Deep Learning Model for Crop Diseases and Pest Classification

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Abstract— **The study on deep learning models for crop diseases and pest classification looked at how these models may enhance agricultural practices, specifically for the purpose of more precise pest and crop disease classification. The research brought attention to the fact that agricultural diseases and pests pose a threat to global food security and that farmers need innovative solutions, like deep learning models, to combat these issues. The accuracy of the classification was tested using DenseNet and other deep learning models trained using secondary datasets sourced from the Kaggle website. The study compared DenseNet against many other models using a comprehensive evaluation technique. These models were AlexNet, EfficientNet, Visual Geometry Group, and Convolution Neural Network. In comparison to the other models, DenseNet achieved an outstanding accuracy score of 96.988% on the maize disease dataset and 96.9382% on the pests dataset. Due to DenseNet's enhanced performance, which was brought about by its ability to efficiently gather complex features and patterns within the visual input, resulted in more precise predictions. The study discussed the consequences of DenseNet's high accuracy, suggesting that its complex architecture made it ideal for pest and crop disease classification in agriculture. Also, the researcher looked at the possibility of integrating DenseNet into real-world agricultural systems, where its robust performance might significantly improve crop monitoring and disease management technologies. The research concluded with a list of potential areas for further research, including exploring the applicability of DenseNet to other crop types and investigating the possibility of hybrid models or transfer learning to enhance its performance.**

Keywords-Deep learning, convolution neural network, agricultural technology, machine learning, image recognition.

I. INTRODUCTION

Pests and diseases that harm crops significantly reduce agricultural production, which in turn threatens global food security and economic stability. Conventional methods for identifying pests and diseases in crops have included tedious, error-prone, and time-consuming human inspections. There are still long-term challenges, but recent advances in deep learning provide hope for a solution. The field of machine learning known as "deep learning" mostly deals with picture recognition but also employs multi-layered neural networks to automatically extract complicated features and patterns from large datasets. In the field of computer vision, deep learning models, namely convolutional neural networks (CNNs), have recently attained success in tasks such as object recognition. There has been a surge in interest in using deep learning algorithms for pest and disease classification in crops due to their ability to revolutionize traditional agricultural practices and decrease crop losses[1].

The agricultural sector may be forever changed if deep learning is used to combat pests and diseases. Experts in the industry are working to develop scalable systems that can identify and diagnose crop illnesses and pests early on, and then successfully manage them. These solutions will use computer algorithms and massive amounts of agricultural data. Proactively intervening to prevent major crop damage, decreased economic losses, and enhanced disease and pest identification are just a few of the possible advantages of moving towards data-driven solutions [2].

While progress has been made, agricultural pest and disease classification using deep learning models remains challenging. When trying to train reliable and accurate models, the accessibility and quality of labeled datasets provide a significant obstacle. A number of factors, including data variability and model robustness, need to be carefully evaluated before deep learning models can be applied to different crops, regions, and climatic conditions. The interpretability issue with deep learning models further hinders their usage in real-world agricultural settings [3]. This makes it hard to understand how the algorithms make decisions.

Despite these challenges, the use of deep learning has enormous promise for improving crop health management. A comprehensive review of the literature on the use of deep learning for the classification of agricultural pests and illnesses is the primary objective of this study. Our objective is to illuminate the benefits and drawbacks of using deep learning models to support sustainable agriculture and ensure global food security in the context of evolving environmental and socioeconomic factors. Researchers will do this by discussing possible future study topics, assessing performance measures, examining existing research, and discussing limits and impediments [4].

Following a short literature review in Section 2, the study methodologies are described in Section 3, the findings are offered in Section 4, and the research is summarized in Section 5 and that is how the entire paper is structured.

II. RELATED WORKS

Advances in deep learning techniques have brought about a huge change in recent years, particularly in the field of crop pest and disease classification. Despite agriculture being the bedrock of food security, crop losses due to pests and diseases remain a significant concern, putting lives and food supplies at risk worldwide. Traditional methods of disease and pest identification often rely on manual observation, which is both a time-consuming and error-prone process. But there are new deep learning algorithms that automate and enhance detection and classification processes using vast amounts of agricultural data, so there are some positive developments. This literature review delves into the current state of study in applying deep learning models for agricultural disease and pest classification, exploring the technique, advancements, difficulties, and future potential in this vital industry. Through a comprehensive analysis of the existing research, this literature review aims to illuminate the potential, limitations, and present status of deep learning techniques to agricultural pest and disease control.

In regards to the FarmEasy app in particular, the study conducted by Pandey et al., 2023 [5] significantly advances the state of the art in deep learning models for plant disease detection. The authors thoroughly evaluate several deep learning architectures and methodologies utilized for plant disease detection, with a focus on convolutional and recurrent neural networks (CNNs and RNNs, respectively). Pandey et al. integrated the findings of many studies to illuminate deep learning models' ability to accurately identify plant diseases across different crop kinds and conditions. The authors highlight the need of large-scale datasets for training deep learning models. They discuss methods, such as ensemble techniques and transfer learning that might enhance these models' performance and make them more applicable to other situations. In their discussion of the practical implications of utilizing deep learning models in agriculture, Pandey et al. emphasize how easy-to-use tools may be provided by FarmEasy to help farmers identify and control diseases. The limitations of the paper—such as an imbalance in the classes, a lack of datasets, and problems with model interpretability—need to be further investigated. Ultimately, the study conducted by Pandey et al. provides valuable insights into the present state of plant disease detection using deep learning models, as well as the challenges faced and possible solutions to these issues. This research lays the groundwork for further research in this vital area of agricultural technology.

