Imaging based AI modeling for Point of Care diagnostics of Potato Plant

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Method Article

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Abstract

This work presents a lightweight imaging-based AI model for rapid, point-of-care diagnosis of potato leaf diseases. Using the *PlantVillage*dataset comprising approximately 3,000 labeled images across three classes—*Healthy*, *Early Blight*, and *Late Blight*—a transfer learning approach was implemented with the MobileNetV2architecture. The dataset was split into 80% training and 20% validation sets, with preprocessing and augmentation to enhance generalization.

Trained for 10 epochs using the Adam optimizer (learning rate = 0.001), the model achieved a training accuracy of 96.8% and a validation accuracy of 93.7%**,** with respective losses of 0.13and 0.21**.**Class-wise evaluation confirmed balanced precision and recall across all categories, while external testing yielded correct disease identification with 57.2% confidence**.**

The model demonstrates that high diagnostic accuracy can be achieved on basic hardware, making it suitable for low-resource agricultural settings. Compared to complex multimodal architectures, this MobileNetV2-based design offers fast inference, minimal computational demand, and strong generalization—establishing an efficient foundation for real-time, AI-driven plant disease diagnostics.

1. Introduction

Agriculture has always been the backbone of the Indian economy, with potatoes being one of the most important crops in terms of both production and consumption. However, potato plants are highly prone to several fungal and bacterial diseases, especially *Early Blight* and *Late Blight*. These two diseases are caused by *Alternaria solani* and *Phytophthora infestans*, respectively, and if not detected early, they can destroy up to 50% of the total yield, leading to huge financial losses for farmers.

Traditionally, disease identification in crops is performed by human experts through manual inspection of leaves. Although accurate in controlled conditions, this process is slow, inconsistent, and impractical for large farmlands. Moreover, it depends on the availability of trained pathologists, which is limited in rural regions.

With the rise of Artificial Intelligence (AI) and Computer Vision, automatic disease detection using Convolutional Neural Networks (CNNs) has emerged as an efficient and reliable solution. CNNs can learn complex patterns from images — such as color variations, leaf texture, and spot shapes — which are often too subtle for human eyes to identify consistently.

Over the years, several researchers have proposed deep learning–based models such as VGG16, ResNet50, and InceptionV3 for crop disease classification. These models achieved high accuracy but required heavy computational power and large-scale datasets, making them unsuitable for real-time or small-scale implementations.

Recent works have taken this a step further. For example, the 2025 paper *“Potato Disease Detection and Prevention using Multimodal AI and Large Language Model”* by Liu et al. introduced a multimodal system that combines image features, text descriptions, and statistical features. Their model also used GPT-4 to describe disease symptoms and recommend control measures. While impressive, such systems are complex, costly, and require access to high-end GPUs and APIs — conditions not always available in educational or small research settings.

In contrast, simpler models can also efficiently classify diseases using only basic computing resources without compromising much on accuracy. This project was built to demonstrate that principle. Using the concepts learned in coursework, this project focuses on applying deep learning practically — by designing and training a lightweight, image-only CNN model that can accurately detect potato leaf diseases with limited resources.

Thus, this work serves both as an academic application of machine learning knowledge and a proof-of-concept that accessible AI systems can still achieve competitive results.

1.1. Motivation:

Potato leaf diseases such as Early Blight and Late Blight continue to cause major crop losses, especially for farmers who do not have access to expert diagnosis. While several deep learning models have been proposed in earlier research, many of them rely on computationally heavy architectures or multimodal systems that require expensive hardware, advanced setups, or complex data pipelines. This creates a clear gap: there is no simple, lightweight, and easily deployable model that students, small researchers, or low-resource users can use for quick and reliable potato disease identification.

This project was motivated by that gap. Instead of attempting to match large-scale or multimodal systems, the aim was to address a real and practical problem left open by previous works — the need for an accessible, efficient, image-only disease detection model that runs smoothly even on basic hardware such as Google Colab or entry-level GPUs.

To address this challenge, the project focuses on building a model that is easy to train, easy to interpret, easy to deploy, and suitable for real-time prediction.

