AI TEAM-4 PROJECT DOCUMENTATION: POTATO DISEASE DATASET

INTRODUCTION:

The dataset was compiled from numerous websites and validated by Bangladesh Agricultural Research Institute (BARI).

Potatoes (Solanum tuberosum) are one of the most important food crops globally, providing a significant portion of the world's dietary needs. However, like any other crop, potatoes are susceptible to various diseases that can significantly reduce yield and quality if not managed effectively. Early detection and proper management of these diseases are crucial for sustainable potato production.

The Potato Diseases Dataset provides a valuable resource for researchers, agronomists, and machine learning practitioners interested in understanding and combating potato diseases. Compiled by Mukaffi Moin, this dataset contains a collection of images depicting different diseases commonly affecting potato plants, alongside images of healthy potato leaves for comparison.

Each image in the dataset is labeled with its corresponding disease category, facilitating supervised learning approaches for disease classification.

The primary objective of this dataset is to enable the development and evaluation of machine learning models for the automatic detection and classification of potato diseases. By training models on this dataset, researchers can create tools capable of identifying diseases early, allowing farmers to take timely and targeted actions to mitigate the spread of diseases and minimize crop losses.

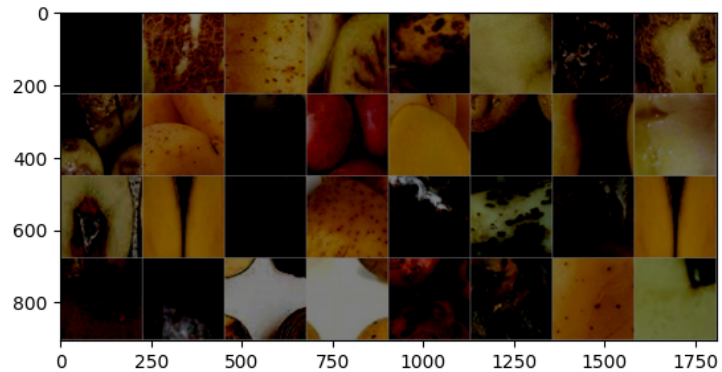
With the increasing demand for sustainable agricultural practices and the adoption of precision agriculture technologies, datasets like this play a crucial role in empowering farmers with the tools they need to ensure the health and productivity of their crops while minimizing the use of pesticides and other inputs.

In summary, the Potato Diseases Dataset provides a valuable resource for advancing research in potato disease management, offering a diverse collection of images to support the development of accurate and efficient disease detection systems.

DATA ANALYSIS AND PRE-PROCESSING:

This file appears to be a Python script that performs various image processing and data preparation tasks for a potato disease classification project:

1. **Data Cleaning**: This section includes functions to remove duplicate images and preprocess (resize and normalize) the images.



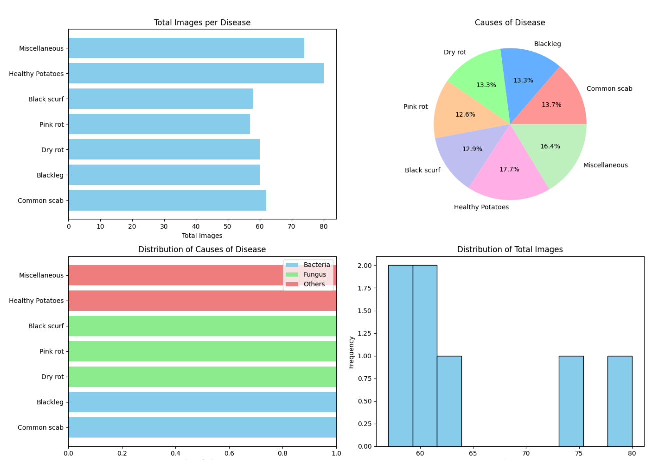
2. **Normalization:** This part contains a function to normalize the training, validation, and test data using the `StandardScaler` from scikit-learn.

3. **Data Augmentation:** This section provides a function to resize and apply data augmentation techniques (e.g., rotation, flipping, color jittering, Gaussian blur) to the images.