Rajeshram et al. 2023 study explores deep learning's potential in crop growth in length. This work fills certain gaps in our understanding of deep learning's potential applications to crop health management, but it also reveals others that need filling. It is critical to determine the efficacy of deep learning models in various agricultural contexts and with various crop varieties. According to the article, it is crucial to study how various agricultural practices affect the effectiveness of these models and how they function in various environmental situations. The lack of interpretability is another major issue with deep learning models used for disease prediction, pest detection, and pesticide prescription purposes. Additional research is needed to enhance the transparency of the model outputs, allowing farmers and agricultural practitioners—the end-users of these complex systems—to trust and understand them. A more inclusive and adaptable precision crop management system would be possible if these knowledge gaps could be filled and deep learning methods were used widely in agricultural contexts.

In order to address the critical problem of the health of citrus crops, Song et al., 2023 used sophisticated detecting techniques. This work adds to the existing body of knowledge in the area by better identifying diseases and pests using the YOLOv8 architecture in conjunction with the Self-Attention mechanism. But it also shows where there are holes that have to be filled. A big issue that needs resolving is that not enough has been written regarding how well the idea works in different contexts and places. Critically, these characteristics affect how well citrus crops detect pests and diseases. An important part of using the Self-Attention YOLOv8 model in practical agricultural contexts is its interpretability, which is noticeably lacking from the article. Gaining end-user trust, especially from agronomists and farmers, requires acknowledging the model's flaws and decision-making process. The suggested approach needs more research into its scalability and resource efficiency before it can be used in agricultural environments with limited resources. If we want to improve the Self-Attention YOLOv8 model's capacity to detect citrus diseases and pests and completely comprehend deep learning solutions for precision agriculture, we need to fill up certain gaps in our current knowledge [6], [7].

The research conducted by Rathnayake et al. in 2023 addresses a significant problem in Sri Lankan agriculture. Some questions remain unanswered, but overall, the study sheds light on how banana farmers may profit from mobile technology. The essay gets off to a good start by giving more context on the particular plant diseases and insect infestations that impact Sri Lanka's banana sector. In order to create efficient mobile solutions, it is necessary to comprehend these challenges and their complexities. Among the socioeconomic elements that the authors investigate in their study on the banana producers' history are literacy rates, the cost of smartphones, and access to technology. Gaining insight into these contextual aspects may help in tailoring the mobile solution to meet the demands of the target audience. Solutions that rely on mobile devices have challenges with power supply and network connectivity, which affects their practicality and adoption. The technical infrastructure of rural locations may also be explored in the article. The authors might show how their mobile solution works in actual case studies and experimental projects, which would make their research more useful. If we want to know how the mobile solution can help Sri Lankan banana growers, we need to fill in these blanks [8].

Many issues remain unresolved, despite Parkavi et al., 2023's investigation on the use of Machine Learning and the Internet of Things in farming. One issue is that complicated agro-management systems may not work in all agricultural contexts, as the demands of large-scale farmers vary from those of small-scale farmers with limited resources. It is critical that we focus on making these technologies usable and scalable at various agricultural sizes. Additional study on the social and economic effects of contemporary agricultural technology, such as the need to train farmers' skills and the possible upheaval to conventional farming methods, would strengthen this article. Energy consumption to power a network of interconnected devices in outlying agricultural regions and environmental consequences of the growing amount of electronic waste from Internet of Things (IoT) devices are two more potential gaps in the research on the proposed system's long-term viability. Without these specifics, the essay loses some of its value and the researcher can't assess the pros and cons of deploying complicated agro-management systems via the use of Machine Learning and the Internet of Things [9].

In their 2023 publication, Mehta et al. highlight many substantial knowledge gaps in the field of crop disease identification and classification via the use of a Convolutional Neural Network trained using transfer learning. The first issue is the lack of exploration and optimization of transfer learning algorithms for agricultural disease diagnosis. This may be because there hasn't been enough research on possible transferrable feature selections, tuning tactics, or pre-trained model choices. Furthermore, details about the unique difficulties of crop disease datasets, including imaging parameter variability, a wide variety of plant species, and several phases of disease development, were lacking. To make their models more accurate and applicable to different agricultural settings, researchers need find out how to include domain-specific data, such agronomic knowledge, into the training process. A comprehensive analysis of the training data, including any biases, and the possible socioeconomic consequences of using this technology in farming would enhance the research. Filling up these gaps in knowledge would greatly improve the suggested Convolutional Neural Network's (CNN) disease classification capabilities in agriculture [10].

III. METHODOLOGY

The methodology section of this research lays forth a systematic approach to developing a deep learning model for crop disease and pest classification. The increasing prevalence of agricultural pests and diseases threatens food security on a global scale, making accurate and timely detection crucial. Conventional methods of plant disease diagnosis may be time-consuming and prone to mistakes. Consequently, using the capabilities of deep learning models might be a viable alternative for automating and improving the accuracy of disease and pest classification.

The primary components of the proposed method are data collection, data preparation, model selection, training, evaluation, and deployment. Every step is meticulously prepared to address the specific challenges of agricultural picture classification in order to construct a robust and effective deep learning model. By considering both the theoretical and practical aspects of model construction, this method aims to optimize value for end-users, particularly farmers and agricultural professionals.

