DETECTION OF PESTS IN AGRICULTURE FARMS USING MODIFIED DENSENET DEEP LEARNING MODEL

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Abstract
Pests can cause significant damage to crops by feeding on the leaves, stems, roots, and fruits. This can lead to reduced crop yields and financial losses for farmers. Deep learning algorithms can be trained to detect pests in images of crops. This can be done by using supervised learning algorithms to classify images as containing or not containing pests, or by using unsupervised learning algorithms to cluster images based on their similarity. Deep learning based pest control has the potential to improve the efficiency and effectiveness of pest control in agriculture, by providing farmers with more accurate and timely information about pests and diseases. This paper presents a deep learning based model for detection of pests in agriculture. The proposed DenseNet model uses dense connectivity between layers, which allows the network to reuse features learned by the earlier layers. This improves the efficiency of the network and reduce the number of parameters. The dense connectivity in DenseNet helps to alleviate the vanishing gradient problem, which is a common issue in deep networks with many layers. This makes it possible to train deeper networks with DenseNet, which can improve the performance.

Keywords: Pest Detection, Pest Control, Deep Learning, DenseNet, Crop Yield.

1. Introduction

Technology in its current form has a tight relationship to the expansion of farming, which is due in large part to the ongoing success of various agricultural reforms. Understanding and exercising authority over information resources are now also essential to the continued growth of modern agriculture. This indicates that the consumption of environmental assets is no longer the only factor that may contribute to the sustainable growth of contemporary agriculture. Because of the ongoing deterioration of the ecological environment over the last several years [1-2], which makes it more unstable, crop diseases and insect pests often have outbreaks that affect a significant number of acres. The widespread occurrence of crop diseases and insect pests may have a direct impact on the quantity as well as the quality of agricultural goods [3], which can ultimately lead to economic losses. In order to prevent losses that aren't absolutely required, it is essential to do research on the management of crop diseases and insect pests.

Due to the fact that a sizeable amount of the crops is destroyed and their quality is diminished as a result of the pest assault, agricultural bug identification is a difficult job for farmers to do [4]. The traditional method of identifying insects has the limitation that it requires highly-trained taxonomists in order to correctly identify insects based on their physical characteristics. Agriculture is in desperate need of more technologically advanced procedures in order to detect pests at an earlier stage and reduce the need for extensive application of potentially harmful pesticides. By draining the sap from the leaves, and other parts of plants, these insects may spread the illness that is caused by sooty mould [5]. The sickness inhibits photosynthesis and causes tissue infections, both of which lead to the loss of crops and a decline in the market value of the commodities generated from such plants, both in terms of the quality and quantity of such products.

When farmers are faced with an infestation of pests, they depend on their own personal experience and expertise to diagnose the problem. Spraying pesticides is the technique of choice for controlling pests due to a lack of information; this approach is favored since it is both quick-acting and scalable. However, because of growing worries about the environment and public health, there should be a reduction in the usage of pesticides. Spraying just in areas that need it is one of the most essential things that can be done to decrease the usage of pesticides [6]. Spot spraying is reported to be able to minimize the cost of applying pesticides by as much as 90%. This practice may also limit the amount of pesticides that are released into the environment and help protect important insects like honeybees. Finding the precise location of the insect pest is the first step in the process of spot spraying for it.

In most cases, the detection of pests is accomplished via the use of manual procedures, which require a significant amount of effort and are, as a result, fraught with mistake. Because of recent advancements in computer vision applied to precision agriculture, the identification of insect pests and diseases has become an essential component of the collection of data on the development and health of crops [7,8]. Large farms and orchards require the detection of objects at various stages of agricultural development in order to successfully estimate future yields, activate intelligent spraying systems, and regulate autonomous pesticide spraying robots. All of which need the detection of objects at various phases of agricultural development. However, it can be difficult to detect target objects with reasonable accuracy because of factors such as the similarity of shape, the complexity of the backgroundNevertheless, the development of technology has made it feasible to identify insect pests via the use of image processing techniques.