4. **Data Splitting:** This part splits the dataset into training, validation, and test sets using the `train_test_split` function from scikit-learn.

5. **Image Resizing and Resampling:** This section includes functions to resize and resample images using different resampling filters (e.g., BILINEAR).

6. **Visualization:** This part generates various plots to visualize the dataset, including a bar plot for total images per disease, a pie chart for causes of disease, a stacked bar plot for the distribution of causes, and a histogram for the distribution of total images.



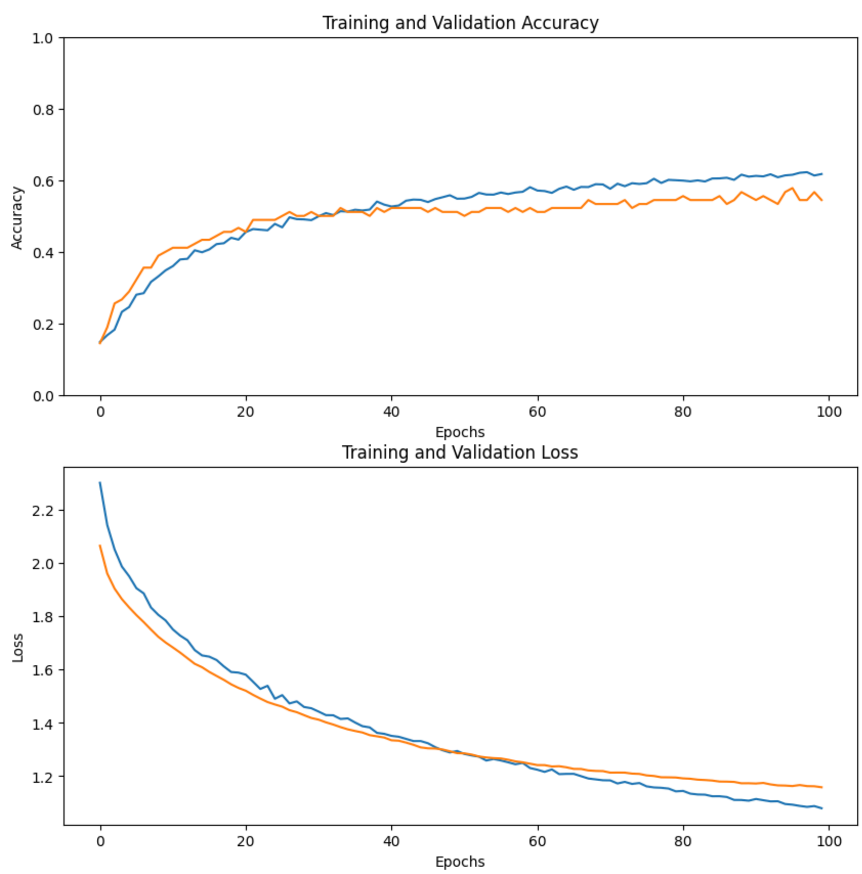
7. **Dataloader:** This section creates a custom dataset and a dataloader using PyTorch's `DatasetFolder` and `DataLoader` classes. It also includes a function to display a batch of images.

The script uses various Python libraries such as OpenCV, scikit-learn, NumPy, Pillow, Matplotlib, and PyTorch for image processing, data manipulation, and deep learning tasks.

MODELS STRUCTURE:

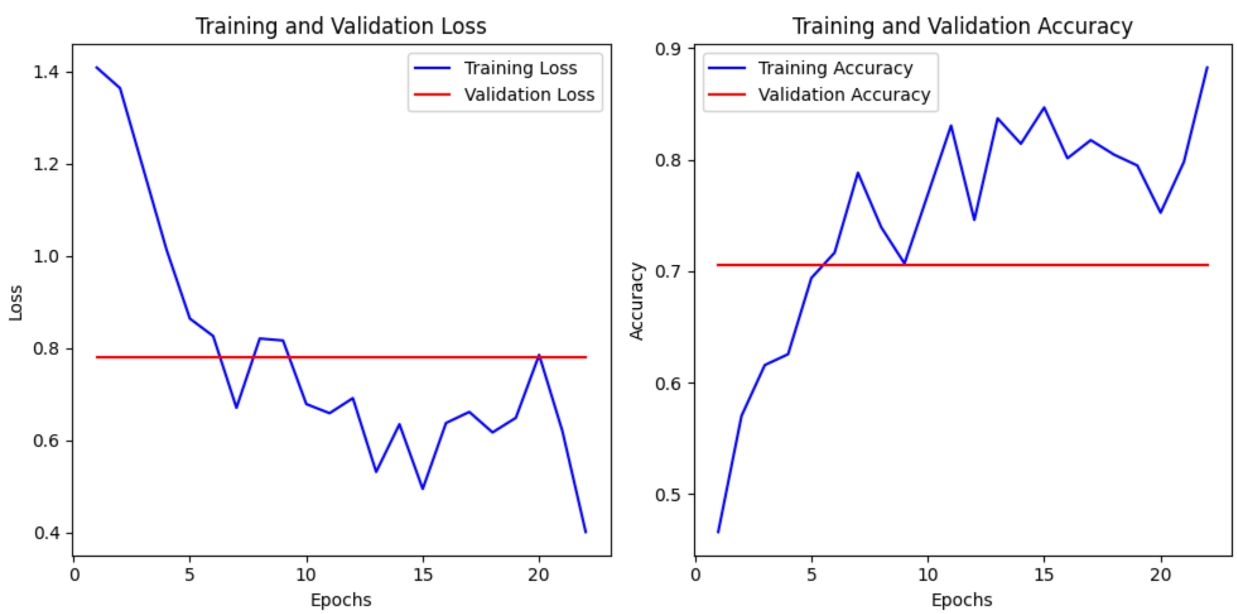
Convolutional Neural Networks (CNNs):

- CNNs are the most commonly used deep learning architecture for image classification tasks due to their ability to automatically learn features from raw pixel data.
- Architectures like VGG, ResNet, Inception, and DenseNet have been widely used and have proven effective for various image classification tasks.
- Hugging Face may not have specific implementations of classical CNN architectures like VGG, ResNet, or DenseNet in their model hub. However, we have implemented these architectures using popular deep-learning libraries like PyTorch or TensorFlow and then fine-tuned them using the Hugging Face libraries.
- For the notebook, we tried using different base models such as MobileNet, ResNet50, and InceptionV3 but all seemed to overfit on the training data and never performed about 55% on the validation data. Using VGG16 with 100 epochs and the Adam optimizer's learning_rate at 0.0001 seems to give me the best results of between 55% - 65%.



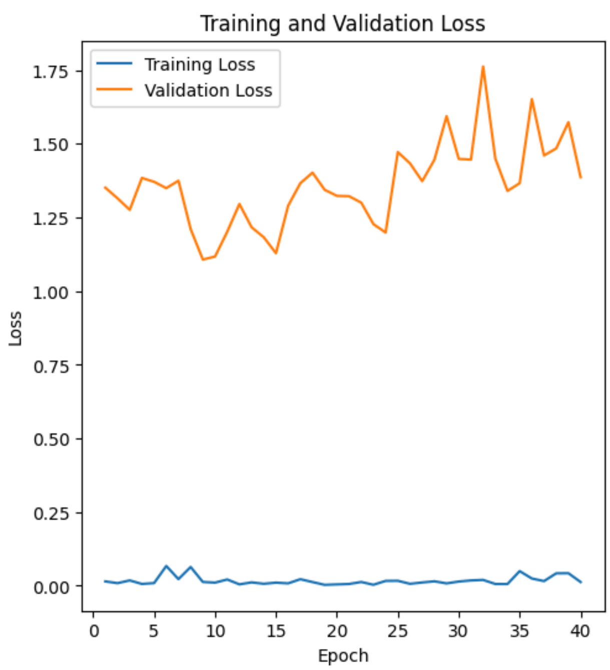
EFFICIENT NET:

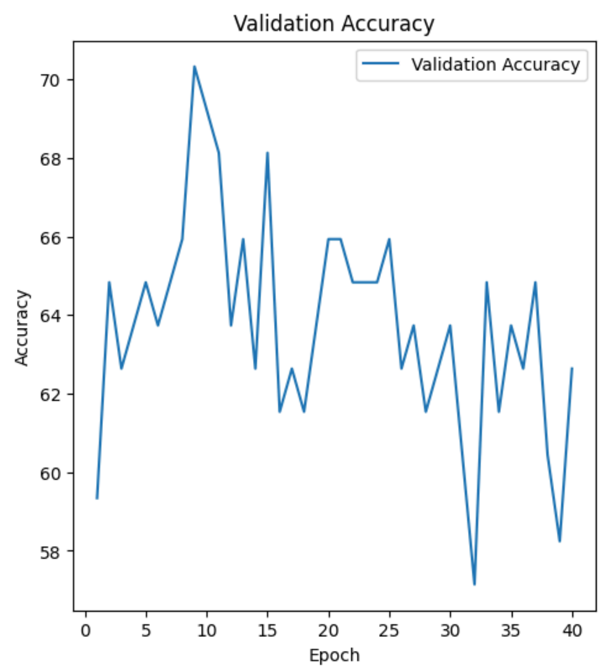
- EfficientNet is another popular architecture that has shown superior performance on various image classification tasks while maintaining efficiency in terms of parameters and computations.
- It is based on a compound scaling method that scales the network in terms of depth, width, and resolution in a balanced way.
- EfficientNet models are generally efficient in terms of both memory and computational resources, making them suitable for deployment on resource-constrained devices.
- Hugging Face provides implementations of EfficientNet through the transformers library for PyTorch. We have pre-trained versions of EfficientNet in the model hub and fine-tune them for our image classification task.
- An EfficientNet-v2 image classification model. Trained on ImageNet-21k and fine-tuned on ImageNet-1k in Tensorflow by paper authors, ported to PyTorch by Ross Wightman.
- EfficientNet is an image classification model family. It was first described in EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks.



RESNET50:

- ResNet-50 is a deep neural network architecture developed by Microsoft Research. It is part of the ResNet family, known for its use of residual connections, which help alleviate the vanishing gradient problem and enable the training of very deep networks.
- ResNet-50 consists of 50 layers and is pre-trained on the ImageNet dataset, making it a powerful feature extractor for various computer vision tasks.
- Hugging Face's model hub provides pre-trained versions of various deep-learning models, including ResNet-50. We can leverage these pre-trained models for transfer learning on CIFAR-10.
- Transfer learning involves using knowledge learned from one task (ImageNet classification in this case) and applying it to a different but related task (CIFAR-10 classification).





CONCLUSION:

Convolutional Neural Networks (CNNs), EfficientNet, and ResNet-50 are all popular choices for image classification on the CIFAR-10 dataset. CNNs are straightforward and effective, making them a good starting point. However, EfficientNet and ResNet-50 offer more advanced architectures with better performance. EfficientNet achieves state-of-the-art results with fewer parameters, making it efficient for both training and inference. ResNet-50, with its deep architecture and skip connections, provides powerful feature extraction capabilities, especially when fine-tuned on CIFAR-10. While CNNs are simpler and easier to implement, EfficientNet and ResNet-50 require more computational resources but offer higher accuracy. Ultimately, the choice depends on factors such as computational constraints, task complexity, and desired performance. Experimentation and evaluation on validation and test sets are essential for selecting the most suitable model for a given task.

Accuracy and Loss:

CNN:
Accuracy- 0.54
Loss- 1.16

EfficientNet:
Accuracy: 0.714
Loss:0.928

Resnet50:
Accuracy: 74.2

RESOURCES & CITATIONS:

DATASET: https://github.com/Mukaffi28/Potato-Disease

1. https://huggingface.co/hassaanik/Potato-Disease-Classfication/tree/main/Data
2. https://www.linkedai.co/dataset/potato-diseases
3. https://pytorch.org/vision/main/models/generated/torchvision.models.quantization.resnet50.html.
4. https://www.kaggle.com/datasets/mukaffimoin/potato-diseases-datasets