Project Report

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Section: 05

Project Title: Potato Blight Disease Classification

Introduction

The project aims to implement machine learning models that are CNN models namely Restnet50, VGG-16 and a 15-layer customized CNN model to accurately classify potato leaf images into three categories: healthy, early blight, and late blight. The goal is to improve agricultural production by doing early detection and management of these diseases. So that the losses incurred due to disease affected crops can be reduced significantly by taking proper measures.

Dataset Description & Visualization

The dataset consists of images categorized into three classes: Potato_Early_blight, Potato_Late_blight, and Potato_healthy. An imbalance in the class distribution required the use of image augmentation techniques such as rotation, width shifting, height shifting, shear range, zoom, and horizontal flipping to increase the dataset's diversity and size. As initially the number of images of early blight and late blight leaves were 1000 but potato healthy leaves were only 152. For which the dataset was balanced through data augmentation.

Data Pre-processing
The images underwent data augmentation to solve the issue of class imbalance and enhance the model's ability to generalize. The dataset was split into training, validation, and testing sets in a 70:15:15 ratio, ensuring uniform representation of each class across these subsets.

Resnet50 Model Implementation
The dataset consists of 3,712 images divided into three classes: Potato_Early_blight, Potato_Late_blight, and Potato_healthy. The images are stored in designated training, validation, and testing directories within Google Drive, ensuring easy access and management during model training.The ResNet50 architecture, pre-trained on ImageNet, was employed with the following modifications:

GlobalAveragePooling2D: Replaces the fully connected layers at the top of the network, reducing model complexity and computational demand.

Dense Layer: A softmax activation function is used to output the probabilities for the three classes.

Training Setup:

Optimizer: Adam with a learning rate of 0.0001.

Loss Function: Categorical Crossentropy, suitable for multi-class classification.

Metrics: Accuracy to measure the model's performance.

Model Training: Conducted over 10 epochs with early stopping implemented to prevent overtraining, observing significant improvements in accuracy and loss reduction on validation data.

Callbacks: Included for early stopping (patience of 5 epochs) and saving the best model based on validation loss.

VGG-16 Model Implementation
ImageDataGenerators were employed to preprocess the images effectively:

- Rescaling: All images were rescaled as part of the preprocessing to normalize pixel values, ensuring that model inputs are consistent.
- Augmentation: The training images underwent augmentation including random rotations, shifts, and flips to improve the model's ability to generalize and to mitigate overfitting.

Base Model: VGG16 pre-trained on the ImageNet dataset, with its convolutional base frozen to leverage learned features without additional training of these layers.

Top Layers: Additional layers included a global average pooling layer to reduce feature dimensions, a dense layer with 512 units for feature interpretation, and a final softmax layer to classify the images into three categories.

Compilation: The model was compiled with the Adam optimizer (learning rate of 0.0001), using categorical crossentropy for loss calculation, and accuracy as the metric.

Training:

The model underwent training over 10 epochs with a batch size of 32:

Early Stopping: Implemented to halt training if the validation loss did not improve for five consecutive epochs, preventing overfitting.

Model Checkpointing: Saved the best model based on validation loss, ensuring that the most effective version of the model was retained.

ML Models Implementation

The dataset includes 2,085 training images, 806 validation images, and 821 test images, categorized into three classes: Potato_Early_blight, Potato_Late_blight, and Potato_healthy. These images are housed within specific directories for structured training and evaluation.

ImageDataGenerators were employed to preprocess and augment the data:

- Training Data: Augmented through rescaling and various transformations (rotation, shifts, shear, zoom, flip) to enhance model robustness by simulating different conditions.

- Validation and Testing Data: Only rescaled to ensure consistency in pixel values during model evaluation.

The custom 15-layer CNN architecture includes:

- Convolutional Layers: Multiple layers with filters ranging from 32 to 256, increasing in complexity to extract detailed features from the images.
- Activation: ReLU activation functions are used for non-linearity, allowing the model to learn more complex patterns.
- Batch Normalization: Applied to each convolutional layer to stabilize and accelerate training.
- Pooling Layers: MaxPooling2D layers are used to reduce spatial dimensions between sets of layers, decreasing the computational load and overfitting risk.
- Dense Layers: A dense layer with 512 units for high-level reasoning followed by a softmax layer for classification.
- Dropout: A 50% dropout rate is employed to prevent overfitting by randomly dropping units during training.

Compilation and Training:

The model is compiled with Adam optimizer (learning rate of 0.0001) and categorical crossentropy loss function. It was trained for 10 epochs, with early stopping and model checkpointing based on validation loss to optimize performance and avoid overtraining.