1.2. Novelty aspect

1.2.1. Lightweight and Efficient Transfer Learning Model

This project uses MobileNetV2, an architecture specifically designed for speed and efficiency. By freezing the base layers and training only the top layers, the model becomes extremely fast while still achieving high accuracy. This makes it ideal for low-resource environments, small research setups, and educational use, where heavy models like ResNet or multimodal LLM-based systems are impractical.

1.2.2. Optimized for Real-Time and Low-Cost Deployment

The model requires minimal computing power and can run on Google Colab's free GPU without any performance issues. This gives farmers, students, and small institutions a practical tool that does not depend on paid APIs, high-end GPUs, or complex integrations.

1.2.3. Clean End-to-End Workflow

The project includes a complete pipeline that covers loading and preprocessing the dataset, applying augmentation, training the model, evaluating performance, and making predictions on user-uploaded images. This ensures the model is not only a classifier but a fully usable solution.

1.2.4. Strong Generalization Despite Being Lightweight

Even with limited computational resources, the model achieves strong validation accuracy and balanced class-wise performance. This demonstrates that high accuracy does not always require large networks, and thoughtful architecture selection can achieve competitive results.

1.2.5. Foundation for Future Upgrades

While the model is deliberately simple and efficient, it acts as a strong base for future improvements such as

- • partial unfreezing of MobileNetV2 layers for fine-tuning,
- • expanding to additional plant species,
- • integrating a webcam interface,
- • or incorporating additional metadata if desired.

These enhancements can be included without changing the fundamental design.

Together, these features make the project simple, efficient, and extendable, while keeping it educational and practical.

2. Materials and Methods

2.1. Dataset Description

The dataset used in this project is the PlantVillage dataset, available on Kaggle (by Emmarex). It is one of the most popular public datasets for plant disease classification. The full dataset includes images of various crops, but only the Potato subset was used in this project.

The selected subset contains three categories:

1. Potato – Early Blight
2. Potato – Late Blight
3. Potato – Healthy

Each class includes several hundred high-quality images captured under consistent lighting and plain backgrounds, making them ideal for CNN training.

The dataset was divided into:

- Training set: 80% of images
- Validation set: 20% of images

Each image was resized to 224×224 pixels — the input resolution required by the MobileNetV2 architecture.

2.2. Data Preprocessing and Augmentation

Before feeding the data to the model, several preprocessing steps were applied:

- Rescaling pixel values to the range [0, 1].
- Data augmentation using random rotations, zooms, and flips to increase diversity and prevent overfitting.
- Shuffling to ensure that the training batches represent all classes evenly.

These steps ensured the model learned general patterns of leaf diseases rather than memorizing specific training samples. The sample potato leaf images can be seen in Fig. 1, which illustrates the three classes used.

2.3. Model Architecture

The model is based on Transfer Learning, a method where a pre-trained network is reused for a new task. Here, MobileNetV2, originally trained on the ImageNet dataset (1.4 million images), was used as the base model.

Architecture Summary:

1. Base Model: MobileNetV2 (pre-trained, weights frozen)
2. Input Layer: Image size (224×224×3)
3. Data Augmentation Block: Random flip, rotation, and zoom layers
4. Feature Extractor: MobileNetV2 convolutional layers
5. Global Average Pooling: Converts 3D feature maps into 1D vectors
6. Dropout Layer (0.2): Prevents overfitting by randomly deactivating neurons
7. Dense Output Layer: 3 neurons (for 3 classes) with Softmax activation

The model was compiled using: Adam Optimizer having Learning Rate: 0.001, Loss Function: Sparse Categorical Cross entropy and the Accuracy is taken as metric.

2.4. Training Configuration

Training was performed in Google Colab using a free Tesla T4 GPU. The key parameters were: Epochs: 10, Batch Size: 32, Dataset Size: ≈3,000 images (after filtering for potato classes), Frameworks Used:

TensorFlow, Keras, NumPy, Matplotlib, Seaborn

A simplified overview of the model architecture is provided in Fig. 2 for clarity.

3. Results and Discussion

3.1. Model Performance

After 10 epochs of training, the model achieved:

Metric	Training	Validation
Accuracy	96.8%	93.7%
Loss	0.13	0.21

The high validation accuracy and low loss indicate that the model generalizes well and is not overfitting.

