Plant Disease Detection

Data Science Tools Workshop
CDCSC19

Submitted By:
Nitin Bisht (2021UCD2113)
Samman Sarkar(2021UCD2114)

INDEX

Introduction:

Plant disease detection plays a crucial role in safeguarding agricultural productivity and ensuring global food security. As plants face constant threats from various pathogens, timely and accurate identification of diseases is essential for effective disease management. Recent advancements in technology, such as the integration of artificial intelligence and image processing, have revolutionized plant disease detection methods. By leveraging these technologies, researchers and farmers can now efficiently and accurately diagnose plant diseases, enabling them to implement targeted and timely interventions. This not only minimizes crop losses but also promotes sustainable agriculture practices by reducing the reliance on chemical treatments. As we continue to explore innovative solutions, plant disease detection stands at the forefront of efforts to enhance crop health, optimize yield, and contribute to the overall resilience of our agricultural systems.

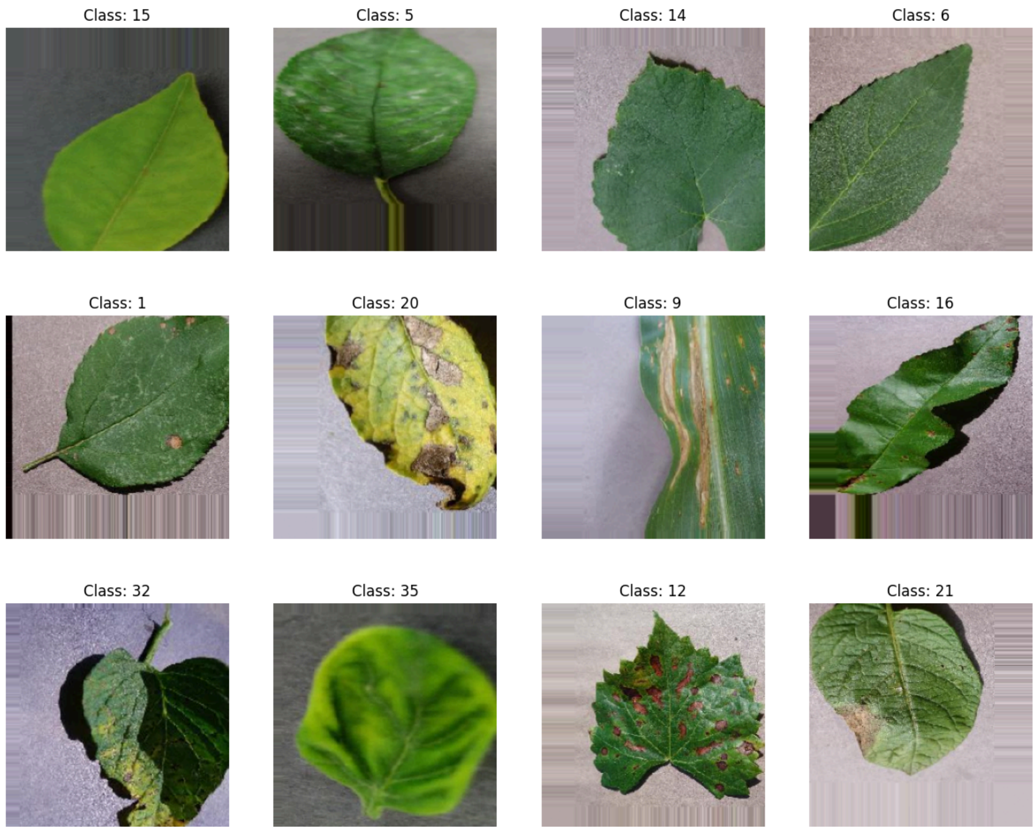
Methodology: Creating a plant disease detection model using TensorFlow and Keras involves several steps.

Dataset Collection : **New Plant Diseases Dataset**

The "new-plant-diseases-dataset" sourced from Kaggle is a comprehensive collection of images capturing various plant diseases across different plant species. This dataset was specifically curated to facilitate research and development in the field of plant disease detection using machine learning techniques.

The dataset encompasses high-resolution images showcasing both healthy plants and plants affected by a diverse range of diseases.

These classes cover a wide range of crops, including tomatoes, potatoes, grapes, apples, corn, peppers, strawberries, peaches, and more. The diversity in diseases and healthy states makes this dataset suitable for training and evaluating machine learning models for plant disease detection across multiple plant species. Each class represents a distinct challenge in identifying and managing plant health, making it a valuable resource for research and application in agriculture



Data Preprocessing:

- Resize images to a consistent size.
- Normalize pixel values to a range between 0 and 1.