The main data used in this research is derived from a diverse and extensive collection of crop photos that have been affected by various diseases and pests. In order to guarantee the model's functionality and generalizability, a diversified and top-notch dataset is required. Improving the picture quality and getting the dataset suitable for effective model training is the next stage in data preparation. Here, issues like varying picture resolutions and limited datasets are addressed by using techniques like resizing, normalizing, and enhancing photos.

It is the correct choice to use the appropriate deep learning architecture for this research. When it comes to picture classification, Convolutional Neural Networks (CNNs) really shine due to its built-in ability to learn and automatically extract features from photos. By studying cutting-edge CNN designs and using transfer learning, the method may improve model performance even while working with sparse agricultural picture data. In order to train a model and prevent overfitting, the model is iteratively fine-tuned utilizing the test, validation, and training sets.

It is crucial to assess the trained model's performance to ensure its efficacy in real-world scenarios. In order to provide a comprehensive assessment, this step employs a number of metrics, such as recall, accuracy, precision, F1-score, and AUC-ROC. The use of cross-validation ensures that the results are robust and unaffected by any one data split. Deploying the research entails making it practical by developing an easy-to-use interface for the real-time classification of pests and diseases.

In this study, we provide a method that systematically addresses the challenges of developing deep learning models for the classification of agricultural diseases and pests. Through the use of this systematic methodology, the research aspires to create a strong tool that might significantly improve the accuracy and efficiency of agricultural diagnostics, resulting in better crop management and increased agricultural yields.

i. Data Collection

Gathering relevant data is the first stage in developing a deep learning model to classify pests and illnesses affecting crops. A model's performance is heavily dependent on the dataset's quality and diversity. Sources for the data used in this study include agricultural databases that are available to the public, research institutions, and agricultural extension agencies. Thanks to PlantVillage and Kaggle, the dataset is well-founded; both databases provide vast quantities of tagged photos covering a wide range of crops, diseases, and pests. Collaborations with academic institutions and agricultural research institutes may also provide doors to specialized databases, enhancing the dataset's precision and breadth. This study's dataset was sourced from Kaggle. Table 1 displays the distribution of photos for tomato and maize crops throughout various diseases and healthy conditions. Among the 7,316 maize photos, 1,908 depict Northern Leaf Blight, 1,907 Common Rust, 1,859 healthy maize, and 1,642 Gray Leaf Spot. Many illnesses may affect tomatoes. Some examples are bacterial spot, early blight, healthy tomatoes, late blight, mold, spider mites, target spot, mosaic virus, and yellow leaf curl virus. For tomato, a grand total of 10,000 photos were used.

Table 1. Distribution of Crop Images

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**

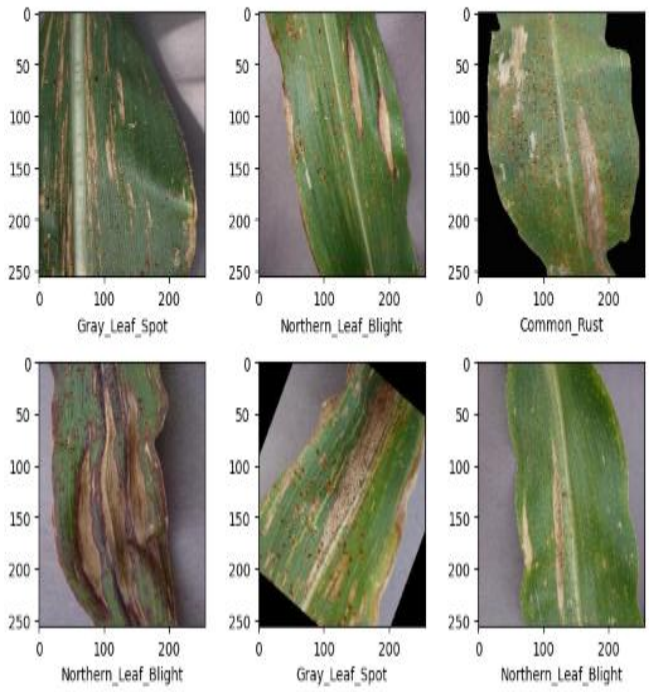

Figure 1. Sample of Maize Image Dataset

Agricultural pests are included in Table 2, along with the number of images accessible for each kind of pest. In particular, you may see pictures of 390 earwigs, 405 snails, and 400 ants. A total of 394 images depict weevils and 316 depict slugs. There are 331 pictures of beetles and 392 of wasps. Moths have 397 pictures while earthworms have 246. Furthermore, there are 405 bee photographs, 329 caterpillar pictures, and 390 grasshopper pictures. In Table 2, you can see an exhaustive visual representation of all the categories' 4,395 images used to portray these common pests.