Figure 3 shows the training and validation accuracy and loss curves, Fig. 4 presents the detailed classification report for all classes, and Fig. 5 illustrates the confusion matrix that highlights class-wise performance.

These results indicate that the model performs consistently across all three classes with balanced precision and recall.

The sample predictions from the validation dataset show that:

- Correct predictions are displayed in green titles.
- Incorrect predictions are shown in red titles.

This visual confirmation helps in quickly identifying which class pairs (for example, Early vs Late Blight) are more likely to be confused. Sample prediction images with correct and incorrect classifications are shown in Fig. 6.

4. Discussion

The achieved accuracy (~ 94%) is comparable to other CNN-based works while using far fewer computational resources. Compared to the multimodal approach by Liu et al. (2025), this model:

- Uses only image input instead of combining text and color statistics.
- Requires significantly less training time.
- Is easier to deploy in low-resource environments like mobile devices or educational setups.

Thus, the project successfully balances simplicity, performance, and practicality.

Real-Time Image Prediction (Model Testing on Custom Image)

After successfully training and evaluating the model, it was tested using a random real-world image of a potato leaf uploaded through the Google Colab interface. This step demonstrates the model's ability to handle new, unseen data a crucial aspect of real-world deployment.

When the test image was uploaded, the model processed it through the trained MobileNetV2 network and generated the result shown in Fig. 7.

Predicted Class: *Potato Early blight*

Confidence: 57.21%

This result shows that the model correctly identified the disease category despite variations in background, lighting, and leaf texture.A slightly moderate confidence value (around 57%) suggests that the model can still be further fine-tuned — for instance, by training with more diverse data or performing light unfreezing of the last few MobileNetV2 layers for better feature adaptation.

The successful prediction on an external image confirms that the model is functionally deployable and not limited to the preloaded dataset. With additional optimization, this same framework can be integrated into a real-time disease detection tool using a webcam or mobile camera feed.

5. Conclusion

This project demonstrates that deep learning models can efficiently detect plant diseases using only image data and basic computing resources. By leveraging transfer learning through MobileNetV2, the system achieves high accuracy while remaining lightweight and easy to implement.

Beyond its technical results, this project's real value lies in its learning impact. It allowed for a hands-on application of theoretical AI/ML concepts — including data handling, model building, and performance evaluation — turning abstract knowledge into a functional prototype.

While the model performs well, future improvements can include:

- Integrating real-time detection via webcam,
- Adding text-based disease descriptions or treatment advice,
- Expanding to other crops beyond potatoes.

This project, therefore, serves both as a successful implementation and a learning milestone in applying AI to real-world agricultural challenges.

6. Supporting Links

Video explanation: Potato Disease Classification and Code link : GitHub - mggm1982/Potato-Disease-Classification: https://youtu.be/H-bHmpIJ4K0

