IMPROVED DENSENET ARCHITECTURE FOR ENHANCED CROP-PEST CLASSIFICATION IN AGRICULTURE

FIELD OF THE INVENTION:

The present invention relates to the field of computer vision, deep learning, and pest management within the agricultural sector. It pertains to a novel enhancement of the DenseNet architecture, which improves pest classification accuracy, providing more reliable automated pest identification.

BACKGROUND OF THE INVENTION:

There is immense loss of food crops all over the world owing to the attack of pests. Accurate and early identification of pests is crucial for effective pest management and to minimize economic loss to farmers. Traditional methods of pest identification involve manual observation, which is time-consuming, requires expertise, and is not scalable.

Machine learning and deep learning have enabled automated pest detection using image classification techniques. Convolutional Neural Networks (CNNs), such as AlexNet, VGGNet, ResNet, and DenseNet, have been effective in this task. However, existing models face challenges in accurately classifying pests due to factors such as small datasets, complex backgrounds, and varying pest appearances. Current convolutional neural networks (CNNs) struggle with noisy backgrounds and low-quality datasets, leading to inaccurate classifications. Misclassification can lead to misinformed pest management decisions, potentially costing the agricultural sector billions in losses annually. The present invention addresses these challenges by modifying the DenseNet architecture, resulting in improved and enhanced crop-pest classification accuracy.

OBJECTS OF THE INVENTION:

The primary objective of this invention is to provide an improved pest classification model based on a modified DenseNet architecture that achieves higher accuracy than existing models. Other objectives include providing a model that can efficiently handle large and imbalanced datasets with diverse pest species, achieving enhanced feature extraction.

SUMMARY OF THE INVENTION:

The invention proposes a novel approach to pest classification using a modified DenseNet architecture, designed to improve the accuracy of pest identification tasks. The proposed model introduces 1 additional dense block to the standard DenseNet121 architecture, optimized with specific hyperparameters: 12 layers, dropout rate of 0.4, and compression factor of 0.7 to minimize overfitting and enhance performance.

The model has been evaluated on three datasets—IP102, Xie (40), and a 9-class dataset, demonstrating superior performance compared to existing deep learning models like ResNet50 and the original DenseNet121. The Proposed Approach achieved an accuracy of 68.34% on IP102, 94.47% on Xie, and 97.56% on the 9-class dataset, outperforming ResNet50 and DenseNet121, which had lower accuracy on the same datasets. The proposed modifications provide better feature reuse and representation, making the model suitable for tasks with limited training data and high variance.

DETAILED DESCRIPTION OF THE INVENTION:

Figure 1 gives an overview of the modified DenseNet architecture with additional dense blocks. An input image (101) of a pest is fed into an initial convolutional layer (102) with a kernel size of 7x7. This layer is followed by batch normalization and a ReLU activation function, which helps normalize the input and introduce non-linearity, respectively. The initial layer is followed by a pooling layer (103) with a kernel size of 3x3 to downsample the feature maps.

The output from the initial pooling layer is passed into the first dense block (104). Each dense block contains convolutional layers where each of the 32 layers receive inputs from all preceding layers, promoting feature reuse. Each layer in the dense block performs batch normalization, a ReLU activation, a 3x3 convolution, and a dropout operation to prevent overfitting.

The dense block is followed by the first transition layer (105). Transition layers consist of a 1x1 convolutional layer, followed by batch normalization, a ReLU activation, dropout, and a pooling layer (2x2) to reduce the size of the feature maps.

The architecture follows with subsequent dense blocks (Dense Block 2 (106), Dense Block 3 (108), Dense Block 4 (110), and Dense Block 5 (112)) interspersed with transition layers (Transition Layer 2 (107), Transition Layer 3 (109), and Transition Layer 4 (111)).

Circles in the diagram represent concatenation points where the outputs from different dense blocks or layers are combined into a single output. These concatenation operations are crucial for DenseNet architectures because they allow feature maps from all preceding layers to be reused in subsequent layers, enhancing feature propagation and reducing the risk of vanishing gradients.