Acquisition of visual information and processing of that information by computer vision are essential components of carrying out insect identification and classification. As a result, deep neural networks, also known as DNNs, are often used in computer vision applications for the purposes of mapping complicated connections and carrying out automated feature extractions. Recent developments in graphics processing units, or GPUs, have made it possible to train artificial neural networks that are deeper, leading to faster and more accurate results. DNN object categorization results are impressive. Regression-based and classification-based object detectors are the two main groups of object recognition algorithms. Two-stage object detectors outperform single-stage detectors in accuracy but are slower in inference speed. In this work, the improved DensNet model has been proposed to accurately detect and classify the pests. Fine-tuning the hyperparameters and the layers of the DenseNet model is done in order to apply the transfer learning method to the pest data set.

2. Literature

In [9] authors developed an anchor-free region convolutional neural network (AF-RCNN) for accurate detection of a total of 24 different types of pests. Deep neural networks have made substantial contributions to object categorization and recognition. There are two primary categories of algorithms that perform object recognition, known as two-stage classification-based detectors and single-stage regression-based detectors. In terms of accuracy, the two-stage detectors tend to perform better, but they also have slower inference times compared to the single-stage detectors. In the end, they combine the anchor-free region perceptron neural network (AFRPN) with the fast region convolutional neural network (Fast R-CNN) to create a single network that they call the anchor-free region convolutional neural network (AF-RCNN). This network is used to detect all 24 classes of pests using an end-to-end method. The authors collected a dataset of pest images including 20k images and 24 classes. The proposed model of AF-RCNN produced a mean Recall of 85.1%.

In [10] authors suggested a diagnostic approach for the diagnosis and identification of pests that is based on transfer learning with CNN. The custom dataset consists of 10 different kinds of pests with 500 images. The technique produced an accuracy of 93.84%. The authors compared the results of the transfer learning technique with those obtained from human experts and a conventional neural network model.

The reference [11] provided a viewpoint on the development and current status of remote sensing technology as well as its applications, in particular the control of insect pests and plant diseases. The measuring, recording, and processing of electromagnetic radiation from the target that is located on the ground are the three essential processes in the process of remote sensing. In a wide variety of remote sensing applications, the importance of the spectral features of live beings cannot be overstated. In today's world, remote sensing has evolved into a powerful instrument that can accurately detect, forecast, and eradicate insect pests and plant diseases in a wide variety of fruit orchards and agricultural fields. These apps are designed to collect data for the purpose of making educated choices on pest management and reducing the negative effect that chemical pesticides have on the environment. The use of airborne remote sensing as a method for the management of insect pests and the identification of weeds has been shown to be both promising and helpful.

In [12] authors presented a solution to autonomous pest monitoring that is based on deep learning and makes use of hybrid and locally activated features. The authors made use of the global information that is contained within feature maps in order to construct our global activated feature pyramid network. This network is used to extract the highly discriminative characteristics of pests across a wide range of scales and at multiple depth and position levels. During the downsampling process, it makes changes in depth or spatially sensitive characteristics more obvious in the pest pictures. The accuracy of the proposed is obtained as 90.27%.

In [13] authors presented a multiple pest identification approach (R-CNN) using federated learning (FL) and an upgraded quicker area CNN. This not only lowers the cost of transmission but also saves time. In order to guarantee that the model would converge and to make the training process move more quickly, the FL algorithm was modified to include a limitation M. This is done to preserve the original structure of small-sized objects while also increasing the speed at which they may be detected. The researchers utilized a comprehensive pest dataset that was accumulated over seven years, consisting of 88,600 images of 16 different pest species and 582,100 manually labeled pest instances. The proposed method showed outstanding results, achieving a mean average precision (mAP) of over 75.03% in industrial settings, outperforming two state-of-the-art approaches: faster R-CNN, with a maximum mAP of 70%, and FPN, with a maximum mAP of 72%.

