**Plant Disease Classification Model Report**

**1. Introduction:**

This report presents the implementation, training, and evaluation of a deep learning model for **plant disease classification** using convolutional neural networks (CNNs). The model was trained on an image dataset with **38 plant disease classes**, utilizing PyTorch and TensorBoard for performance tracking.

**2. Model Architecture:**

The [**DiseaseClassifier**](https://drive.google.com/drive/folders/10a_3ar07gcf-j4-mtfOc4vBuxnpqmsu4?usp=sharing) model is a **custom CNN** inspired by AlexNet, with additional batch normalization layers for better stability. The model consists of:

* **Feature Extraction Layers**:
  + Five convolutional layers with ReLU activation.
  + Batch normalization to improve training speed and stability.
  + Max pooling to reduce spatial dimensions.
* **Fully Connected Layers**:
  + Adaptive average pooling for size reduction.
  + Two linear layers with dropout for regularization.
  + Softmax activation for classification.

**3. Training and Hyperparameters:**

* **Dataset**: Image dataset containing **38 plant disease classes**.
* **Image Preprocessing**:
  + Resized to **224x224** pixels.
  + Data augmentation: horizontal flip, rotation, color jitter, affine transformation.
  + Normalization using ImageNet mean and standard deviation.
* **Training Details**:
  + **Loss Function**: CrossEntropyLoss with **label smoothing (0.1)**.
  + **Optimizer**: Adam with an initial **learning rate of 0.0005**.
  + **Gradient Clipping**: Applied to **prevent exploding gradients** (max norm = 1.0).
  + **Learning Rate Scheduler**: ReduceLROnPlateau (factor = 0.1, patience = 3).
  + **Early Stopping**: Triggered if validation loss does not improve for **4 epochs**.
  + **Training Duration**: Model trained for **up to 20 epochs**.

**4. Performance Metrics:**

The model was evaluated using the following metrics:

* **Accuracy**: Overall classification correctness.
* **Precision**: Proportion of correctly predicted positive samples.
* **Recall**: Proportion of actual positive samples correctly identified.
* **F1-score**: Harmonic mean of precision and recall.

**4.1 Training Results:**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Epoch** | **Loss** | **Accuracy** | **Precision** | **Recall** | **F1-score** |
| 1 | 2102.033 | 0.578291 | 0.571974 | 0.578572 | 0.573891 |
| 2 | 1450.64 | 0.802361 | 0.801116 | 0.802642 | 0.801612 |
| 3 | 1254.198 | 0.871556 | 0.870965 | 0.871652 | 0.871199 |
| 4 | 1143.959 | 0.907134 | 0.907003 | 0.90711 | 0.907003 |
| 5 | 1080.548 | 0.92567 | 0.925581 | 0.925591 | 0.925558 |
| 6 | 1037.863 | 0.938915 | 0.938903 | 0.938774 | 0.938805 |
| 7 | 1001.509 | 0.950082 | 0.949984 | 0.949997 | 0.949969 |
| 8 | 975.4166 | 0.957323 | 0.957243 | 0.957187 | 0.957199 |
| 9 | 955.3445 | 0.961832 | 0.961708 | 0.961779 | 0.961729 |
| 10 | 936.6456 | 0.967395 | 0.967222 | 0.967299 | 0.967242 |
| 11 | 920.9822 | 0.971292 | 0.971178 | 0.971214 | 0.97118 |
| 12 | 907.8973 | 0.97391 | 0.973867 | 0.973735 | 0.973786 |
| 13 | 893.8625 | 0.977694 | 0.977592 | 0.97764 | 0.977606 |
| 14 | 883.9714 | 0.979657 | 0.979538 | 0.979541 | 0.979532 |
| 15 | 872.5863 | 0.982659 | 0.982583 | 0.982564 | 0.982568 |
| 16 | 868.7512 | 0.982531 | 0.98246 | 0.982454 | 0.982454 |
| 17 | 859.3434 | 0.984835 | 0.984759 | 0.984726 | 0.984736 |
| 18 | 854.0457 | 0.985916 | 0.985829 | 0.985824 | 0.985823 |
| 19 | 848.019 | 0.987353 | 0.987283 | 0.987278 | 0.987277 |
| 20 | 845.0408 | 0.987709 | 0.987698 | 0.98766 | 0.987674 |

**4.2 Validation Results:**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Epoch** | **Loss** | **Accuracy** | **Precision** | **Recall** | **F1-score** |
| 1 | 465.0744 | 0.711416 | 0.795022 | 0.710892 | 0.699968 |
| 2 | 373.6571 | 0.856192 | 0.876477 | 0.85678 | 0.856917 |
| 3 | 299.8428 | 0.91623 | 0.92104 | 0.916168 | 0.91473 |
| 4 | 370.1141 | 0.8472 | 0.890447 | 0.8501 | 0.846615 |
| 5 | 276.9079 | 0.941099 | 0.945322 | 0.940862 | 0.940479 |
| 6 | 265.7364 | 0.943433 | 0.948316 | 0.943596 | 0.943628 |
| 7 | 235.3692 | 0.965684 | 0.968794 | 0.964429 | 0.964802 |
| 8 | 267.4549 | 0.945083 | 0.950553 | 0.945239 | 0.944663 |
| 9 | 229.6821 | 0.968814 | 0.970599 | 0.968506 | 0.96842 |
| 10 | 229.3553 | 0.984293 | 0.984585 | 0.984168 | 0.984242 |
| 11 | 234.2607 | 0.972513 | 0.975129 | 0.971775 | 0.972373 |
| 12 | 221.7953 | 0.972627 | 0.974339 | 0.972449 | 0.972476 |
| 13 | 232.5823 | 0.979854 | 0.980774 | 0.979731 | 0.979823 |
| 14 | 207.7525 | 0.987822 | 0.987922 | 0.987564 | 0.987607 |
| 15 | 215.4212 | 0.987309 | 0.987736 | 0.986973 | 0.987182 |
| 16 | 205.9647 | 0.9897 | 0.989699 | 0.989517 | 0.989563 |
| 17 | 205.4138 | 0.98896 | 0.989016 | 0.988798 | 0.988853 |
| 18 | 213.4913 | 0.978204 | 0.980423 | 0.978122 | 0.978337 |
| 19 | 204.2469 | 0.98822 | 0.988393 | 0.987955 | 0.987963 |
| 20 | 202.6924 | 0.990781 | 0.990911 | 0.99068 | 0.990672 |

**5. Use Case:**

This plant disease classification model can be applied in various real-world agricultural scenarios, including:

* **Smart Farming**: Assisting farmers in **early disease detection** to prevent crop loss.
* **Precision Agriculture**: Automating plant disease diagnosis for **targeted pesticide use** and optimal yield.
* **Agricultural Research**: Providing a tool for researchers to analyze **plant disease trends**.
* **Mobile & IoT Integration**: Deploying the model in **mobile applications** for on-field disease detection using smartphone cameras.

**6. Conclusion:**

The Plant Disease Classification Model achieved promising performance on the dataset, leveraging a custom CNN architecture with advanced regularization techniques. Future improvements could include:

* Exploring **transfer learning** with a pretrained model (e.g., ResNet, EfficientNet).
* Increasing dataset size and diversity for better generalization.
* Hyperparameter tuning for further optimization.