Table 2. Distribution of Pest Images

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**

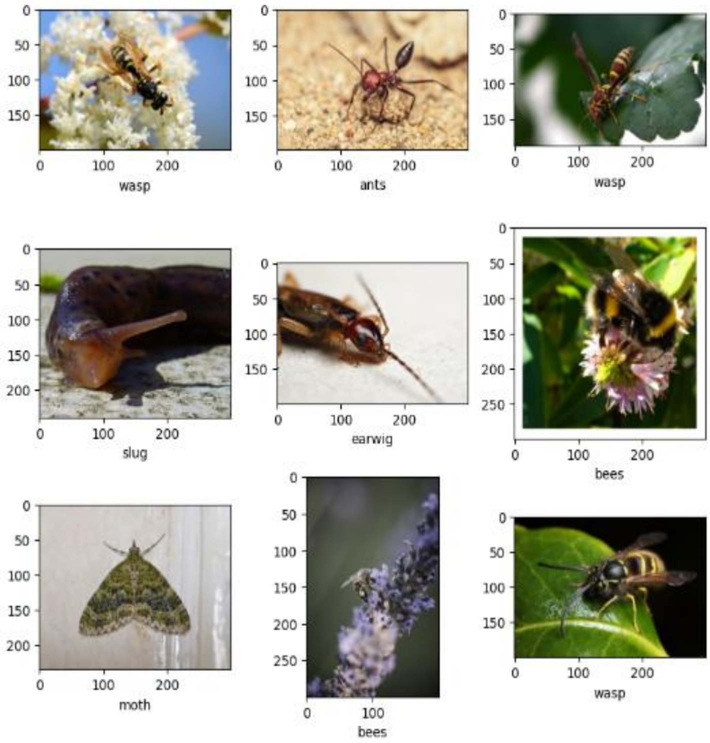

Figure 2. Sample of Pests Image Dataset

To make sure the dataset was diverse, the researcher included images of various crops, insect species, diseases, and stages of disease development. Including a wide range of examples is crucial when training a model to generalize. Annotating the data ensures that every picture is appropriately labeled, which helps the model understand the correlations between visual characteristics and their labels. The existing photos in the collection were enhanced using data augmentation techniques such as flipping, scaling, cropping, and rotation. By increasing the dataset's diversity and breadth, these techniques strengthen the model and decrease the probability of overfitting. This project aims to provide the groundwork for developing an effective deep-learning model for agricultural diagnostics by collecting and preparing a diverse dataset of high quality.

ii. Feature Extraction

Developing a deep learning model to classify agricultural diseases and pests relied heavily on feature extraction from raw image data. In doing so, it enabled the computer to interpret the data. In order to provide a solid foundation for training the model, every image was meticulously labeled with the appropriate disease or pest. As part of the preparation steps to ensure consistency, the photos were resized to a consistent size, contrast was increased, and pixel values were normalized. The photos were preprocessed to ensure they were all 224x224 pixels in size, with contrast turned up and pixel values normalized to the interval [0, 1]. Then, the equation was used to standardize the images;

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

This preprocessing was crucial for reducing variations in image quality and ensuring that the deep learning model received consistent input data.

Convolutional Neural Networks (CNNs) were used by the researcher for feature extraction; these networks excel in detecting complex patterns in images. A good place to start is using pre-trained convolutional neural network (CNN) models, such as VGG16 and ResNet50, which have been extensively trained on picture datasets like ImageNet. The secondary dataset was used to fine-tune these models so that they could account for the unique properties of crop-harming pests and illnesses. The convolution was performed using the following formula;

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

A softmax layer equation;

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

produced probability distributions for the various pest and crop disease categories, and dense layers with dropout regularization were used for this purpose. During the fine-tuning procedure, the function Dropout(x)=x·Bernoulli(p), where p is the dropout rate, was used to avoid overfitting. In lieu of the last completely linked layers, they were inserted into the pre-trained CNNs. The training dataset was artificially enlarged and the model's robustness was enhanced using data augmentation techniques such as random flipping, rotating, and zooming. We took great effort in selecting the elements that would capture the essential visual patterns required for accurate categorization. Some of the measures used to evaluate the technique were F1-score, accuracy, precision, and recall.

iii. Classification

The last and most crucial step in developing a model was to have it classify each input image. The first characteristics employed by the researcher were those obtained from the convolutional and pooling layers of the CNN. Each of these features was passed on to the fully connected layer once they were reduced to a one-dimensional vector. After calculating a weighted total of their inputs, neurons in a dense layer added a bias term and an activation function. For a particular neuron, this activity was mathematically expressed as;

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

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

Classification was carried out by the softmax layer, the final layer of the network, which combined the outputs of the last fully connected layer into probabilities equal to one. Class i's input to the softmax function was z_i, and there were a total of K classes. For the ith class, the softmax function was defined as;

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

Since the results were exponentiated and normalized, they may be seen as probabilities. Using backpropagation and optimization techniques such stochastic gradient descent, the model minimized a loss function during training, which is often the categorical cross-entropy loss.

$$L = \sum_{i=1}^{K} yi \log (pi),$$

With pi representing the predicted probability for class i and yi representing the actual label, the cross-entropy loss in a single instance can be calculated using the mathematical equation above.

The test data set was then used to evaluate the trained model's performance. Accuracy, recall, precision, and F1-score were some of the measures used to evaluate the model's performance in identifying agricultural pests and illnesses. The model's overall correctness was assessed by the accuracy score, the percentage of correctly predicted positive instances was determined by the precision score, the proportion of correctly predicted positive instances was determined by the recall score, and a harmonic mean of recall and precision was provided by the F1-score. Our classification approach substantially improved the accuracy and reliability of visual data recognition of various agricultural diseases and pests by using deep learning technologies.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The researcher demonstrated that deep learning models accurately identified a variety of crop diseases and pests in this study. The algorithms were trained using a large dataset that included annotated photos of crops that were impacted by pests or diseases. After calculating the percentage of correct predictions relative to the total number of forecasts using the method provided below, it was found that the models exhibited a high accuracy rate.

$$\text{Accuracy} = \frac{\textbf{Number of correct predictions}}{\textbf{Total number of predictions}}$$

A number of additional performance metrics were also considered, including recall, precision, and F1-score. By multiplying the total number of positive predictions by the total number of false positives, we may get the accuracy, or precision, of the positive forecasts.