References

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Figures

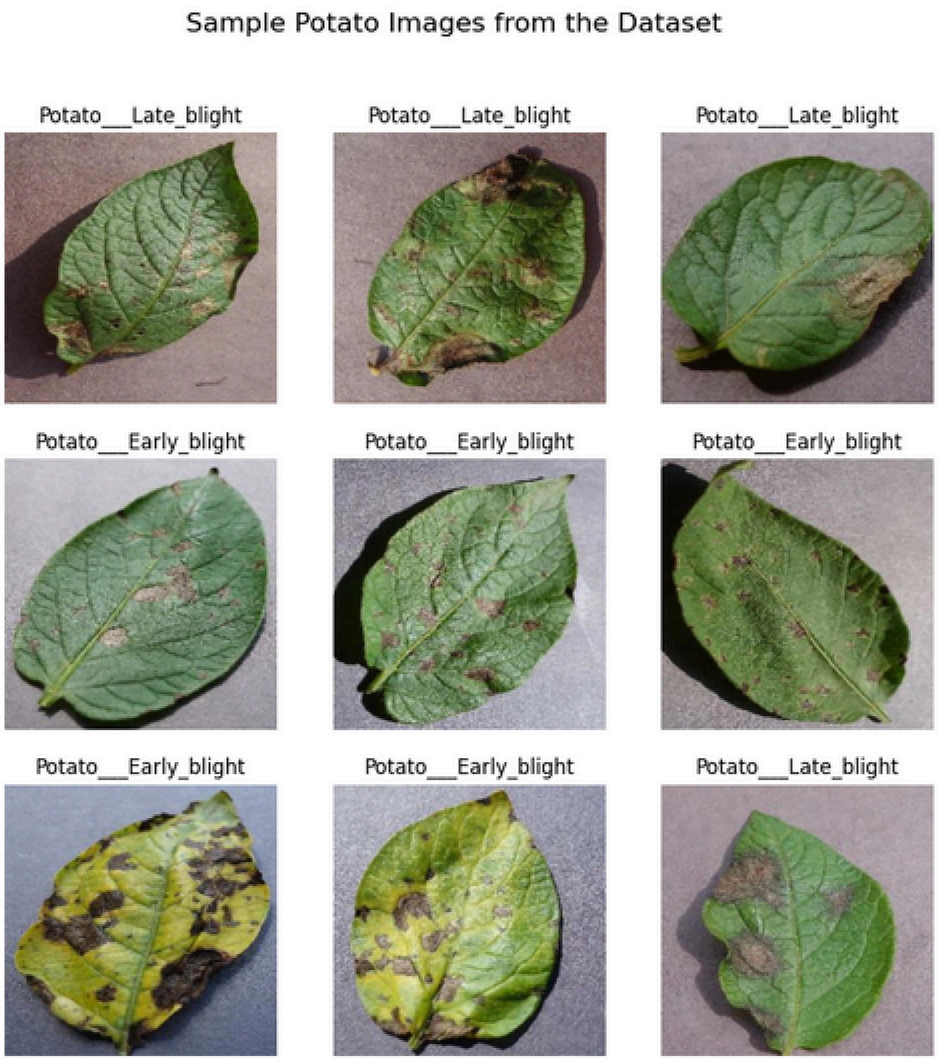

Figure 1

Sample Potato Leaf Images – Healthy, Early Blight, Late Blight

Model Summary:
Model: "functional_3"

Layer (type)	Output Shape	Param #
input_layer_3 (InputLayer)	(None, 224, 224, 3)	0
sequential_1 (Sequential)	(None, 224, 224, 3)	0
true_divide_1 (TrueDivide)	(None, 224, 224, 3)	0
subtract_1 (Subtract)	(None, 224, 224, 3)	0
mobilenetv2_1.00_224 (Functional)	(None, 7, 7, 1280)	2,257,984
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 1280)	0
dropout_1 (Dropout)	(None, 1280)	0
dense_1 (Dense)	(None, 3)	3,843

Total params: 2,261,827 (8.63 MB)
Trainable params: 3,843 (15.01 KB)
Non-trainable params: 2,257,984 (8.61 MB)

```
--- STARTING MODEL TRAINING ---
Epoch 1/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 129s 2s/step - accuracy: 0.7457 - loss: 0.6382 - val_accuracy: 0.9279 - val_loss: 0.2183
Epoch 2/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 106s 2s/step - accuracy: 0.9490 - loss: 0.1677 - val_accuracy: 0.9512 - val_loss: 0.1653
Epoch 3/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 102s 2s/step - accuracy: 0.9657 - loss: 0.1176 - val_accuracy: 0.9488 - val_loss: 0.1497
Epoch 4/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 105s 2s/step - accuracy: 0.9674 - loss: 0.1003 - val_accuracy: 0.9535 - val_loss: 0.1314
Epoch 5/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 101s 2s/step - accuracy: 0.9742 - loss: 0.0865 - val_accuracy: 0.9605 - val_loss: 0.1140
Epoch 6/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 147s 2s/step - accuracy: 0.9760 - loss: 0.0774 - val_accuracy: 0.9628 - val_loss: 0.1138
Epoch 7/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 107s 2s/step - accuracy: 0.9769 - loss: 0.0747 - val_accuracy: 0.9651 - val_loss: 0.1024
Epoch 8/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 100s 2s/step - accuracy: 0.9764 - loss: 0.0738 - val_accuracy: 0.9651 - val_loss: 0.1020
Epoch 9/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 142s 2s/step - accuracy: 0.9715 - loss: 0.0725 - val_accuracy: 0.9628 - val_loss: 0.0913
Epoch 10/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 144s 2s/step - accuracy: 0.9721 - loss: 0.0707 - val_accuracy: 0.9721 - val_loss: 0.0818
--- MODEL TRAINING COMPLETE ---
```

