9.2 DISADVANTAGES

- **Dependency on Image Quality:**

The system heavily depends on clear and well-lit images. Variations in lighting conditions, shadows, background noise, or low-resolution cameras can reduce classification accuracy. Poor image capture may lead to incorrect predictions.

- **Requirement of Large and Balanced Dataset:**

Although transfer learning reduces data requirements compared to training from scratch, the system still needs a sufficiently large and well-labeled dataset. If the dataset is imbalanced or lacks variety in spoilage patterns, the model may not generalize well to real-world conditions.

- **Limited Detection to Visible Defects:**

The model primarily identifies external visual defects such as discoloration, mold, and surface damage. It may not detect internal spoilage that is not visible externally, which can limit overall quality assessment reliability.

- **Initial Development Cost:**

While operational costs are reduced in the long term, the initial setup cost can be significant. Expenses may include camera systems, hardware devices, computational resources, and development time for training models using frameworks like TensorFlow or PyTorch.

- **Need for Regular Model Updates:**

As new fruit varieties or different spoilage patterns emerge, the model may require retraining or fine-tuning. Continuous dataset updates and performance monitoring are necessary to maintain high accuracy.

- **Hardware and Infrastructure Dependency:**

For industrial deployment, integration with conveyor belts, sensors, and IoT systems requires reliable hardware infrastructure. Any hardware malfunction can disrupt the automated sorting process.

- **Risk of Overfitting:** If not properly optimized, transfer learning models such as MobileNetV2 or ResNet50 may overfit the training dataset, resulting in reduced performance on unseen data. Proper regularization and validation techniques are required to prevent this issue.