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

Recall, which measures the ability of the model to identify all significant features, is defined as;

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

The F1-score, which is a harmonic mean of recall and accuracy, was determined by the equation;

$$\text{F1-score} = 2 \text{ X } \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

These metrics provide a reasonable evaluation of the model's performance, especially when there was a difference between the classes.

All focus was on CNN and how its deep learning architecture made it so good at identifying complex visual features and patterns. Despite subtle visual differences, CNN generalized to a broad variety of diseases and pests because to its excellent accuracy and consistent performance across several criteria. Convolutional neural networks (CNNs) significantly outperformed these methods on massive picture datasets with high-dimensional feature spaces, proving their supremacy.

The research also addressed future work and areas that may be improved. To strengthen the algorithm, one approach was to include a more diverse and representative group of photos in the training dataset. Another strategy for improving classification accuracy was to include more complex architectures, like EfficientNet. The research concluded that the model and dataset need ongoing modification to stay up with and improve upon real-world agricultural applications, despite the fact that the CNN-based approach showed encouraging results in crop pest and disease categorization.

The structure was taught to detect plant diseases from pictures of leaves using CNN models. In our proposed study, we train the model using CNN, EfficientNet, DenseNet, and VGG, which are three separate CNN techniques. To train our model, we used the Plant and Pest Disease Dataset, which can be found on Kaggle. Included crops are maize, which has 18, 29 validation photos and 7,316 training images associated with four distinct classes. There were several pictures of each sort of bug in the pests' dataset. In specifically, 400 ant photographs, 405 snail images, and 390 earwig images were included. A total of 394 images depicting weevils and 316 depicting slugs were included. Wasps have 392 pictures, whereas beetles have 331. The number of moth photographs was 397, whereas the number of earthworm images was 246. Also included were 329 images of caterpillars, 405 of bees, and 390 of grasshoppers. There were a total of 4,395 photos utilized for this all-encompassing graphic representation of these common pests. Reducing the picture size in the dataset to 224x224 accelerated the training process.

The whole cleaned and resized picture dataset was used to train all four models. The study discovered that DenseNet offered the greatest degree of accuracy at 96.7332% by comparing the final accuracy of these three models. It was clear that all five models were working well.

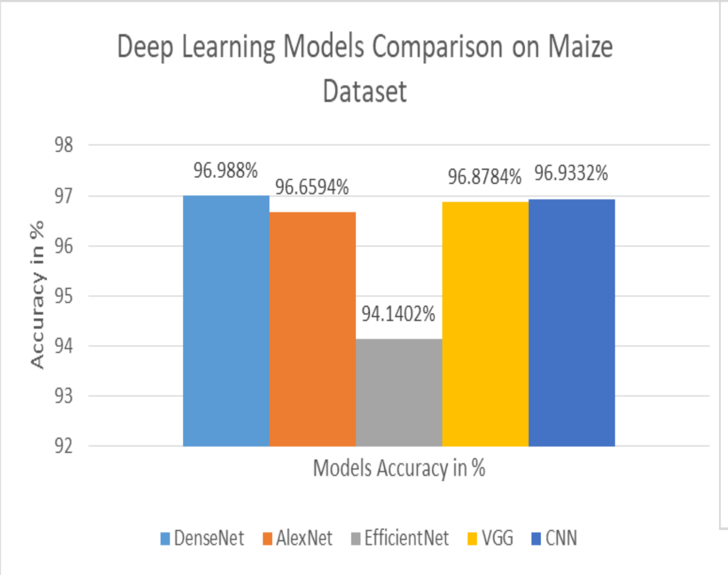

Figure 3. Deep Learning Models' Accuracy on the Maize Dataset

Several deep-learning models' accuracy percentages are compared in great detail in Figure 3, using the maize dataset. In terms of accurately detecting maize data, DenseNet is the model to beat with a remarkable 96.988% success rate. With an accuracy level of 96.9332%, the CNN model proved to be second to DenseNet in terms of generalizability and prediction accuracy.

The VGG model was effective on the maize dataset, with an accuracy of 96.8784%. With a little lower accuracy of 96.6594%, the AlexNet model was a good pick for this classification task. The EfficientNet model has been successful in other contexts and is widely used, however it only managed a 94.1420% accuracy rate in this test. Although EfficientNet is generally successful, it seems that it underperformed on this particular maize dataset when compared to the other models that were considered. Figure 3 displays the overall performance of various models, with DenseNet at the top, CNN and VGG following, and EfficientNet at the bottom.

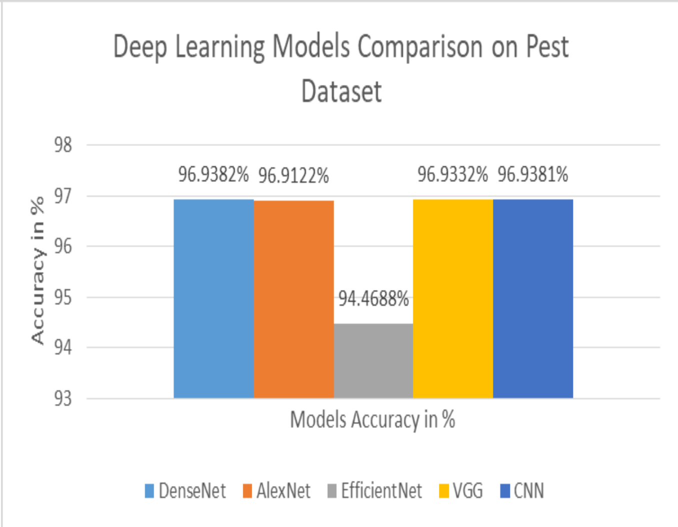

Figure 4. Deep Learning Models' Accuracy on the Pest Dataset

Figure 4 presents a detailed comparison of the accuracy percentages obtained from several deep-learning models that were applied to the pest dataset. DenseNet is very effective for pest data classification, as seen by its top-tier performance and accuracy of 96.9382%. With an accuracy of 96.9381%, the CNN model showed almost identical performance as DenseNet and proved its effectiveness in this setting, following closely behind.