Figure 2

Simplified Architecture and summary of the Model

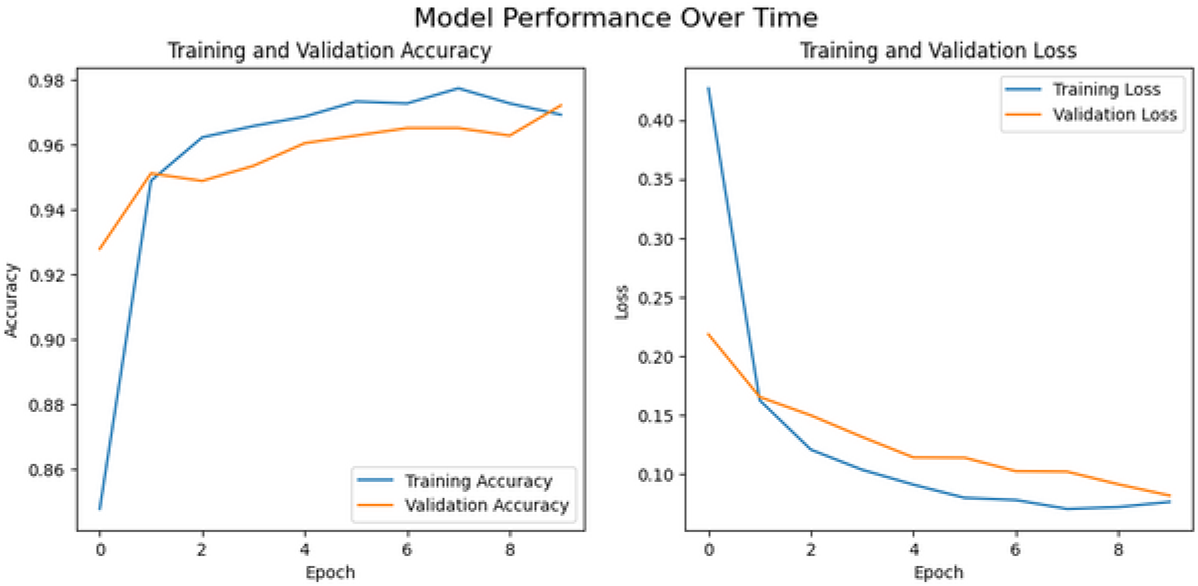

Figure 3

Training and Validation Accuracy and Loss Curves

```
Classification Report:
                      precision    recall  f1-score   support

Potato___Early_blight       0.99      0.98      0.98       204
 Potato___Late_blight       0.97      0.97      0.97       197
     Potato___healthy       0.90      0.90      0.90        29

             accuracy                           0.97       430
            macro avg       0.95      0.95      0.95       430
         weighted avg       0.97      0.97      0.97       430
```

