Disease Detection in Crops Using a Convolutional Autoencoder and Convolutional Neural Network Hybrid Model

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Introduction

Paper:
Plant disease detection using a hybrid model based on convolutional autoencoder and convolutional neural network, Bedi et al. 2021

Problem:
Build a model that can accurately detect plant diseases from images, while keeping the number of training parameters low.

What's Novel:
- Combines Convolutional Neural Networks (CNNs) and Convolutional Auto-Encoders (CAEs) into a hybrid system.
- Achieved over 98% testing accuracy with fewer than 10,000 training parameters.
- Focused specifically on classifying healthy vs. unhealthy peach plant leaves (only bacterial spot disease) using the PlantVillage dataset.

Our Project Expansion:
- Trained on a larger subset of the PlantVillage dataset
- Built both a binary classifier (healthy vs. unhealthy) and a multiclass classifier (species and specific disease).
- Enhanced preprocessing with data augmentation (random rotations, shifts, and vertical flips) to improve model robustness

Why it's important:
- Helps automate plant disease detection to aid farmers and researchers.
- Demonstrates an efficient, lightweight model suitable for deployment on devices with limited computational resources.

Data

Data Set: PlantVillage
- Started with 54,303 images across 38 classes from the PlantVillage dataset.
- Final dataset: 40,000 images across 33 classes (removed incomplete classes)

Preprocessing:
- Reorganized dataset into train, validation, and test sets with a 70-20-10 split.
- Ensured all 33 classes were equally represented across splits.
- Used **ImageDataGenerator** from Keras to:
  - Preprocess images into tensors.
  - Split off 12.5% of training data to form the test set.
- Created two sets of labels:
  - **Binary classification:** Healthy vs. Unhealthy.
  - **Multiclass classification:** 33 specific plant-disease combinations.

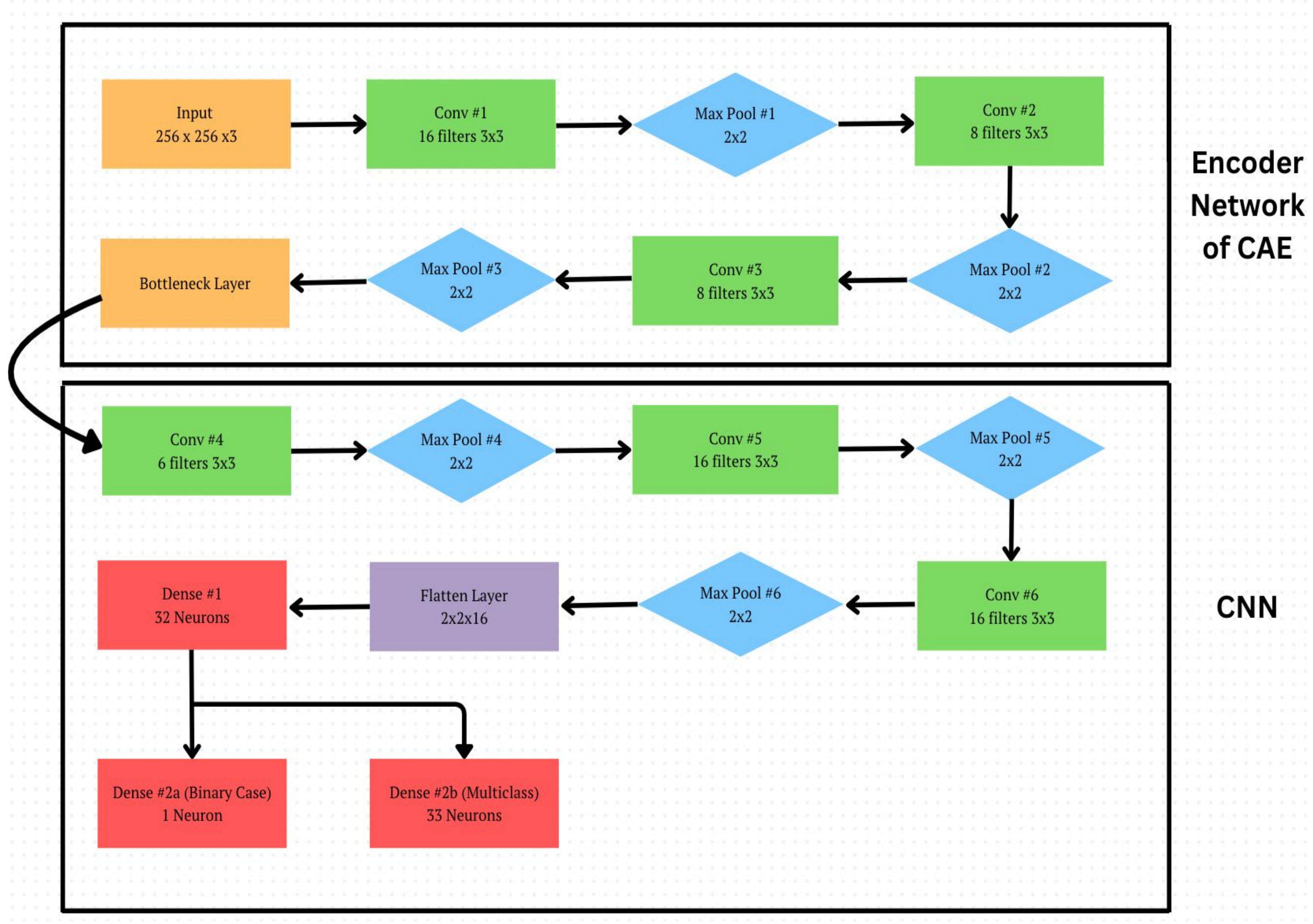
Example: Leaf Scorch Strawberry (left) vs. Healthy Strawberry (right)

Architecture

We preprocess input images of various plant species and feed them into a Convolutional Autoencoder (CAE). The CAE compresses the input into a lower-dimensional latent representation, allowing the model to focus on the most important features necessary for disease identification. The compressed features from the bottleneck layer are then passed to a Convolutional Neural Network (CNN) classifier, which outputs predictions: either a binary classification (healthy vs. diseased) or a multiclass classification (specifying the type of disease).