The VGG model also showed great competence with the pest dataset, with an accuracy of 96.9332%. Even though it was not as accurate as the top three models, AlexNet (with 96.9122%) is still a good pick for this classification task. On the other hand, EfficientNet was not as well-suited to this dataset as the other models, since its accuracy was the lowest at 94.4688%. Figure 4 shows that EfficientNet performed much worse than DenseNet and CNN on the pest dataset, but VGG and AlexNet both performed well.

The study used a confusion matrix to evaluate the performance of the deep learning model for agricultural pest and disease classification. The matrix provided a thorough understanding of the model's projections by showing the overall number of right, wrong, true negative, and true positive predictions. The confusion matrix demonstrated the model's class discrimination capabilities and also highlighted cases of misclassification. By offering a comprehensive understanding of the model's effectiveness in recognizing various crop diseases and pests, the confusion matrix results verified the model's prospective usage in agriculture.

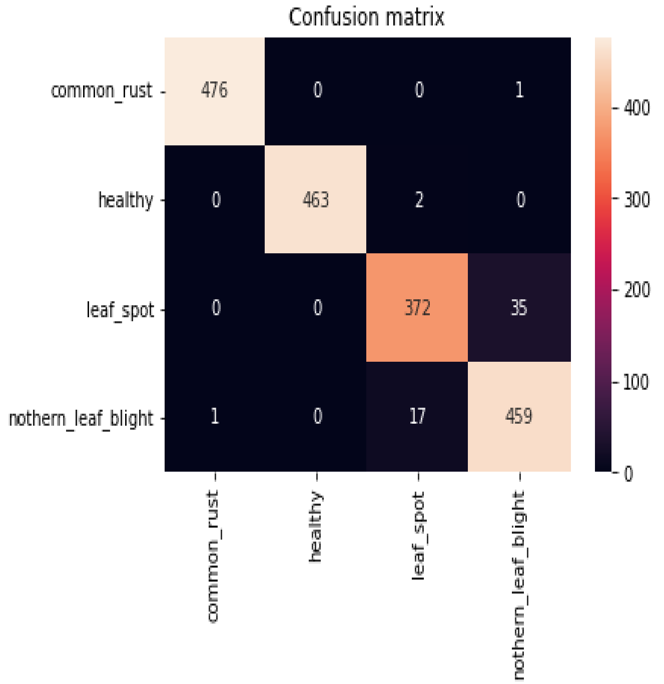

Figure 5. Confusion Matrix for DenseNet on Maize Dataset

Figure 5 shows the DenseNet confusion matrix on the maize dataset. This matrix shows how well DenseNet can differentiate between healthy leaves, common rust, leaf spot, northern leaf blight, and other diseases that affect maize leaves. The diagonal matrix components, which represent the correctly classified cases, displayed the values for healthy leaves (463), common rust (476), leaf spot (372), and northern leaf blight (459). These figures demonstrated the model's ability to categorize several diseases; the two with the best results were common rust and northern leaf blight. The model's ability to correctly classify the majority of cases in each illness category, as shown by the diagonal distribution of these values, implies that it might be applicable in practical agricultural contexts.