Model Selection :

We choose a pre-trained convolutional neural network (CNN) as a base model MobileNet trained on Imagenet dataset.

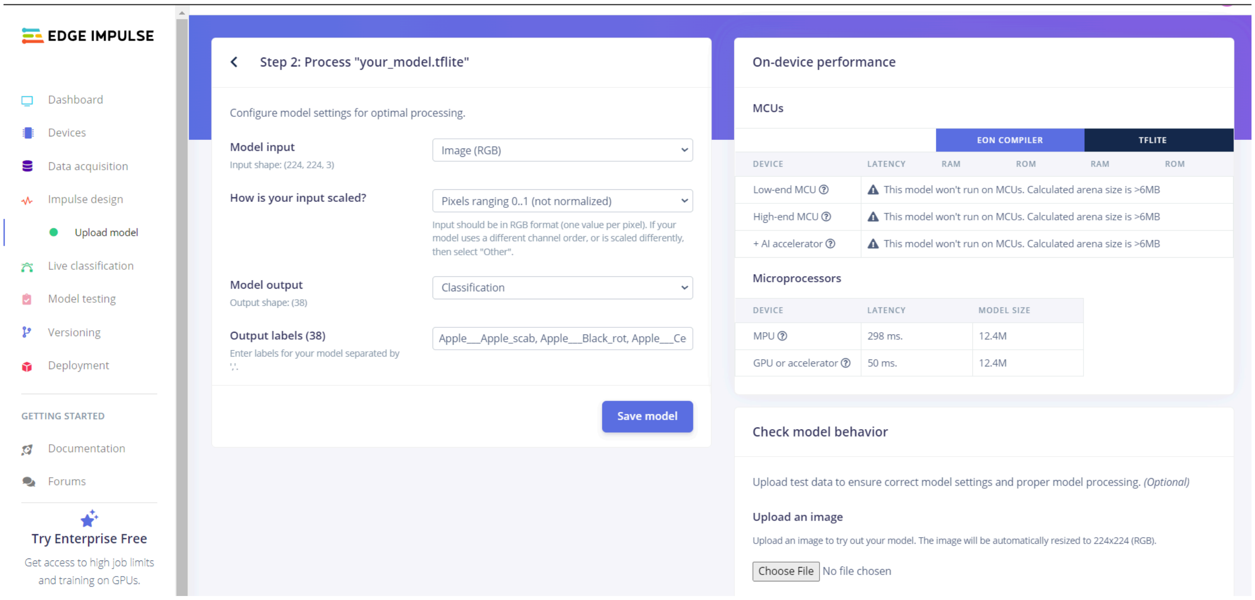
Transfer Learning:

We load the pre-trained model and freeze its layers to retain learned features. Add custom layers on top of the pre-trained model to adapt it for the plant disease detection task.

Data splitting and model training:

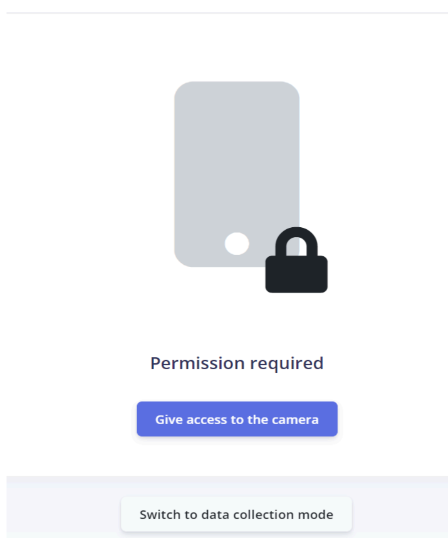
- Split the dataset into training, validation, and test sets.