In [14], the authors describe an approach to the pest identification and classification problem by presenting the DeepPestNet architecture. The proposed model has a total of eleven learnable layers, with eight convolutional and three fully connected (FC) layers included. strategies for picture rotations to enhance the size of the dataset as well as ways for image augmentations to evaluate the generalizability of the proposed DeepPestNet methodology were investigated. In order to evaluate the proposed DeepPestNet architecture, they made use of the data set including Deng's crops. the approach that has been developed to identify and categorize agricultural pests into ten different classes, with an accuracy of one hundred percent.

In order to conduct effective insect pest identification, the authors make use of three cutting-edge Deep Convolutional Neural Network (DCNN) models [14]. These models are referred to as Faster-RCNN, Mask-RCNN, and Yolov5. On top of that, the authors created two coco datasets on their own using the insect detection dataset from Baidu AI and the IP102 dataset. The experimental findings strongly support Yolov5 for the identification of insect pests due to the fact that its accuracy reaches over 99%, while both Faster-RCNN and Mask-RCNN reach above 98%. This is in reference to the insect detection dataset used by Baidu AI, which has a basic backdrop. In the meanwhile, Yolov5's computational speed is superior than that of both Faster-RCNN and Mask-RCNN.

Reference [16] introduces a new method for locating and quantifying agricultural pests. The approach, known as MCPD-Net, is a multi-category pest detection network that combines adaptive feature region proposal and multiscale feature pyramid networks. The multiscale feature pyramid network integrates multiscale pest information, enhancing detection accuracy. The adaptive feature region proposal network addresses the issue of misalignment in the region proposal network during iteration, which is particularly problematic for microscopic pests. Testing on the Multi-Category Pests Dataset 2021 (MPD2021) revealed that the proposed method significantly improves average precision (AP) and average recall (AR). MCPD-Net achieved 67.3% AP and 89.3% AR.

3. Proposed Model

The suggested procedure may be broken down into five distinct parts. To begin, we gather images of a wide variety of insect pests for the purposes of training and assessing deep learning (DL) models. Second, we perform a preprocessing step on the full dataset, during which we annotate and enrich the data in order to get a larger number of samples. Image data augmentation is a method that slightly alters existing images depending on given criteria in order to artificially enlarge the training dataset. Machine learning is one of the most popular applications for this technology. Third, we put DenseNet object identification models through their paces by training them on the dataset and then using transfer learning to assess how well they performed. In order to verify the accuracy of the findings, we partitioned the dataset into many portions. In the end, we choose the most successful model for actual application in the agricultural sector.

3.1 Proposed DenseNet Model

The CNN model's convolutional layers are the ones in charge of both the feature extraction and creation processes. As a result, several researchers have concentrated their efforts on expanding both the depth and breadth of their categorization systems. On the other hand, the DenseNet that was proposed and developed to enhance the usage of parameters. In order to accomplish this objective, a sophisticated cross-channel operation was selected for the purpose of refining feature maps, and the concatenation approach was used for the purpose of feature reuse.

The backpropagating gradient becomes weaker as it travels from the input layer to the output layer in deep CNNs, causing problems in their performance. However, the ResNet architecture solved this problem of fading gradients by incorporating skip connections between layers, which combine the outputs of previous layers with the outputs of stacked levels. By eliminating certain random layers during training, ResNets were able to decrease the network's stochastic depth, which resulted in improved gradient and information flow. In this way, the capability of training deeper networks is increased. DenseNets is an alternative to ResNets that guarantees an optimum flow of information inside the layers while also linking all of the levels directly to each other. This is accomplished through a straightforward connection architecture. Instead of adding the residual, like ResNet does, the DenseNet appends all of the feature maps together. As a result, they are able to go deeper than typical networks and may easily be optimized with this new residual utilization. Architecture that has been proposed for the improved DenseNet is shown in Figure 1.