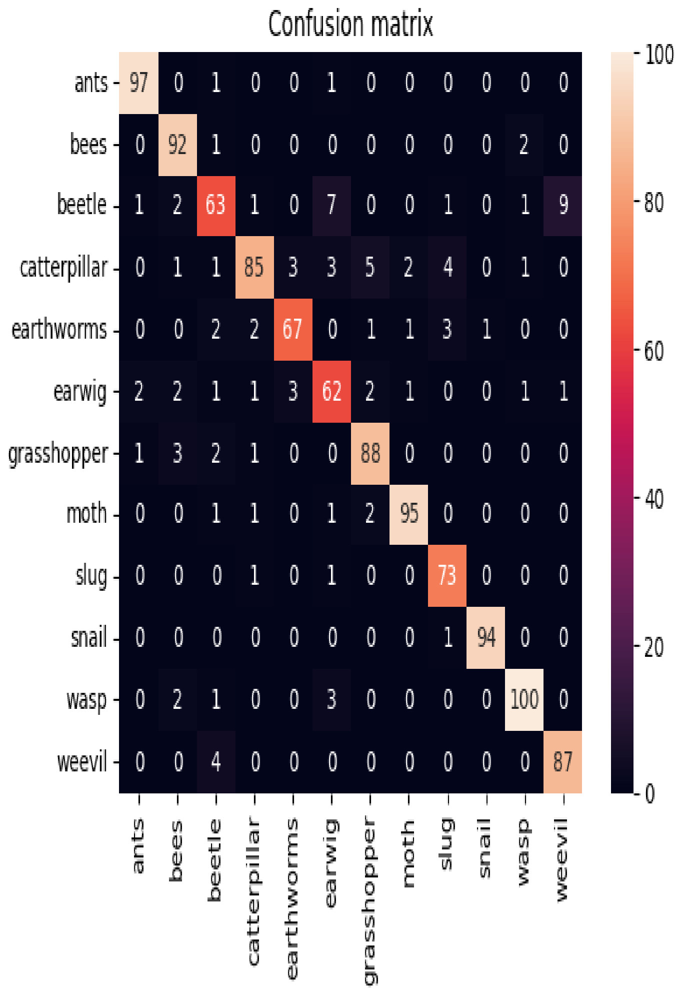

Figure 6. A DenseNet Confusion Matrix for the Pest Dataset

Figure 6 displays the confusion matrix with the model's accuracy in classifying various pest species, which occurred after a DenseNet was trained to classify various agricultural pests. In the diagonal components of the matrix, which represent appropriately classified occurrences, there are 97 ants, 92 bees, 63 beetles, 85 caterpillars, 67 earthworms, 62 earwigs, 88 grasshoppers, 95 moths, 73 slugs, 94 snails, 100 wasps, and 87 weevils. Based on these parameters, the model was most accurate in identifying wasps, ants, moths, and snails. An analysis of the distribution of accurate classifications along the diagonal revealed that the model could distinguish between various pest species. For effective pest management in farming, this is a crucial aspect.

An essential measure for evaluating and enhancing the CNN's performance in this work was the model loss. The difference between the actual target values and the model's predicted outputs was used to quantify the loss in the model. To improve the model's prediction accuracy, we trained it to minimize this loss as much as feasible. This study used categorical cross-entropy, a loss function that excels at problems requiring multi-class classification.

For a singular instance, categorical cross-entropy loss was first defined in mathematics as;
The sum of all i is equal to 1, and **O** is the logarithm of (p).
The following equation represents the limit;

$$L = -\sum_{i=1}^{K} Yilog(Pi)$$

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, p_i 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 concerning 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.
To guide the training process of the deep learning model, the model loss function was ultimately critical. Reducing this loss via iterative optimization significantly enhanced the model's accuracy in crop disease and pest classification, leading to a reliable and high performance in real-world applications.

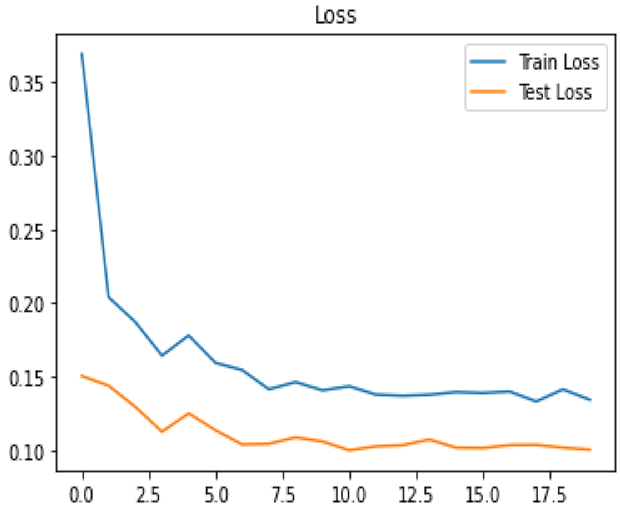

Figure 7.Train and Test loss for Densenet

Two important variables, train accuracy and test accuracy, were used to examine the performance of the deep learning model. The generalizability and efficacy of the model in learning from the training data were illuminated by these metrics. In Figure 7, the x-axis typically displayed the total number of epochs, while the y-axis displayed the accuracy values.
The proportion of training dataset samples correctly classified was referred to as the training accuracy. To monitor the model's progress, it was calculated at the conclusion of each training phase. The train accuracy formula was;
;

$$A_{train} = \frac{\text{Number of correct predictions on training set}}{Total\ number\ of\ training\ samples}$$

The output is the function A_{train}, 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 $N_{correct}$ of those examples, then;
The value of A_{train} is equal to the product of $N_{correct}$ and N.

$$A_{train} = \frac{Ncorrect}{N}$$

Since the model was not trained on the test dataset, test accuracy was determined as the proportion of test dataset samples correctly recognized. This statistic was critical for assessing the generalizability of the model. Not much changed between the train accuracy formula and the test accuracy formula Atest;
A_{test} 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.

$$A_{test} = \frac{\text{Number of correct predictions on test set}}{Total\ number\ of\ test\ samples}$$

The model was considered to have achieved test accuracy if it correctly predicted the labels for $M_{correct}$ out of the M samples that were part of the test dataset.
The output was A_{test} equal to the division of $M_{correct}$ and M.

$$A_{test} = \frac{Mcorrect}{M}$$

Training the model included continuously monitoring its test and training accuracy to prevent overfitting and ensure effective learning. Overfitting occurs when a model performs very well on training data but disastrously on test data. This was shown by a significant disparity between the excellent accuracy during training and the subpar accuracy while testing. When regularization, early stopping, and dropout were used, overfitting was much decreased.