Results & Analysis

Resnet50:

The model demonstrated excellent performance with a accuracy of 98%. The precision, recall, and F1-score metrics are as follows:

- Precision: High across all classes, indicating a low rate of false positives.
- Recall: Also high, showing that the model successfully identifies a high percentage of relevant instances.
- F1-Score: Balanced mean of precision and recall, reflecting the model's robustness.

Confusion Matrix:

- Illustrates the model's ability to classify each class accurately, with particularly high accuracy in distinguishing between the different types of blight.

VGG-16:

- Accuracy: The model exhibited high accuracy in classifying the three types of potato leaf conditions. The test accuracy is 99% in this case.
- Precision, Recall, and F1-Score: These metrics were calculated for each class, indicating the model's precision in identifying true positives and its ability to handle false negatives and false positives effectively.

The visualization clearly displays the model's performance across classes, with a high number of correct predictions and few misclassifications, showcasing the model's robustness.

15-Layer CNN Model:

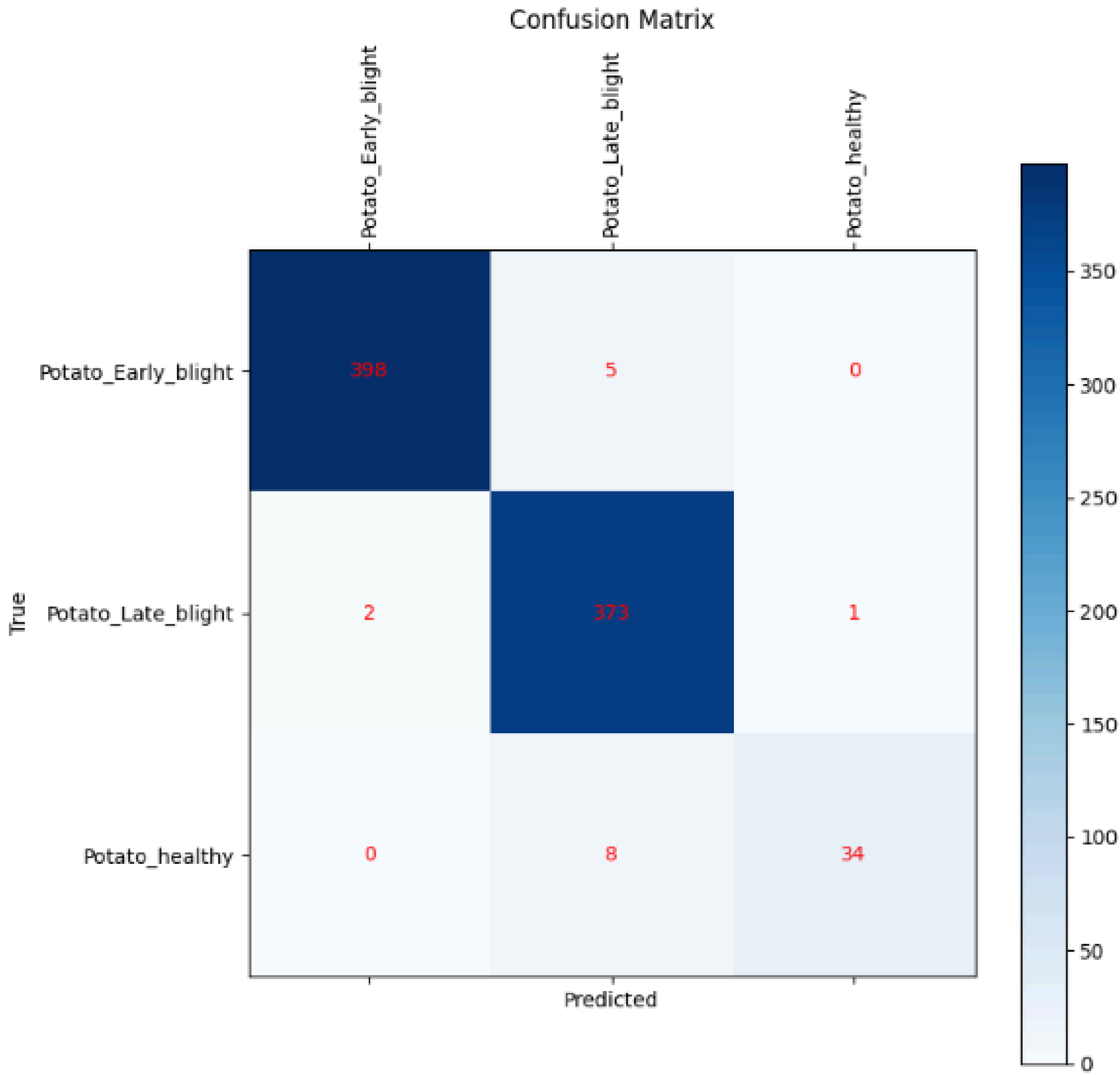
The model reached a training accuracy of 96.50% and a validation accuracy of 90.07%. The performance on the test set was evaluated using precision, recall, f1-score, and support metrics:

- Accuracy: Achieved 90% overall accuracy on the test set.
- Precision and Recall: High precision (0.84-1.00) across classes indicates few false positives, while recall (0.67-1.00) highlights the model's ability to detect most positives.
- F1-Score: Balanced scores (0.80-0.91) demonstrate the model's effectiveness.

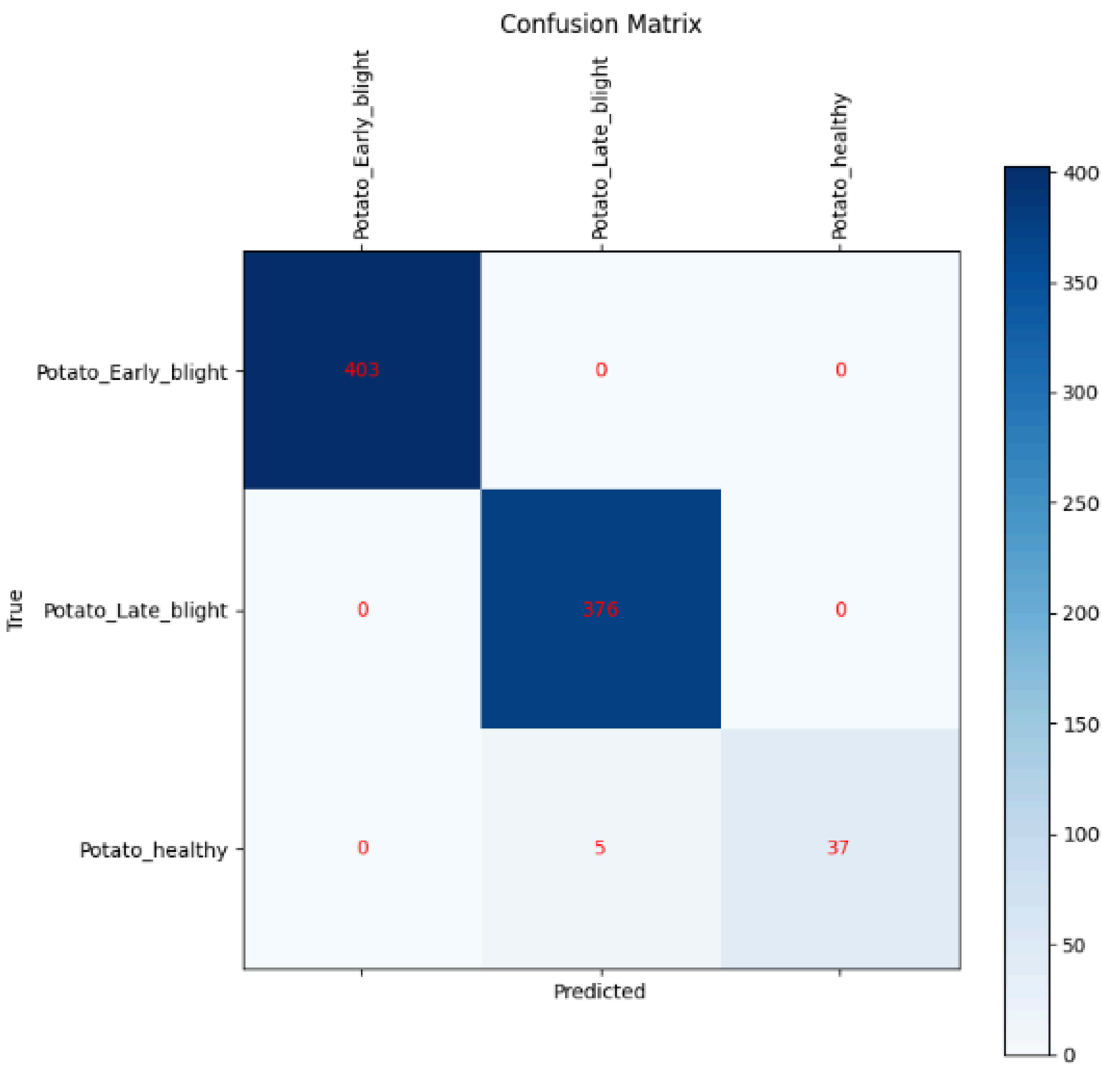
Confusion Matrix Analysis:

- The model excellently identified all instances of early blight (403/403).
- It performed well for late blight with some misclassifications.
- Healthy leaves saw some misidentification, likely due to fewer training samples.