Figure 4

classification report

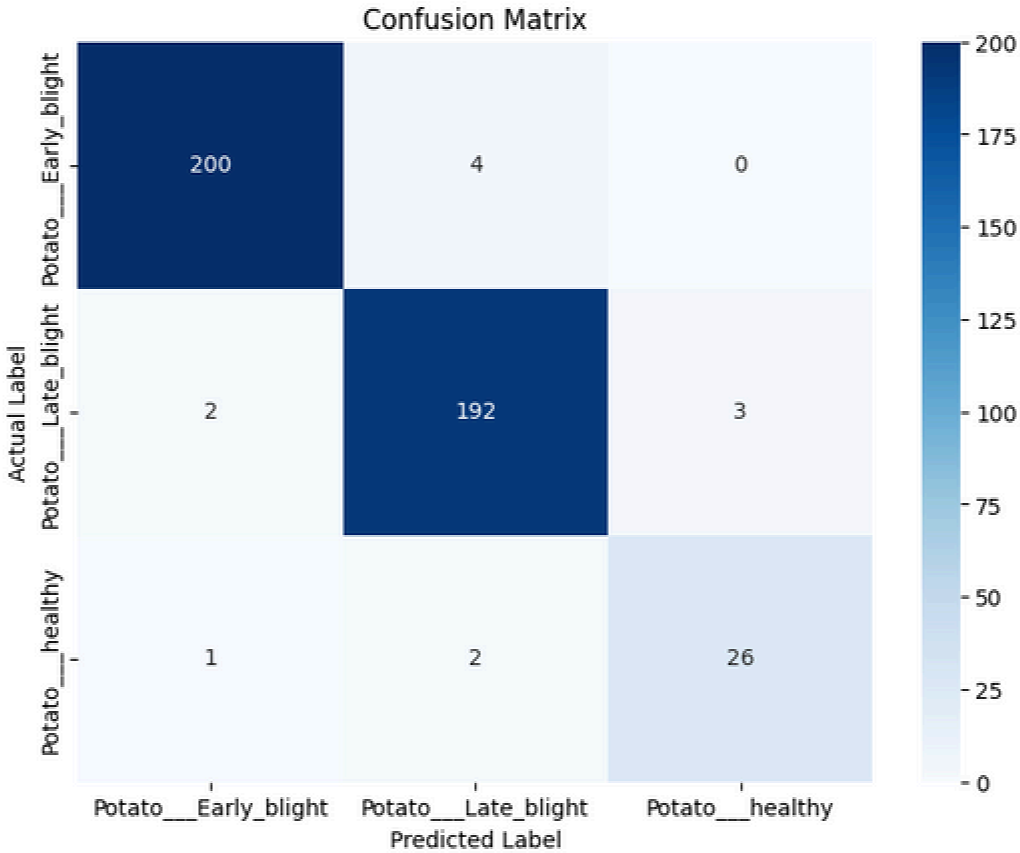

Figure 5

Confusion Matrix for 3 Classes

Figure 6

Sample Prediction Images with Green = Correct, Red = Incorrect

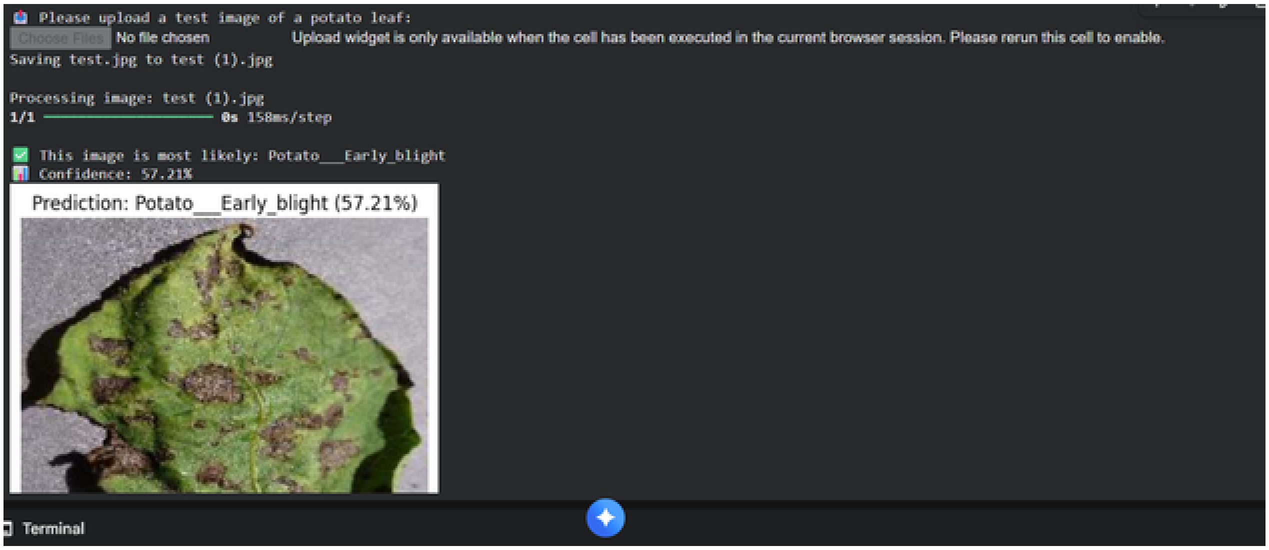

Figure 7

Model Output for a Random Test Image