After the final dense block (Dense Block 5 (112)), a pooling layer with a kernel size of 7x7 (113) is applied. This layer aggregates the feature maps into a single vector. The aggregation reduces the dimensionality of the data while retaining the most important features extracted from the image.

The aggregated vector is then passed through a dropout layer (114) to further prevent overfitting. Following this, a Fully Connected (FC) layer (115) with C* units is applied. The value of C* corresponds to the number of classes in the dataset used: 102 for the IP102 dataset, 40 for the Xie dataset, and 9 for a smaller dataset.

Finally, the output from the FC layer is passed to the output layer (116), which uses a softmax activation function to generate probability distributions over the possible pest classes. This output provides the predicted class label for the input pest image.

The proposed approach is then rigorously tested on three datasets: IP102, Xie (40), and a 9-class dataset. The model achieved a classification accuracy of 68.34% on the IP102 dataset, 94.47% on the Xie dataset, and 97.56% on the 9-class dataset. These results demonstrate a significant improvement over existing models like ResNet50(56.16%, 54.02%, and 50%) and DenseNet121 (60%, 93.13%, and 96.88%) on the respective datasets.

CLAIMS:

1. A method for pest classification using a modified DenseNet architecture, comprising:
   Adding one additional dense block with 12 layers to DenseNet121 to enhance feature reuse; setting a growth rate of 32; utilizing a compression factor of 0.7 for transition layers; and incorporating a dropout rate of 0.4.

2. The method of claim 1, wherein the model is trained on the IP102, Xie (40), and a 9-class dataset.

3. The method of claim 2, further comprising:
   Using data augmentation techniques, including rotation, shear, and horizontal flip, to improve generalization.

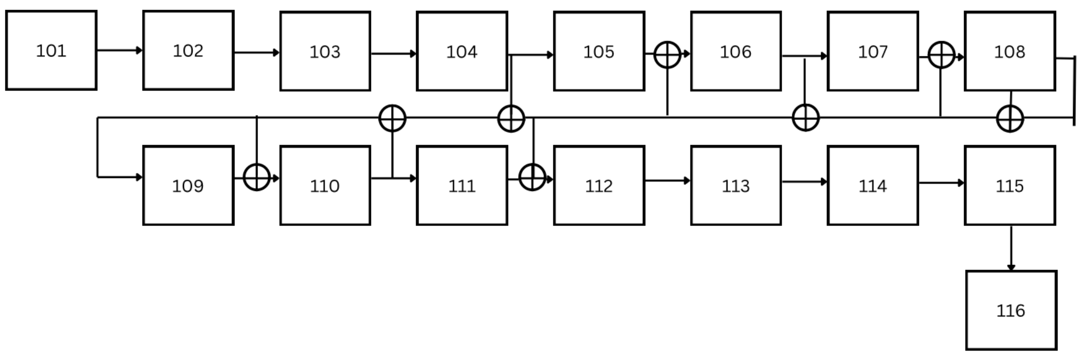
4. The method of claim 3, wherein the trained model achieves higher classification accuracies than ResNet50 and DenseNet121 in crop-pest classification.

5. A system for crop-pest classification, comprising:
   A GPU configured to execute the method as claimed in any of claims 1 to 4.

6. The system of claim 5, further comprising:
   A Solid-State Drive (SSD), wherein the SSD stores instructions for executing the modified DenseNet architecture, pest image datasets, and associated model parameters.

7. The system of claim 5, further comprising:
A USB flash drive, formatted with a compatible file system, storing instructions that, when executed by the GPU, cause the GPU to perform the method as claimed in any of claims 1 to 4.

DIAGRAM



ABSTRACT:

This invention relates to a system and method for crop-pest classification using an improved DenseNet architecture. A GPU executes a modified DenseNet121 model with an additional dense block for enhanced accuracy. Key hyperparameters include a growth rate of 32, dropout rate of 0.4, and compression factor of 0.7. Data and model instructions are stored on an SSD or deployable via USB. Evaluation on multiple datasets demonstrates superior performance over existing models, improving automated crop-pest management in agriculture.