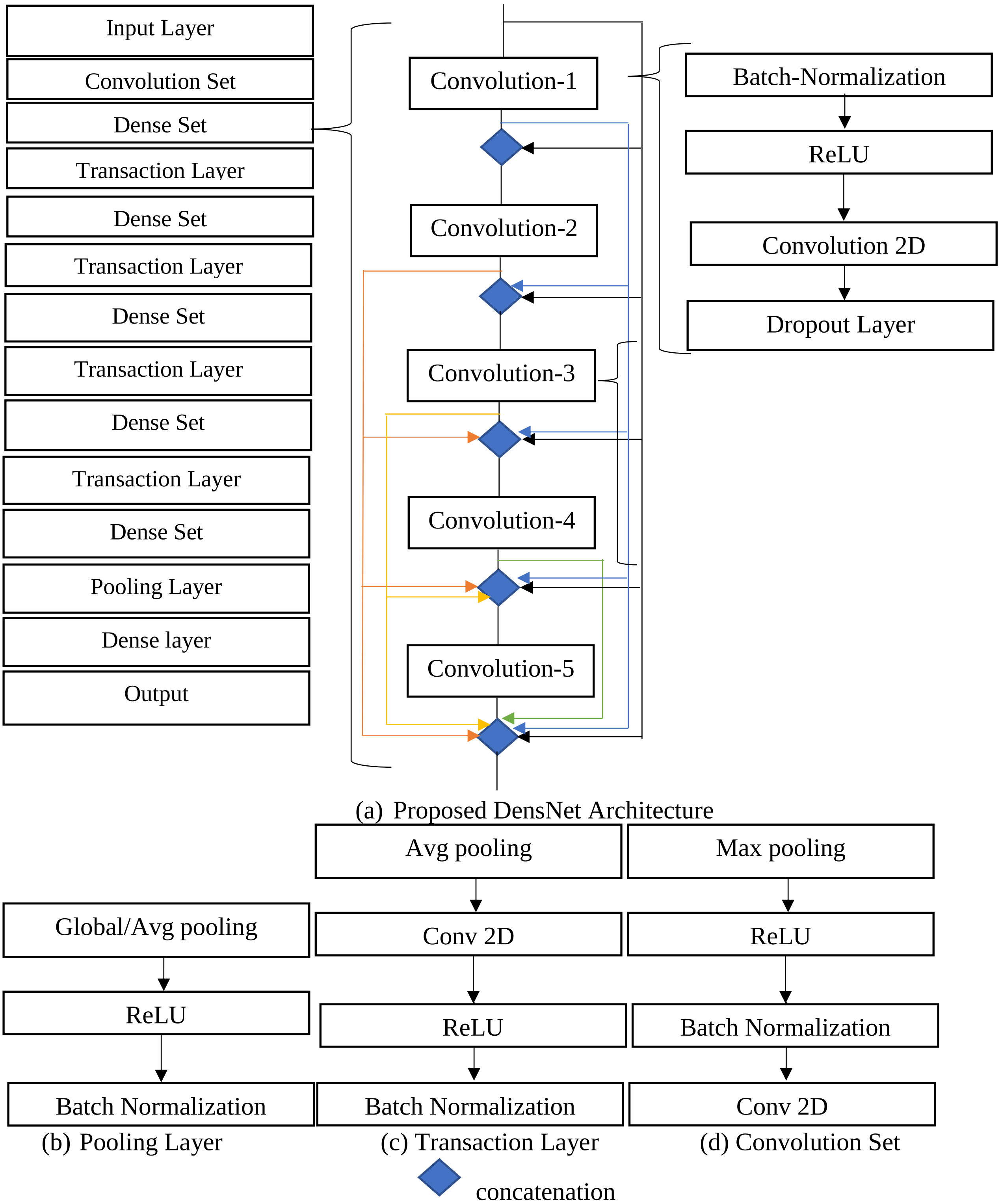


Figure 1: Proposed DensNet Architecture

In order to recognise and categorise leaf diseases, a DenseNet model that has been tuned and trained is used. DenseNet receives its input in the form of multi-channeled pictures in batches of 32, each of which has dimensions of 250 by 250 by 3. The input is first placed through a Conv2D layer, which, in turn, builds a feature map and extracts features from the data. After that, this map is transmitted to the first dense block, which consists of five convolution layers. A dropout layer, a batch normalization layer, a ReLU activation layer, and a 3x3 Conv2D layer are included in each of the layers that make up the dense block. The input is mixed with the results of the first convolution layer in the block's block, which yields four feature maps. After that, a further convolution layer is added, which results in the production of four new feature maps that are then concatenated with the ones that came before. After that, the feature map progresses to the next dense block, which consists of five convolution layers. This activity of concatenation is used in each and every one of the dense blocks. Because it is impossible to concatenate feature maps of various sizes, the convolution layers that make up a dense block are required to yield feature maps with the same dimension.

Convolution layers take advantage of the spatial locality of the data, meaning that pixels in an image that are close to each other are likely to have similar patterns. By using convolution, the model can learn these patterns, which can be very useful in image classification and segmentation tasks. These layers share their parameters across the entire input, reducing the number of parameters in the model. This makes the model more computationally efficient and less prone to overfitting. Convolution layers are capable of automatically learning complex and abstract features in the input data, which can be used as inputs to subsequent layers in the network.

Batch normalization helps to stabilize the training process by reducing the internal covariate shift, which occurs when the distribution of the activations changes during training. This makes the training process less sensitive to the choice of initialization and can speed up convergence. It acts as a form of regularization by adding noise to the activations, making the model more robust to overfitting. It can also significantly speed up the training process by reducing the number of epochs required to converge. This is because the normalization helps to avoid the vanishing and exploding gradient problems, which can slow down training.

The output from one dense block is a combination of the outputs from five convolutional layers. As a result, the output from a single dense block consists of five feature maps, which are four times larger in size than the original input (with 20 feature maps per dense block). Through convolution and average pooling, the size of the feature map may be altered by the layer that is between the two dense blocks that are close to one another. This layer is known as the transition layer. In the transition layer, we begin with a convolution that is 1 by 1, then we go on to an average pooling that is 2 by 2. The suggested design is comprised of four transition levels in addition to five dense blocks. A transition layer is added after the completion of each dense block, with the exception of the last one. After the last dense block comes the global average pooling layer, and then the softmax classifier comes after that.