****Custom CNN Confusion Matrix:****

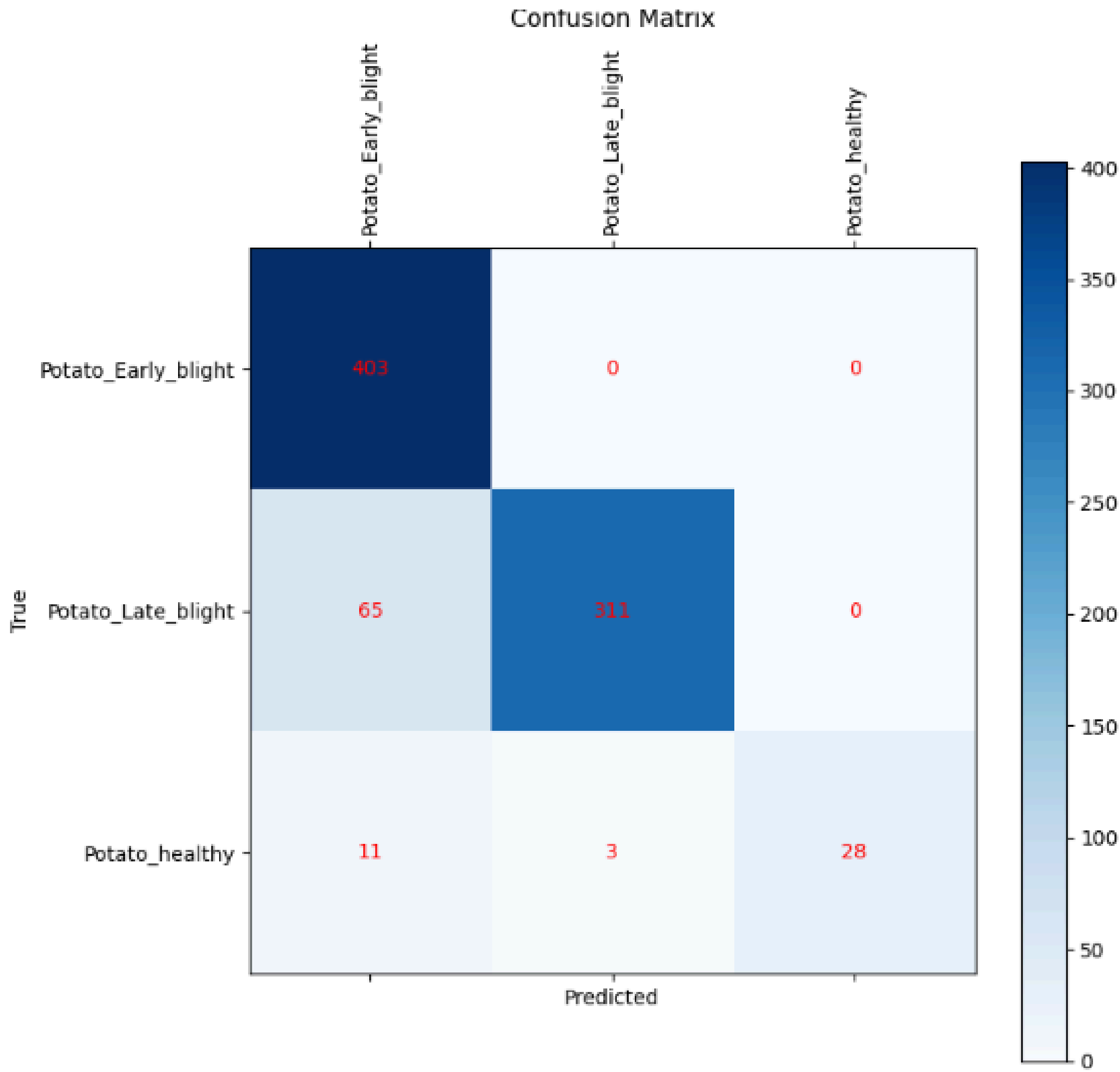

Confusion Matrix
Potato_Early_blight
Potato_Late_blight
Potato_healthy
Potato_Early_blight
Potato_Late_blight
Potato_healthy
True
Predicted
398
5
0
2
373
1
0
8
34
350
300
250
200
150
100
50
0

