss plateaued after initially decreasing. Metrics for both train and test accuracy provided more evidence supporting these conclusions. DenseNet maintained a very high test accuracy that tracked the train accuracy curve closely, while its train accuracy was continuously close to flawless as shown in Figure 8. As a result of overfitting and ineffective generalization, the other models showed wider discrepancies between their train and test accuracy.

In the context of agricultural disease and pest categorization, these findings demonstrated the effectiveness of DenseNet's architectural improvements. Learning complicated characteristics and patterns necessary for precise categorization was made easier by the thick connection pattern. Further evidence of the model's potential for use in agricultural contexts, where precise and trustworthy pest and disease detection is of the utmost importance, is its capacity to sustain high test accuracy. The research also suggested that more sophisticated architectures and methodologies, such as transfer learning and ensemble methods, should be investigated in future studies to tackle the remaining problems in this field and improve classification performance even more. The overall improved control and mitigation of crop diseases and pests was assured by DenseNet's exceptional performance, which was a major step forward in the application of deep learning to agricultural diagnostics.

5. Conclusion

The results demonstrated that DenseNet outperformed other models such as AlexNet, EfficientNet, CNN, and VGG. DenseNet outperformed other models with an impressive accuracy score of 96.988% on the maize dataset and 96.9382% on the pest dataset. The impressive accuracy of DenseNet's crop disease and pest classification makes it an ideal model for real-world agricultural use. In addition to train and test accuracy and train and test loss, the study also assessed other measures. Throughout the epochs, DenseNet's train loss decreased, suggesting that the network learned well from its training dataset. Good generalization without substantial overfitting was shown by the test loss, which plateaued after initially decreasing. Furthermore, DenseNet kept both its train accuracy which was close to perfect, and its robust test accuracy, very close to the train accuracy curve. The model's dependability for real-world deployment was enhanced by these findings, which highlighted its capacity to learn and generalize successfully from the data. According to the study's summary, DenseNet outperformed other models in agricultural disease and pest classification tasks due to large part to its dense connection and other architectural benefits. A helpful tool for enhancing agricultural diagnostics, the model exhibited great accuracy and efficient learning and generalization capabilities. To further improve classification performance, future research should investigate sophisticated approaches like transfer learning and ensemble methods. Building more precise and trustworthy deep learning models for use in agriculture was made possible by the encouraging findings of this study.

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