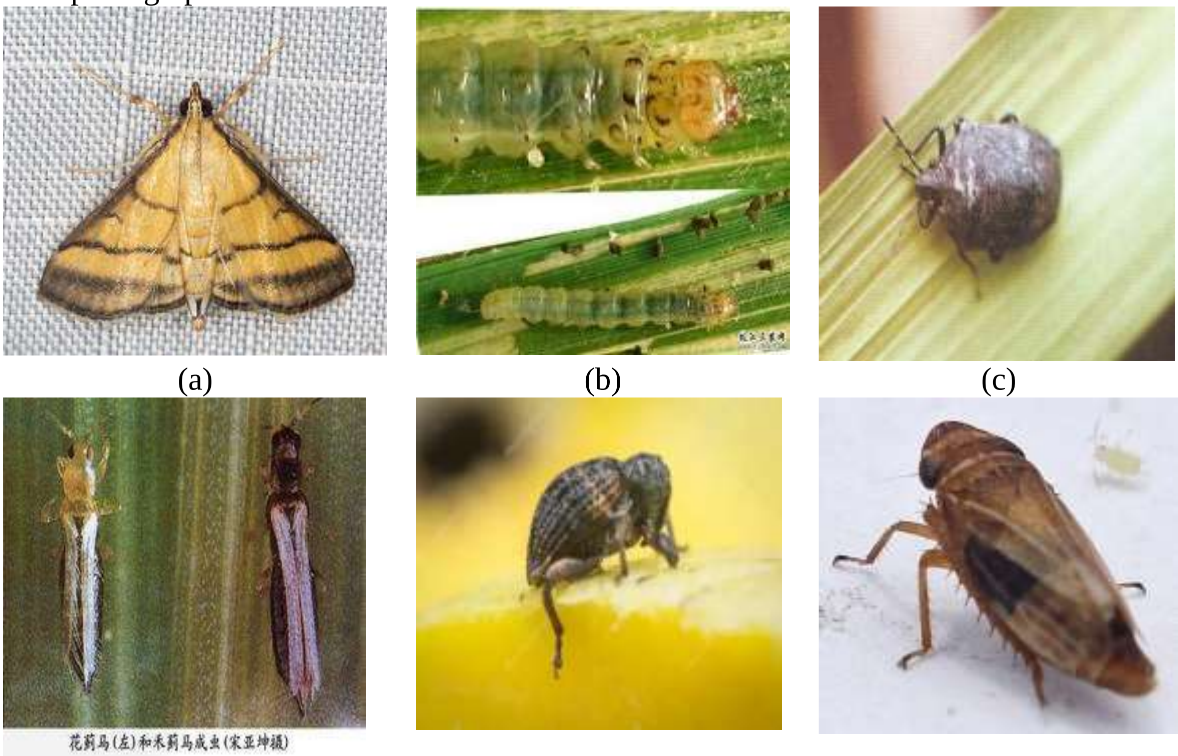
Dense layers can be used to model a wide variety of functions, making them suitable for many different types of deep learning tasks, such as image classification and language translation. Dense layers are robust to small changes in the input, making them suitable for tasks where the input is noisy or contains missing values. It can provide a global representation of the input, allowing the model to capture complex relationships between different features.

The output of a softmax layer is a probability distribution over the classes, making it easy to interpret the model's predictions. Softmax layers are well-suited for multi-class classification problems, where the goal is to predict one of several possible classes. The outputs of a softmax layer are well-calibrated probabilities, which can be used to estimate the uncertainty in the model's predictions. Softmax layers are differentiable, making it possible to optimize the model using gradient-based methods such as stochastic gradient descent.

DenseNet reuses features from earlier layers, which helps to reduce the number of parameters and improve efficiency. This also allows the model to take advantage of features learned at different levels of abstraction. DenseNet mitigates the vanishing gradient problem, which can occur in very deep networks, by allowing gradients to flow more easily from the lower layers to the higher layers. This makes it easier to train very deep networks.

4. Simulation Results

The IP102 dataset, which contains somewhere in the neighborhood of 75222 photographs, was used for the purpose of this particular research investigation. The collection is comprised of photographs of a wide variety of pests, each of which is unique in comparison to the others and, on the basis of the traits they share, belongs to a certain category within the more comprehensive categorization system. The exam portion and the train portion each account for twenty and eighty percent, respectively. In addition to this, we consider four distinct categories of pests, and we train 200 images for each category. The following is a breakdown of the dataset according to its proportions: 6:1:3. There are a total of eight distinct kinds of super classes. The term "field crops" refers to agricultural products such as rice, maize, wheat, and alfalfa, whereas the term "economic crops" refers to agricultural products such as citrus, mango, and grapefruit (EC). In Figure 2, you can see a selection of the photographs that were extracted from the IP102 dataset.