Resnet50



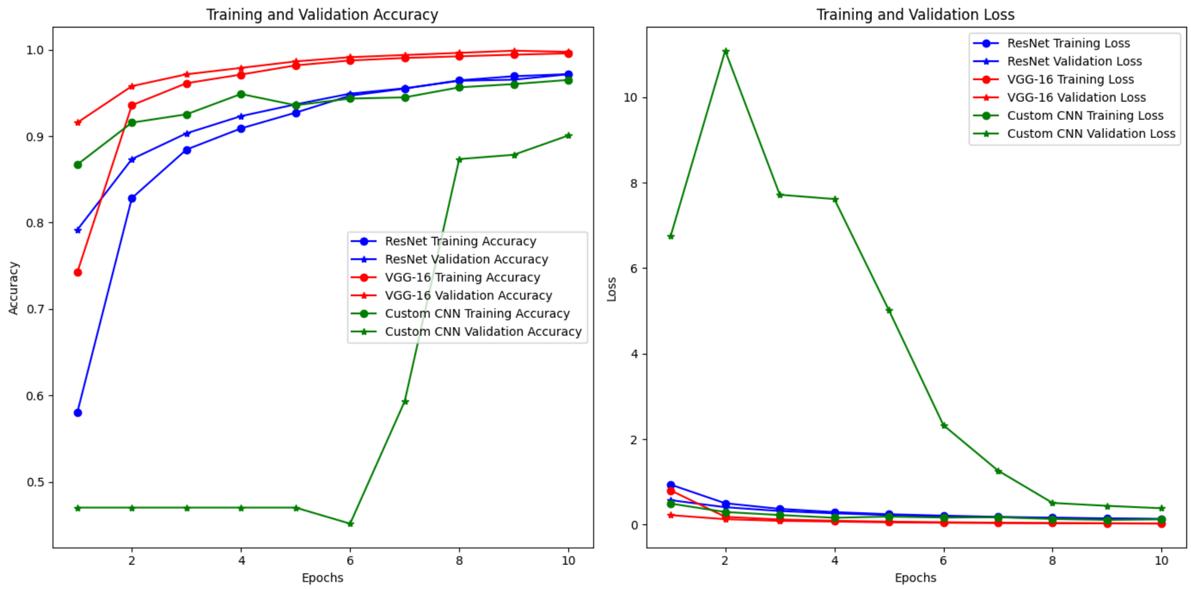
Confusion Matrix
Potato_Early_blight
Potato_Late_blight
Potato_healthy
Potato_Early_blight
Potato_Late_blight
Potato_healthy
True
Predicted
403
0
0
0
376
0
0
5
37
400
350
300
250
200
150
100
50
0

VGG-16



15 - Layer CNN model

Graphical Representation of Training and Validation of the Models:



F1 Score comparison:

Class	Model	Precision	Recall	F1-Score	Support
Potato_Early_blight	ResNet50	0.99	0.99	0.99	403
	VGG-16	1.00	1.00	1.00	403
	15-layer CNN	0.84	1.00	0.91	403
Potato_Late_blight	ResNet50	0.97	0.99	0.98	376
	VGG-16	0.99	1.00	0.99	376
	15-layer CNN	0.99	0.83	0.90	376
Potato_healthy	ResNet50	0.97	0.81	0.88	42
	VGG-16	1.00	0.88	0.94	42
	15-layer CNN	1.00	0.67	0.80	42
Overall	ResNet50	0.98	0.98	0.98	821
	VGG-16	0.99	0.99	0.99	821
	15-layer CNN	0.92	0.90	0.90	821

Conclusion

Among all the 3 models the highest accuracy was shown by VGG-16 model which was 99% and second highest accuracy was given by Resnet50 which was 98%.

The custom CNN with 90% accuracy demonstrated effective performance in classifying potato leaf diseases. The model's architecture was instrumental in learning discriminative features necessary for accurate classification. Throughout the project, challenges such as data imbalance and ensuring model generalization were effectively addressed through strategic data augmentation and the use of dropout and batch normalization.

Overall, this experience showed the importance of tailored model architecture and comprehensive dataset preparation in achieving high performance in image-based classification tasks.