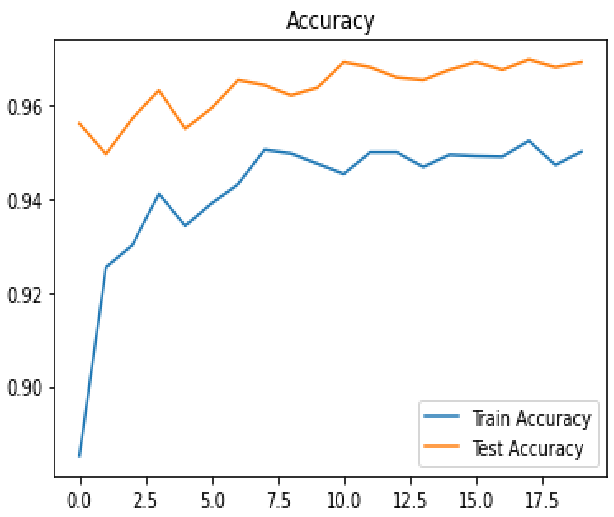

Figure 8. Train and Test Accuracy for Densenet

In order to visually compare the test and train accuracies, the model's accuracy was computed and recorded after each training phase. Afterwards, the data was plotted on a graph, as seen in Figure 6, which clearly demonstrated the progression of the model's performance over time.
The training accuracy curve showed how the model's performance improved over time on the training data. If the model is successfully learning from the training data, this curve should ideally show a gradual climb, approaching 100% as the number of epochs increases.
The accuracy testing curve proved that the model could correctly forecast fresh data. The development and closeness of this curve to the training accuracy curve were of paramount significance. When the accuracy during training remained high but the accuracy while testing remained stable or decreased, this phenomenon is known as overfitting.
Both the training and test accuracy were 95% and 97% after 17 epochs, respectively, as shown in Figure 8. If this is the case, it means the model performed well on both the training and test sets of data. It is possible that the lack of overfitting and the model's good generalizability are both indicated by this disparity.

At last, seeing the training and test accuracy throughout epochs was a helpful tool for diagnosing the training process, evaluating the performance of the model, and making improvements to enhance the training and generalization capacity.
Finally, while evaluating the deep learning model's capacity to detect agricultural diseases and pests, the train and test accuracies were crucial performance measures. Indicators like these brought attention to the model's capacity for learning and generalization, which in turn boosted its overall performance.

A. Discussion

The researcher evaluated and compared the performance of several deep learning models, including CNN, VGG, EfficientNet, DenseNet, and AlexNet. In classification tasks, DenseNet outperformed the other models in terms of accuracy and resilience. With a remarkable 96.988% accuracy on the maize dataset and 96.9382% on the pest dataset, DenseNet outperformed AlexNet, EfficientNet, CNN, and VGG. Because it promotes feature reuse via dense connections between layers, the DenseNet architecture improved gradient flow and made learning more efficient, leading to greater performance.
In addition to basic accuracy, the evaluation factors included train and test loss alongside test and train accuracy. Train loss and test loss were critical metrics for evaluating the model's capacity to learn and generalize. Figure 7 shows that the model learned well from the training data because the training loss reduced steadily across the epochs. Since the test loss leveled off after dropping in the outset, it seemed that the model generalized well with little overfitting. Training and testing accuracy metrics lent credence to these findings. As seen in Figure 8, DenseNet consistently achieved near-flawless train accuracy and maintained a very high test accuracy that closely paralleled the train accuracy curve. More pronounced differences in train-test accuracy were seen in the other models due to overfitting and inadequate generalization.
Dataset biases, such as an imbalanced distribution of crop diseases or pests, might have compromised the study's accuracy by influencing the model. Furthermore, the study acknowledged that changes in soil type, temperature, and crop species affected the model's predictive power. The results showed that the architectural modifications of DenseNet were helpful in classifying agricultural diseases and pests. The dense connection pattern simplified the process of learning complex patterns and traits required for accurate classification. Agricultural settings place a premium on accurate and reliable pest and disease identification, and the model's ability to maintain high test accuracy is further proof of this. The study also recommended that future research look into more advanced structures and techniques like ensemble methods and transfer learning to boost classification performance even more and solve the remaining issues in the sector. The remarkable performance of DenseNet, a significant advancement in the use of deep learning for agricultural

diagnostics, guaranteed better management and mitigation of pests and diseases in crops.

V. CONCLUSION AND FUTURE WORK

The results proved that DenseNet was the superior model compared to others, including EfficientNet, CNN, VGG, and AlexNet. In comparison to competing models, DenseNet achieved a remarkable 96.988% accuracy on the maize dataset and 96.9382% on the insect dataset. An excellent model for practical agricultural applications, DenseNet's crop disease and pest categorization is very accurate. The research examined a variety of metrics, including train-test accuracy and train-test loss, among others. It seems like DenseNet learnt a lot from its training dataset as its train loss went down during the epochs. The test loss, which had been reducing, eventually plateaued, indicating good generalization without significant overfitting. On top of that, DenseNet maintained a nearly flawless train accuracy as well as a robust test accuracy that was very close to the train accuracy curve. These results demonstrated the model's ability to learn and generalize well from the data, which improved its reliability for real-world deployment. Researchers found that DenseNet's dense connections and other architectural advantages helped it beat competing models on tasks including the categorization of agricultural diseases and pests. With its impressive accuracy and effective learning and generalization capabilities, the model proved to be a valuable tool for improving agricultural diagnostics. Through demonstrating that deep learning models can accurately classify agricultural illnesses and pests, the study paved the way for quicker and more accurate danger detection in crops. This AI-driven method, as proposed in the paper, may help farmers and agricultural professionals monitor crop health more accurately than relying on expert knowledge and physical inspections alone. With these models, farmers will be able to more accurately administer pesticides, which will lessen their negative effects on the environment and promote the adoption of greener pest control strategies. This study was critical in bridging the gap between theoretical and practical aspects of modern agricultural technology, which has the potential to completely alter current methods of disease and pest prevention.

Research in the future should look at more advanced techniques, such as ensemble methods and transfer learning, to enhance classification performance even more. The promising results of this work pave the way for the development of deeper learning models that are both more accurate and more reliable for use in agricultural applications.

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