(d) (e) (f)

Figure 2: Pest Images of IP102 Dataset

The training method begins by assigning the model a learning rate of 0.001, which is Adam's standard learning rate. This rate is used throughout the training process. After just a little amount of time spent training the model, an accuracy of 87% is achieved in the training process. Even though Adam makes use of exponential decay to slow down the learning rate, there is still regular fluctuation in the accuracy because of the fast learning rate. This is due to the fact that Adam learns so quickly. Because of this, we can't say for certain that the model is stable. As a result, we started the training process for the model using the same Early Stopping setup and a learning rate of 0.0005 iterations per second. After a few rounds of iteration, we were able to achieve a level of accuracy that was more than 91% in both the training and validation phases.

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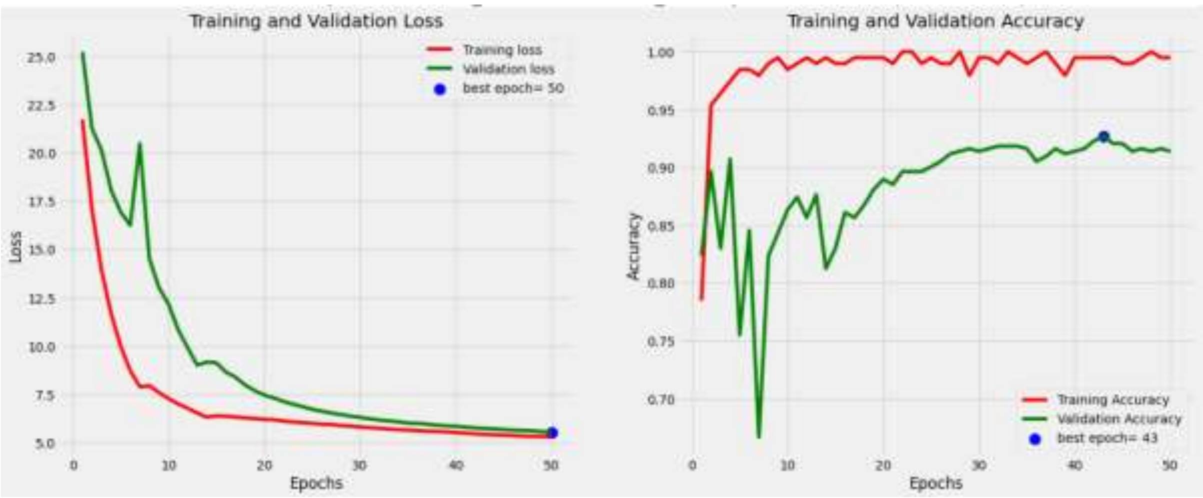

Figure 3: Validation loss and Accuracy plots of Proposed DensNet

In addition, as we can see from Figure 3, the model exhibited a high level of stability, as shown by the fact that the validation accuracy showed almost little variation. It was revealed when the model was being trained that a very low learning rate does not ever progress, but a very high learning rate could generate instability and so does not ever converge. This was discovered during the process of training the model. Consequently, it is essential to choose a suitable learning rate for the Adam; otherwise, the network will either be unable to train at all or would take a much longer period of time to converge. Choosing an appropriate learning rate for the Adam is essential. It is very essential to choose an appropriate learning rate for the Adam. Table 1 provides information on the proposed model's sensitivity, septicity, precision, area under the curve (AUC), and accuracy. Table 2 presents the results of a comparison between the proposed model and many alternative network models.

Table 1: Performance metrics of the Proposed Model

Parameter	**Proposed Network model**
Sensitivity	1
Septicity	1
Precision	92.6%
AUC	89.2%
Accuracy	**91.39%**