Our model architecture closely follows the design proposed in the paper, combining the strengths of CAEs and CNNs to achieve high accuracy while maintaining a relatively low number of trainable parameters. The CAE consists of multiple convolutional and max pooling layers with "same" padding to preserve spatial dimensions. In the CNN portion, deeper convolutional layers use "valid" padding to enhance feature abstraction for our classifier. Then, dense layers use this information to make the final prediction about if the plant has a disease or not in the binary case, or what specific type of disease the plant may have in the multiclass classification case.

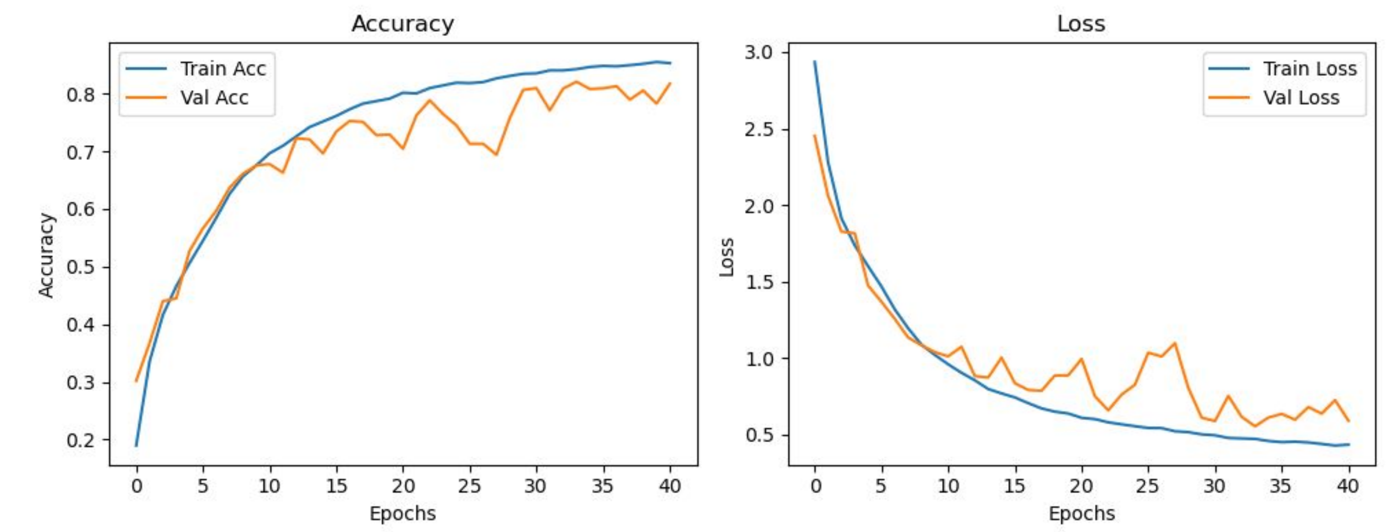
Overall, the hybrid model includes 7 convolutional layers, 6 max pooling layers, and 2 dense layers. This results in 8,560 trainable parameters for the binary classification task, and 9,583 trainable parameters for the multiclass disease classification. Other models like VGG-19 (143 million) and GoogleLeNet (7 million) use far more parameters to get similar accuracy.



Results

Model Type	Test Accuracy	F1 Score	Number of Params
Our Binary Model	97.58%	97.58%	8,560
Our Multiclass Model	84%	79%	9,583
Bedi & Gole (2021) Binary Model	98.38%	98.36%	9,914

Multiclass Model Training Performance:



- Our multiclass model fell into our target range of ~85% accuracy
- Our binary model achieved our goal of **>90% accuracy** on the testing set
- Both our binary and multiclass models achieved extremely low numbers of parameters
  - In comparison to Bedi & Gole, we managed a **13.6%** reduction in parameter count with only a 1% accuracy decrease

Conclusion

Using a hybrid model allowed us to recreate the paper's excellent performance with far fewer parameters than other models that achieved similar results.

Issues:
- Removing incomplete classes to ensure balanced healthy vs. diseased examples.
- Managing the large size of the dataset while maintaining efficient preprocessing and training.
- Designing label structures for both binary (healthy vs. unhealthy) and multiclass (specific disease) classification tasks.

Future Works:
- **Hyperparameter Tuning:** Further optimizing model parameters such as learning rate, number of CAE and CNN layers, and filter sizes to maximize classification accuracy
- **Expand Disease and Species Coverage:** Train and evaluate the model on additional crops and diseases beyond the current 33-class subset to improve generalizability.
- **Real-World Image Testing:** Validate model performance on field images with varying lighting conditions, leaf angles, and backgrounds to assess validity outside of the PlantVillage dataset.