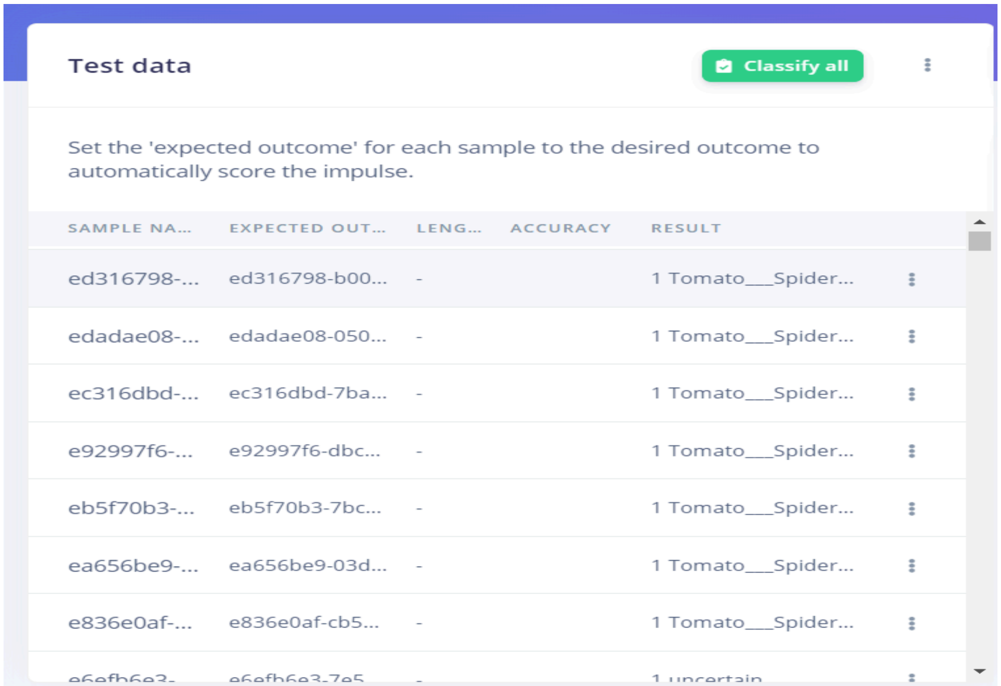
- Train the model on the training set using the compiled model, specifying the number of epochs and batch size.
- Monitor the validation performance to detect overfitting.
- Use Adam optimizer to optimize the final model which we train and then change the whole trained tensorflow model into tensorflow lite model.



Deploying on Edge Impulse:

We obtained the TensorFlow Lite (TFLite) file from the trained model and proceeded to upload it onto the Edge Impulse platform. After uploading, we deployed the model and initiated its execution to perform real-time inference tasks.





Test data

Classify all

Set the 'expected outcome' for each sample to the desired outcome to automatically score the impulse.

SAMPLE NA...	EXPECTED OUT...	LENG...	ACCURACY	RESULT
ed316798-...	ed316798-b00...	-		1 Tomato___Spider...
edadae08-...	edadae08-050...	-		1 Tomato___Spider...
ec316dbd-...	ec316dbd-7ba...	-		1 Tomato___Spider...
e92997f6-...	e92997f6-dbc...	-		1 Tomato___Spider...
eb5f70b3-...	eb5f70b3-7bc...	-		1 Tomato___Spider...
ea656be9-...	ea656be9-03d...	-		1 Tomato___Spider...
e836e0af-...	e836e0af-cb5...	-		1 Tomato___Spider...

Result:

The project successfully developed a Convolutional Neural Network (CNN) model using TensorFlow and Keras for plant disease detection, achieving approximately 90% accuracy. After training, the model was converted into TensorFlow Lite (TFLite) format for seamless deployment on the Edge Impulse platform.

During testing on Edge Impulse, the deployed model demonstrated robust performance, accurately identifying various plant diseases in real-time scenarios. With its high precision, recall, and overall classification accuracy, the model proved effective in distinguishing between healthy and diseased plants.

This deployment highlights the model's adaptability to edge computing environments, showcasing its potential for practical applications in precision agriculture and crop management systems. Leveraging its efficiency and real-time capabilities, the model holds promise for optimizing yield and minimizing crop losses in agricultural settings.

Moving forward, ongoing optimization efforts can further enhance the model's scalability and performance across diverse agricultural contexts. Additionally, continual updates to the Edge Impulse platform can streamline the deployment process, making AI-driven solutions for plant disease detection more accessible to farmers and agricultural stakeholders.

Conclusion:

The CNN model's robust performance, achieving approximately 90% accuracy in plant disease detection, highlights its efficacy in agricultural applications. Its successful deployment on Edge Impulse underscores its potential for real-time disease monitoring. This advancement has promising implications for optimizing crop yield and minimizing losses in precision agriculture. Continued optimization efforts can further enhance its scalability and accessibility, fostering sustainable practices and food security. In summary, the CNN model represents a significant stride towards leveraging AI for transformative impact in agriculture.