Figure 4: Comparison with proposed model and other network models

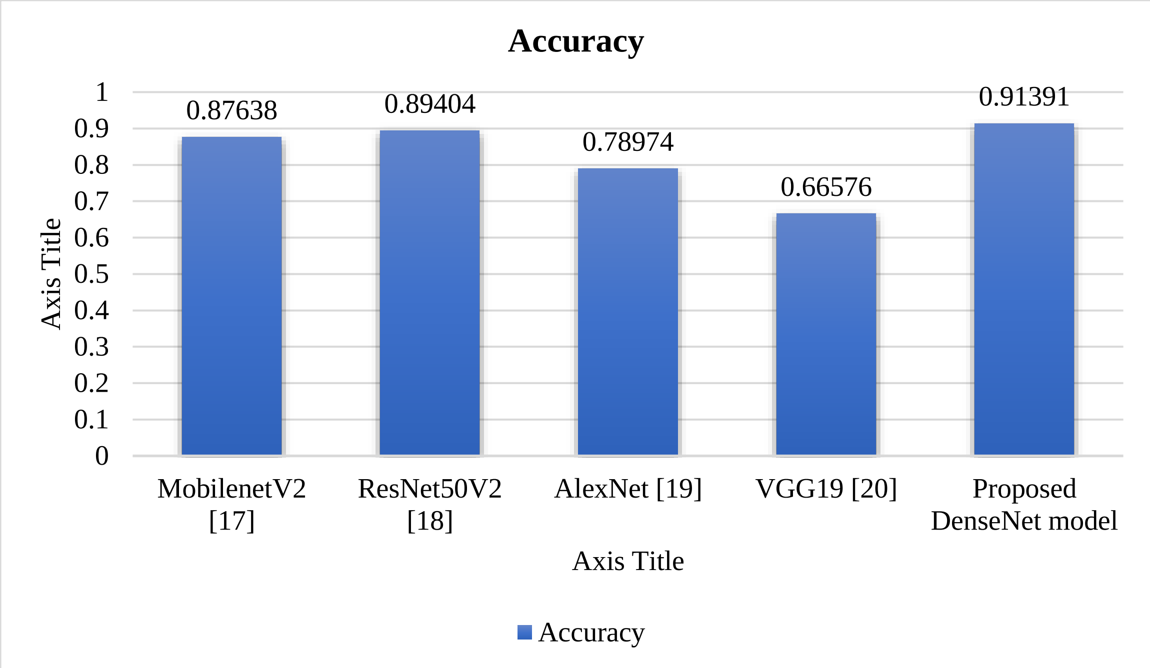

Figure 4 displays the results obtained from the training of each of the models. Proposed DenseNet had the greatest results in terms of the accuracy of classification, followed by MobilenetV2, ResNet50V2, AlexNet and VGG-19. The accuracy of the Proposed DenseNet model was 2% higher than that of the ResNet50V2 model, which had been the benchmark in the past. Since the optimised DenseNet that was provided has an overall accuracy of 91%, it is pretty obvious that it is better to the CNN models that have previously been developed, especially considering the fact that it was presented. The results that have been produced up to this point are promising; hence, this body of work may be further developed by identifying more species of pest and creating a more optimum model that can be computed with much less time and effort invested.

Conclusion

Pests can cause significant damage to crops, leading to reduced yields and financial losses for farmers. Early detection and control of pests can help to minimize these losses. Some pests can carry diseases or parasites that can be harmful to humans if consumed. Pest detection can help to ensure that crops are safe for consumption. Some pests can act as vectors for plant diseases, which can have devastating effects on crops. Early pest detection can help to prevent the spread of plant diseases. DenseNet (Densely Connected Convolutional Networks) is a type of convolutional neural network (CNN) architecture that is characterized by its dense connections between layers. In a traditional CNN, each layer only receives input from a subset of the neurons in the previous layer, through a process called subsampling. In contrast, in a DenseNet, each layer receives input from all the neurons in all the previous layers. This is achieved by concatenating the output of the previous layers to the input of the current layer, rather than summing or averaging them. It helps to alleviate the vanishing gradient problem, which is a common issue in deep networks with many layers. It allows the network to reuse features learned by the earlier layers, which can improve the efficiency of the network and reduce the number of parameters. It can also make the network more robust to the initialization and the choice of hyperparameters. The proposed model obtained the highest accuracy of accuracy of 91.39%.

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